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Basic Concepts, Methodological Issues and Applications

Second Edition

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We again dedicate this book to the fond memory of Herman O. A. Wold (25 December 1908 to 1916 February 1992), whose energy and creativity were an inspiration to those of us who had the good fortune to work with him. His pioneering work lives on and provides the platform on which this book rests.

Wold and a few other pioneering structural equation modeling scholars established a firm foundation for later PLS methodologists that have extended their initial work. These more recent scholars, mostly emerging in the past couple of decades (2003–2023) have published numerous meaningful extensions of the original algorithm which have literally transformed the analytical capabilities of his innovative platform. We recognize and applaud the individuals who authored these recent enhancements, some of which are described in this book and others likely to be included in future editions of this book.

Foreword

Before you lies the Second Edition of *Partial Least Squares-Path Modeling: Basic Concepts, Methodological Issues and Applications*. Why, you might wonder, would you want to invest time in reading yet another book on PLS? How much novelty could this book possibly offer, and for that matter, how much novelty could a *Second Edition* possibly offer? Isn't PLS the 'wannabe' approach to structural equation modeling (SEM) whereas the covariance-based SEM (CB-SEM) approach is the superior approach? If such questions sound familiar, then this book is for you, and I recommend you keep reading.

SEM has an extensive and well-documented history, rooted in an impressive number of statistical developments that can be traced back to over a century ago. Important developments include the invention of Maximum Likelihood (ML) estimation by R. A. Fischer in the early 1920s and its application to factor analysis by D. N. Lawley almost two decades later. It wasn't until the 1970s with the emergence of software support, most notably LISREL, that SEM became a viable tool for researchers. LISREL combined path analysis with ML estimation for factor analysis, committing to a 'common factor' approach to model theoretical concepts. ML makes several important assumptions, most notably multivariate normality, and a requirement of a sufficiently large sample size to ensure that the asymptotic properties are present (though exactly how large a sample size, is topic of much discussion without straightforward answers). LISREL allowed researchers to apply the various techniques that had been discovered before but were too tedious to apply by hand.

The common factor model is based on the idea that a theoretical concept can be represented by a (statistically) 'common factor': the theoretical concept, which itself is not observable and only hypothesized by a researcher to exist, can be measured through a number of indicators. The latent variable is assumed to be the 'common' source of changes in a set of independent variables (indicators), i.e., the change in the latent variable is 'reflected' in changes in its indicators; hence, the term 'reflective' model. It is common convention that this assumption can be justified as long as at least 50% (0.50) of the variation in an item can be explained by the common factor; or stated technically, the loading of each item should be at least $\sqrt{0.50} \approx 0.708$. If an indicator's value is not primarily affected by the common factor, then it's probably not a good indicator.

PLS, originally proposed by Herman Wold, has its own history, rooted in other statistical advances. It is important to acknowledge the difference between PLS Path Modeling (PLS-PM) and PLS Regression. The former refers to Herman Wold's approach to structural equation modelling, whereas the latter was developed by Herman's son Svante Wold, based on his father's work, but represents a distinct flavor of the iterative PLS algorithm and does not imply SEM. In the remainder, 'PLS' implies PLS-PM. In particular, it combines Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA). Rather than modeling a theoretical concept as a common underlying cause, or common factor, that effects change in a number of observed variables (its indicators), PLS (as well as related approaches such as Generalized Structured Component Analysis (GSCA)) is used to estimate composites, which have also been referred to as 'forged' concepts. It is important to note that PLS is not simply PCA first, followed by CCA. Instead, the PLS-PM algorithm is iterative, as briefly described below.

When we speak of composites, the concepts that they represent and about which we theorize aren't naturally occurring phenomena; rather, they represent things that are composed of one or more parts—a composite *emerges* as a (in the case of PLS, weighted) sum of its constituent components. It represents an alternative approach to modeling constructs when a reflective (factor) model is not appropriate. In technical terms, PLS algorithms first create intermediate proxies (composites), that represent the theoretical variables of interest. These proxies are then used in the evaluation of the structural (or inner) model, the set of hypotheses that the structural equation model represents. The values for the proxies and the inner model are then updated iteratively until some stop criterion is fulfilled. This is a key difference with covariance-based SEM estimators, which evaluates *all* equations (representing both the measurement model and the structural model) at the same time.

The debate over whether or not PLS is an appropriate method for structural equation modeling, and its comparison to factor-based SEM seems to have only increased in intensity over the past years and continues today. The debate is at times fierce, and complicated at times as there are at least three perspectives. There are those who argue fiercely against the use of PLS, there are those who present PLS in a very positive light, perhaps too uncritically, and there are those who actively conduct methodological research to explore its limitations and develop new extensions. The critiques of PLS should be seen as a blessing, and part of a healthy scientific discourse. Through this debate, proponents and opponents have laid out their points of view, their arguments, and their assumptions, which have helped to understand different perspectives. But it has also instigated vigorous research on PLS to better understand its limitations, and has given rise to a deeper reflection on the mechanics of PLS which laid bare several misconceptions about PLS and its use have become more clear. There are widespread misunderstandings about PLS, for example, that it is suitable for small samples, or more appropriate when modeling so-called formative (as opposed to reflective) constructs. Yes, PLS can be used with smaller samples, for the simple reason that a covariance-based SEM estimator may not converge to a solution, leaving the researcher with no results at all. But that is not to say that using a small sample is unproblematic; the use of small samples leads to biased results.

Despite the ongoing debate between opponents and proponents of PLS, there is a growing body of literature that helps us to understand the place of PLS, but also that the traditional CB-SEM versus PLS debate doesn't tell the whole story. SEM represents a larger family of approaches. PLS is not simply a single or 'cheaper' alternative to CB-SEM, but represents its own family of approaches to composite (rather than factor-based) estimation. PLS is not a replacement for CB-SEM (or vice versa); they rely on a different logic. For example, the use of PLS to estimate a common factor model is incorrect because PLS isn't suitable for that. It is these fundamentals that are often not understood by researchers.

SEM techniques can be classified according to three dimensions: estimation model (factor versus composite), optimization criterion (variance-based versus covariance-based), and the information that serves as input into the estimation (full versus limited). Whereas covariance-based SEM (using Maximum Likelihood estimation) is the most common approach to a factor-based model, PLS is the most common approach to a composite-based model. The classification comprises a range of other techniques, including GSCA and variants, and Consistent PLS (PLSc).

Ultimately, awareness of, and a pro-active attitude to learning the wide range of analytical methods that are available to us is key in conducting high-quality research. A well-considered choice based on rigorous methodological research is key, and as researchers we have an obligation to keep learning. Several other issues apart from the choice of modeling approach are, in my opinion, important.

First, no study must be taken on its own as presenting sufficient evidence for (or against) the existence of relationships that scholars seek to understand. Modeling real-world phenomena is incredibly complicated and fraught with challenges, and there are many things that can go wrong in the research process. For a true evidence-based clinical or industry practice, professionals must rely on a cumulative evidence base that grows over time, whereby findings are replicated and confirmed using a variety of methods. Somewhat related is the well-known concern about p-hacking, and that hypotheses with a p-value of 0.048 are 'supported' (failed to be rejected), and those with a p-value of 0.052 are 'not supported' (rejected).

Second, as others before me have said, there are occasions where CB-SEM simply doesn't work; the model doesn't converge, the sample turns out to be too small, or it seems that the selected operationalization of latent variables is, in hindsight, not representing a common factor that causes change in its indicators, but more a group of 'related' items that are better modeled as a composite. I have seen published papers that 'measured' a common factor through a series of items that were effectively three versions of the same paraphrased statement; no wonder that those CB-SEM models performed wonderfully! Clearly, authors, editors, and reviewers all have a responsibility in reflecting critically on how our theoretical variables of interest are measured. Authors must take care in operationalizing their theoretical constructs, and editors and reviewers must remain cognisant of the latest methodological developments.

Third, a major concern in much published SEM research is not the analytical method, but rather the research design itself. Cross-sectional surveys represent a single snapshot in time, and cannot provide hard evidence for a *causal* relationship between an exogenous and endogenous variable. What is needed, and what is increasingly required by quality journals, is more advanced research designs such as longitudinal or time-series approaches.

Finally, for those researchers who start out with any SEM analysis, whether that's covariance-based or variance-based SEM, and are struggling with the technical challenges and complexities of conducting the analysis, it is easy to forget about the role of theory. Real-world data is messy, and hardly ever resembles the stylized examples in SEM textbooks. Finding a model that works for you is exciting when you start out, but it is important that we not forget about the theoretical justification of that model; the theory represents the conceptual thinking, the rationale for doing all the analysis. While Wold suggested that PLS may be useful when you are "data rich" and theory poor, this can be no excuse to analyze data without any theoretical framework, merely looking for statistical significance.

The book that I hope you are about to read presents a wealth of new insights on PLS as a family of approaches to conduct structural equation modeling. There are a number of reasons to be excited about PLS, and this book provides excellent entry points. First, as researchers we are continuously in pursuit of answering interesting research questions. As our questions become more complicated, involving mediators, moderators, data heterogeneity, hierarchical modeling, and necessary condition analysis, we need to master more advanced tools. This volume offers a number of new developments in the suite of PLS analyses as well as practical applications that can serve as excellent examples and inspiration for your own research agenda. Another reason to be optimistic is the range of software solutions that are available today. Long gone are the days that SEM software (both for PLS and CB-SEM) was hard to use, or expensive. There are excellent software tools for PLS analyses, both open source and with affordable commercial licenses. One of the chapters in this book presents an updated overview of tool support.

This book contributes to the continued development of PLS as a set of tools that can help scientists in answering their research questions. It also contributes to the methodological literature that demonstrates and clarifies how to use PLS, and that helps us move away from outdated notions and misconceptions about PLS. Whether you are a novice PLS user or an experienced researcher who has used PLS before and who seeks to keep up-to-date, I hope this book helps in your learning journey.

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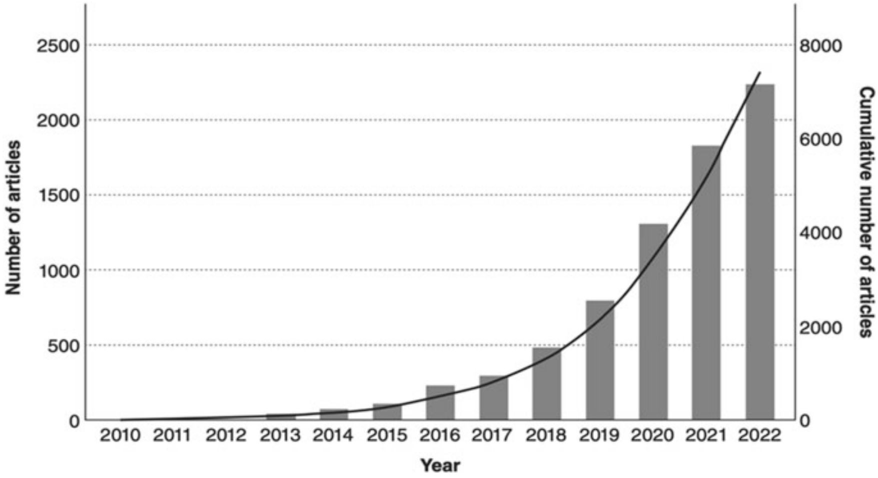
Preface

Partial least squares-path modeling (PLS-PM) is a multivariate statistical technique first introduced by Herman Wold in the late 1960s. The period from that time until the late 1980s can be viewed as the 'gestation period,' during which methodologist extended the initial capabilities to include latent variables in path models and scholars began to recognize the potential of this alternative structural equation modeling method. User-friendly software to obtain solutions emerged in the mid-1990s when Wynne Chin introduced PLSgraph but applications of the method were slow to develop until Christian Ringle and colleagues introduced the SmartPLS software in 2005.

A period of rapid development began in 2011 with two seminal publications: 'Partial Least Squares Structural Equation Modeling: Indeed a Silver Bullet,' by Hair, Sarstedt, and Ringle (2011), and a couple of years later the introductory book *A Primer on Partial Least Squares Structural Equation Modeling* (PLS-SEM) by Hair, Hult, Ringle, and Sarstedt (2014), with combined citations of almost 58,000 times (Google Scholar, 2/14/23). More specifically, these publications and other related ones expanded the knowledge base of PLS-PM, increasingly known as PLS-SEM, to research in various other fields, including accounting, business ethics, education, family business, information systems, international business, marketing, operations management, human resources, hospitality, strategic management, sustainability, linguistics, entrepreneurship, and tourism. As can be seen in the below graph, the growth in PLS-SEM publications has grown exponentially.



Note The above chart used with permission from (Hair, Sarstedt, Ringle, & Gudergan, *Advanced Issues in Partial Least Squares Structural Equation Modeling*, Sage, 2nd edition, 2023)

Along with the rapid pace of development, and thankfully not as widespread, the PLS-PM methodology has not escaped controversies. Some of the criticisms, such as its use with small sample sizes, the absence of a goodness of fit indices, alleged bias in parameter estimation, and measurement model confusion, have spawned two groups debating among scientists, academics, and practitioners. These criticisms appear to be similar to those from almost 60 years ago that attempted to attack exploratory factor analysis (EFA) when scholars did not understand the value of the method. Today, scholars might note the limitations of EFA but would be very unlikely to question the benefits of the method. Hopefully, the eventual course of events will be continued expansion of PLS where the benefits far outweigh the limitations, most of which are typical of all statistical analysis techniques.

In the past decade, many loyal supporters of the PLS-PM have demonstrated the method is feasible to maintain, provides many advantages not available with other analytical methods, and will continue to develop for many years to come. New breakthroughs ranging from heterotrait–monotrait (HTMT) ratio for discriminant validity, measurement invariance of composites (MICOM), PLS predict for out-of-sample prediction, higher-order models (HOCs), non-linear SEM model solutions, importance-performance map analysis (IPMA), observed heterogeneity modeling options such as MICOM and multigroup analysis (MCA), unobserved heterogeneity approaches such as finite mixture PLS (FIMIX) and PLS prediction-oriented segmentation (PLS-POS), cross-validated predictive ability test (CVPAT), consistent partial least squares (PLSc), goodness of fit indices (i.e., SRMR and NFI), and other features have led to a lively discussion of the emancipation of the PLS-PM method. At the same time, the outdated discourse has been left behind to build solid inferential statistics from the PLS-PM method. Indeed, there is a glimmer of hope and a possible intersection between the debating groups now, where consent and conclusion can likely be established. Thus, PLS-PM is no longer merely an alternative to covariance-based SEM but has transformed into a stand-alone method capable of solving many real-world problems.

The purpose of this book is to introduce what we believe are essential recent developments and techniques in the PLS-PM field. If you are a new reader of this book, we recommend that you start with the first edition of the book which can be found here https://link.springer.com/book/10.1007/978-3-319-64069-3. It is important to underline that the second edition of this book covers different topics and broadens the scope of the first edition of the book. The second edition of this book provides a comprehensive overview and complements the first edition of our book of recent developments in the PLS-PM method and the current state of the most advanced research related to the PLS-PM field. By focusing primarily on major advances in the PLS-PM technique, with example cases and applications, we hope the contributions are both enlightening and instructional. Each chapter assumes the reader has mastered the equivalent of a basic multivariate statistics course that included coverage of most fundamental PLS-PM techniques.

Each chapter in this book contains an up-to-date description of a recent development or technique in PLS-PM and is written by one of the authors who originally proposed or contributed substantially to its development. Each chapter also provides complete references to the pertinent literature on the topic. Decisions regarding the selection and organization of the chapters for the second edition of the book were quite challenging. In order to maintain the balance and continuity of the editions of this book, we limit ourselves to repeating the topics discussed in the first edition, unless there is significant progress on these topics. Obviously, within the book only a limited number of topics could be addressed. In the end, the choice of the material for the second edition of this book was governed by our observations regarding the most important new developments within the PLS-PM field, as well as the ability of contributors to fit this task into their busy schedules.

The book is divided into three main parts. Part I consists of five chapters emphasizing the basic concepts and extensions of the PLS-PM method.

In Chap. 1, "Introduction to the Partial Least Squares-Path Modeling: Basic Concepts and Recent Methodological Enhancements," *Hengky Latan, Joseph F. Hair Jr., Richard Noonan, and Misty Sabol* provide a brief overview of the three primary structural equation modeling approaches, which include partial least squares-path modeling (PLS-PM), covariance-based structural equation modeling (CB-SEM), and generalized structure component analysis (GSCA). This chapter also provides guidelines regarding the appropriate situation to apply each of the three SEM methods. In addition, their article describes recent methodological developments in SEM, particularly the method of PLS-PM, as well as applications of selected essential features of PLS-PM which are considered as essential emerging tools for PLS-PM scholars since increasingly their understanding and application will be required in research utilizing PLS-PM. In the end, this chapter summarizes observations and conclusions regarding the evolving state of PLS-PM.

In Chap. 2, *Cristina Davino, Pasquale Dolce, Giuseppe Lamberti, and Domenico*

Vistocco, introduce the reader to "Quantile Composite-Based Path Modeling with R: A Hands-on Guide." Their chapter provides step-by-step instructions to implement, estimate, and interpret a Quantile Composite-based Path Model. This alternative composite-based approach relies on the qcpm package (https://rdrr.io/cran/qcpm/), freely available for the R software. The chapter includes the methodological aspects of this recent quantile approach to PLS-PM, as well as real data applications. It also is a comprehensive 'how-to' guide for readers interested in applying the method with their own data. Finally, a step-by-step process for data loading, pre-processing, coefficient estimation, and model validation is also described, including the options and functionalities of the package and methodology.

In Chap. 3, *Stacie Petter and Yasamin Hadavi*, in their article entitled "Use of Partial Least Squares-Path Modeling Within and Across Business Disciplines," identify the prevalence of PLS-PM use within and across business disciplines. Acceptance and application of PLS-PM varies dramatically across business disciplines. Some business disciplines, such as marketing and information systems, have used PLS-PM for decades. Other disciplines, such as accounting and management, have been much slower at incorporating path models and PLS-PM in their research studies. The differences in adoption of PLS-PM across business disciplines can be confusing for authors interested in applying, using, and reporting the PLS-PM results in published research within their own discipline or across business disciplines. This chapter addresses this concern by reviewing the use and application of PLS-PM based on the Financial Times (FT50) journals. A review of rationales provided by authors for their use of PLS-PM within and across business disciplines identifies questionable and appropriate rationales for applying PLS-PM and offers guidance for authors intending to publish articles using PLS-PM.

In Chap. 4, *Ke-Hai Yuan and Zhiyong Zhang* describe the "Statistical and Psychometric Properties of Three Weighting Schemes of the PLS-SEM Methodology." Their Chapter initially notes that while covariance-based SEM (CB-SEM) permits estimating the regression relationship among latent constructs, the parameters governing this relationship do not apply to the construct scores, which are required for prediction, classification, and/or exploration of individuals/respondents. In contrast, the partial least squares approach to SEM (PLS-SEM) first obtains weighted composites for each case, including determinant scores, and then estimates the structural relationships between the composites. This feature makes PLS-SEM the preferred method for predicting and/or classifying individuals, both in-sample and out-of-sample. At the same time, however, the properties of PLS-SEM still depend on how the composites are formulated. Herman Wold proposed using mode A to compute composite scores when reflective indicators are theorized. But Yuan and Deng recently demonstrated that composites following mode B have better psychometric properties. To do so, they proposed a structured transformation from mode A to mode B, denoted as Mode B_A. This chapter summarizes the properties of the three modes of PLS-SEM and provides analytical and numerical results showing: (1) Mode A does not possess any solid statistical or psychometric properties, (2) Mode B possesses good theoretical properties but is overly sensitive to sampling errors, and (3) Mode B_A possesses good theoretical properties as well as numerical stability. Finally, the three modes are illustrated with two real data examples.

In Chap. 5, *Sergio Venturini, Mehmet Mehmetoglu, and Hengky Latan*, in their article entitled "Software Packages for Partial Least Squares Structural Equation Modeling: An Updated Review", the authors note the increased attention in recent years of the partial least squares (PLS) approach to structural equation modeling (SEM) from applied researchers and practitioners in numerous fields. One reason for this growth in interest is demonstrated by the many theoretical contributions emerging from the PLS-SEM research community, which have enabled scholars to extend our knowledge of the method as well as its capabilities into new contexts. These contributions likely would have remained confined to academic journals if not for a parallel and similar development in the software packages available to implement these methodological innovations. Indeed, the lack of advanced and user-friendly software has been the main reason for the delay in the diffusion of this method in the applied sciences. Fortunately, today many high-quality packages are available for performing all varieties of PLS-SEM analyses. This chapter presents an updated review of the most popular commercial and open-source software packages for PLS-SEM. In particular, the main features of the ADANCO, SmartPLS, WarpPLS, XLSTAT-PLSPM, the Stata package for plssem, and the cSEM and SEMinR packages for R, are illustrated in this chapter using a publicly available data set. Their corresponding strengths and weaknesses are also summarized.

Part II of the book discusses methodological issues that are the focus of recent developments in the PLS-PM method. This part consists of five chapters.

In Chap. 6, *Tamara Schamberger, Gabriele Cantaluppi, and Florian Schuberth* in their article entitled "Revisiting and Extending PLS for Ordinal Measurement and Prediction," the authors note that applications of both partial least squares (PLS) and consistent partial least squares (PLSc) traditionally assume the indicators are continuous. In contrast, ordinal partial least squares (OrdPLS) and ordinal consistent partial least squares are extensions of PLS and PLSc that take into account the nature of ordinal measurement variables modeled as either exogenous or endogenous constructs. In the PLS context, assessing the out-of-sample predictive power of models has increasingly gained interest. In contrast to PLS and PLSc, performing out-of-sample predictions is not a straightforward process for OrdPLS and OrdPLSc because the two approaches assume ordinal indicators are the outcome of categorized unobserved continuous variables, i.e., they rely on polychoric and polyserial correlations. This chapter includes examples of the application of OrdPLSpredict and OrdPLScpredict to perform out-of-sample predictions, as well as a Monte Carlo simulation demonstrating and evaluating our proposed approach. Finally, concise guidelines are provided for using the open-source R package cSEM to enable researchers to apply the OrdPLSpredict and OrdPLScpredict procedures.

In Chap. 7, *Sandra Streukens and Sara Leroi-Werelds*, in their article "Multicollinearity: An Overview and Introduction of Ridge PLS-SEM Estimation," note that multicollinearity, defined as the existence of high correlations among (combinations of) predictor variables, is a commonly encountered phenomenon that affects (PLS-SEM) parameter estimates. The chapter provides an extensive overview of multicollinearity, its consequences, detection, and possible solutions. Critical to this overview is the explicit distinction among three types of multicollinearity: (1) canonical structural multicollinearity, (2) numerical multicollinearity, and (3) common factor multicollinearity. In addition, ridge PLS-SEM—an approach that combines the principles of ridge regression and PLS-SEM modeling—is introduced as an effective approach to mitigate the effects of canonical structural multicollinearity on estimation results.

In Chap. 8, *James Gaskin, Samuel Ogbeibu, and Paul Benjamin Lowry*, in their article entitled "Demystifying Prediction in Mediation Research and the Use of Specific Indirect Effects and Indirect Effect Sizes," summarize the maturing state of partial least squares structural equation modeling (PLS-SEM) research, noting it has seen exceptional knowledge advances over the past decade. In contrast, applications among lay researchers have increased at a much slower pace. The authors conclude this gap between PLS-SEM scholarly research and practice may be attributed to the sophisticated and arcane approach to detailing new methodological advances. Moreover, to date prediction has been a peripheral topic in PLS-SEM mediation literature. This chapter is at the intersection of these two gaps. First, to enhance our understanding of the intertwining roles of prediction and mediation. Second, to offer practical demonstrations of two particularly obscure topics in mediation research: (1) specific indirect effects, and (2) indirect effect sizes.

In Chap. 9, *Rosanna Cataldo, Maria Gabriella Grassia, and Carlo Natale Lauro*, in their article entitled "Alternative Approaches to Higher Order PLS Path Modeling: A Discussion on Methodological Issues and Applications," the authors note that in the context of PLS-PM, higher-order constructs (HOCs) have enjoyed increasing popularity in the last few years when investigating models with a high level of abstraction, particularly in cases where the conceptualization of a system of indicators depends on different levels of information. Higher-order constructs in PLS-PM are considered explicit representations of multidimensional constructs which are related to other constructs at a higher level of abstraction, thereby mediating completely the influence received from, or exercised on, their underlying dimensions. This chapter reviews the status and evolution of research studies on higher-order constructs in PLS-PM and focuses attention on the potential offered by their recent methodological developments, specifically on how they can help researchers to estimate complex and multidimensional phenomena. Different approaches are discussed and compared using a case study in a social context.

In Chap. 10, *Nicole Franziska Richter, Sven Hauff, Christian M. Ringle, Marko Sarstedt, Aleksandar E. Kolev, and Sandra Schubring*, in their article entitled "How to Apply Necessary Condition Analysis in PLS-SEM," the authors illustrate the application of necessary condition analysis (NCA) in the context of partial least squares structural equation modeling (PLS-SEM). The joint application of the two methods using the SmartPLS 4.0 software, which incorporates PLS-SEM as well as the core NCA computation capabilities, explains background information on the key steps and interpretations associated with the combined application. In addition, the fundamentals of necessity logic and NCA are summarized, outlining key differences to

PLS-SEM and its underlying logic. Using recently published guidelines and an illustrative example of the combined application of the two methods, the chapter provides guidance on generating results and interpreting 'must-have' and 'should-have' factors in the PLS-SEM context, enabling researchers to identify necessary conditions that may underlie their significant and also nonsignificant structural model relationships. The consideration of both must-have and should-have factors through the joint use of PLS-SEM and NCA is a unique way of assessing causality that may advance research in multiple fields. This chapter contributes to the further diffusion of the two logics in research applications. Additionally, guidelines and systematic application of the two methods will assist researchers in exploiting the most meaningful potential of their study findings.

Part III of this book discusses the real-world applications of the PLS-PM method in various disciplines. This section consists of four chapters.

In Chap. 11, *Diana Ingenhoff, Dominique Richner, and Marko Sarstedt*, in their article entitled "New Insights for Public Diplomacy Using PLS-SEM to Analyze the Polyphony of Voices: Value Drivers of the Country Image in Western European and BRICS countries," the authors describe successful public diplomacy of a nation state. They confirm it is essential to thoroughly analyze the country image in strategically relevant countries and develop coherent communication strategies that take into consideration the polyphony of voices raised by different countries when fostering a good country image abroad. Their study applied the five-dimensional country image measurement scale to data collected in cooperation with the Federal Department of Foreign Affairs in Switzerland (Presence Switzerland). Specifically, the similarities and differences were examined between the (drivers of) country image in neighboring and close countries (France, Germany, Italy, and United Kingdom) and those with a substantial geographical distance from Switzerland (Brazil, Russia, China, and South Africa). Furthermore, they performed a cluster analysis, resulting in a Western European cluster and a BR(I)CS cluster. By applying the news values theory and stereotypes, they empirically tested and confirmed their hypothesis that countries differ in their image of other countries regarding geographical, cultural, and political proximity to the target country. Finally, the potential benefits for public diplomacy when applying PSL-SEM and developing coherent communication strategies were explored.

In Chap. 12, *Jubalt Alvarez-Salazar and Jean Pierre Seclen-Luna*, in their article entitled "To Survive or Not to Survive: Findings from PLS-SEM on the Relationship Between Organizational Resources and Startups Survival," the authors explored the phenomenon of startup survival in an incipient entrepreneurship ecosystem. Multiple, simultaneous relationships between organizational resources, incubation, and startup survival were examined empirically. The analysis used PLS-SEM with a sample of 119 startups operating in different markets in Peru. The results show survival is explained directly by a combination of entrepreneurial and organizational capital and indirectly by a chain of causal links. In this way, social capital determines human capital, and human capital also determines entrepreneurial capital.

The study contributes to the literature in management and entrepreneurship, therefore, as an alternative approach to measure a phenomenon of greater complexity and demonstrate the survival of Peruvian startups.

In Chap. 13, *Manuel Cano-Rodríguez and Ana Licerán-Gutiérrez*, in their article entitled 'Influence of Earnings Quality Dimensions on the Perception of Earnings Quality: An Empirical Application of Composite PLS Using Archival Data,' the authors note that previous empirical research on Earnings Quality (EQ) has identified a wide range of earnings properties anticipated to be related to EQ. Research on how these properties affect investors' perceptions of earnings quality is sparce, however, as most studies of EQ focus on a single EQ dimension. Moreover, extant research has several limitations, including that most studies rely on first-generation statistical methods (mainly OLS) and do not empirically assess the validity of the indicators used to measure the underlying EQ dimension. This Chapter explores how the different EQ properties map onto stockholders' perceptions of EQ. Using PLS-SEM, our results show that some of the more widely studied properties in accounting research (such as accruals quality) have little influence on stockholders' perceptions of earnings quality. At the same time, other less frequently studied properties (such as persistence and smoothing) exhibit a stronger relationship with stockholders' perceptions of EQ. Finally, their findings indicate the typical indicators used in previous research to represent accounting conservatism do not converge into a single construct, possibly indicating those diverse indicators may represent different underlying concepts and would be better conceptualized as a higher-order construct (HOC).

In Chap. 14, *Umme Habiba Rehman*, *Ambreen Rehman*, *Zeeshan Ahmed*, *Muhammad Maaz Sajid*, and *Fasih Ur Rehman*, in their article entitled "Importance-Performance Map Analysis of Capital Structure Using PLS-SEM: Evidence from Non-financial Sector," the authors identify the most important determinants influencing capital structure decisions of non-financial firms listed on the Pakistan Stock exchange (PSX). The study uses balanced panel data of firm, industry, and macroeconomic-specific observations for a 14-year period (2006–2019) and partial least squares structural equation modeling (PLS-SEM). Importance-Performance Map Analysis (IPMA) was executed to determine the most important determinants of capital structure decisions for non-financial firms listed on the PSX. Findings of the study indicate asset structure is the most important determinant of long-term debt selection in the capital structure decision for non-financial firms. More specifically, leverage performance is increased by the effects of asset structure, and tangibility is the most important indicator of asset structure, when modeling the trend of capital structure requiring managerial attention to achieve the optimal outcome. The prospects for financial managers and policymakers to implement improved capital structure strategies and achieve better firm performance are identified based on considering the importance of individual factors for increasing investment and boosting the economy.

This book could not have been compiled without the assistance and support provided by many individuals. First, we would like to thank all the contributors for their time and effort in preparing chapters for this book. We would particularly like to thank the reviewers who evaluated each chapter and prepared meaningful comments consisting of: Alexandre Sukhov (Karlstad University, Sweden), Ana Irimia-Dieguez (University of Seville, Spain), Arturs Kalnins (University of Iowa, USA), Christian M. Ringle (Hamburg University of Technology, Germany), Christian Nitzl (University of the German Federal Armed Forces Munich, Germany), Cristina Davino (University of Naples Federico II, Italy), Dirk Temme (University of Wuppertal, Germany), Florian Schuberth (University of Twente, Netherlands), Gabriel Cepeda Carrion (University of Seville, Spain), Gabriele Cantaluppi (Catholic University of the Sacred Heart, Italy), Galit Shmueli (National Tsing Hua University, Taiwan), Hao Cheng (National Academy of Innovation Strategy, China), Héctor Cuevas-Vargas (Technological University of the Southwest of Guanajuato, Mexico), Heungsun Hwang (McGill University, Canada), James Gaskin (Brigham Young University, USA), Jan Dul (Erasmus University Rotterdam, Netherlands), Jun-Hwa Cheah (University of East Anglia, UK), Lăcrămioara Radomir (Babeş-Bolyai University, Romania), Marko Sarstedt (Ludwig Maximilian University of Munich, Germany), Mehmet Mehmetoglu (Norwegian University of Science and Technology, Norway), Michael Klesel (University of Twente, Netherlands), Murad Moqbel (University of Texas Rio Grande Valley, USA), Nicole F. Richter (University of Southern Denmark, Denmark), Pasquale Dolce (University of Naples Federico II, Italy), Pratyush N. Sharma (The University of Alabama, USA), Rosanna Cataldo (University of Naples Federico II, Italy), Santha Vaithilingam (Sunway University, Malaysia), Soumya Ray (National Tsing Hua University, Taiwan), Stacie Petter (Wake Forest University, USA), Sandra Streukens (Hasselt University, Belgium), Shikha Bhatia (International Management Institute New Delhi, India), Tamara Schamberger (University of Würzburg, Germany) and Wilfred H. Knol (Radboud University, Netherlands). Moreover, we are greatly indebted to our publisher, Springer, for publishing this book, and to the wonderful people on the editorial staff. Their prompt response and assistance in compiling this volume were essential. Finally, we thank our families for their love and support, and for continually enduring a seemingly endless list of projects.

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Abbreviations

2SLS	Two-stage Least Squares
ADANCO	Advanced Analysis of Composites
AIC	Akaike's Information Criterion
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
B2B	Business-to-Business
B2C	Business-to-Consumer
B2G	Business-to-Government
BC	Bias-corrected [confidence interval]
BCa	Bias-corrected and accelerated [confidence interval]
BIC	Bayesian Information Criterion
BLUE	Best Linear Unbiased Estimates
BRICS [countries]	Countries belonging to the association of five major emerging national economies: Brazil, Russia, India, China, and South Africa
C	Ceiling Zone
C2C	Consumer-to-Consumer
CA	Correspondence Analysis
CAIC	Consistent AIC
CBSEM	(Also CB-SEM). Covariance-based Structural Equation Model
CCA	Canonical Correlation Analysis. Also refers to Confirmatory Composite Analysis; similar process for PLS as CFA—Confirmatory Factor Analysis
CE-FDH	Ceiling Envelopment—Free Disposal Hull
CFI	Comparative Fit Index
CFM	Composite Factor Model
CI	Confidence Interval
CR	Coefficient of Reliability. Also called Composite Reliability
CRAN	Comprehensive R Archive Network
CR-FDH	Ceiling Regression—Free Disposal Hull

cSEM	Composite-Based Structural Equation Modeling (R Package)
CTA	Confirmatory Tetrad Analysis
CVIF	Corrected VIF
CVPAT	Cross-validated Predictive Ability Test
dG	Geodesic discrepancy. Try GD or Gd
DGP	Data Generating Process
dULS	Unweighted Least Squares discrepancy
EQ	Earnings Quality
ERC	Earnings Response Coefficient
FIMIX-PLS	Finite Mixture PLS
FT50	Journals included in the Financial Times' list of the top 50 academic publications
GCCA	Generalized Canonical Correlation Analysis
GFI	Goodness of Fit Index
GLS	Generalized Least Squares
GoF	Goodness of Fit
GSCA	Generalized Structured Component Analysis
GSCAm	Generalized Structured Component Analysis with Measurement Errors Incorporated
HQ	Hannan-Quinn criterion
HTMT	HeteroTrait-MonoTrait [ratio of correlations] based on arithmetic means
HTMT2	HeteroTrait-MonoTrait [ratio of correlations] based on geometric means
IFI	Incremental Fit Index
IGSCA	Integrated Generalized Structured Component Analysis
IPMA	1. Importance-Performance Map Analysis. 2. Importance-Performance Matrix Analysis
Istat	Italian National Institute of Statistics
lavaan	Latent Variable Analysis [R package]
LISREL	Linear Structural Relations
LM	Linear model
LV	Latent Variable
MAE	Mean Absolute Error
MCD	Minimum Covariance Determinant
MER	Misclassification Error Rate
MGA	Multigroup Analysis
MICOM	Measurement Invariance of Composites across Groups
MIMIC	Multiple Indicators, Multiple Causes
ML	Maximum Likelihood
MLR	Multiple Linear Regression
MSE	Mean Squared Error
MTB	Market-to-Book [ratio]
MV	Manifest Variable
MVP	Minimum Viable Product

NCA	Necessary Condition Analysis
NFI	Normed Fit Index
NIPALS	Nonlinear Iterative Partial Least Squares
NML	Normal-distribution-based Maximum Likelihood
NNFI	Non-normed Fit Index
OLS	Ordinary Least Squares
OrdPLS	Ordinal PLS
OrdPLS(c)	Reference to *both* OrdPLS *and* OrdPLSc
OrdPLSc	Ordinal Consistent PLS
OrdPLScpredict	An approach to performing predictions based on a model estimated by OrdPLSc
OrdPLSpredict	An approach to performing predictions based on a model estimated by OrdPLS
PCA	Principal Components Analysis
PLS	Partial Least Squares
PLSc	Consistent PLS
PLS-PM	Partial Least Squares-Path Modeling
PLS-POS	PLS Prediction Oriented Segmentation
PLSpredict	Out-of-Sample Prediction Metric
Plssem	Open-source software package for PLS-SEM that runs in Stata
PLS-SEM	See PLS; SEM
PML-PLS	Partial Maximum Likelihood PLS
POT	Pecking Order Theory
PR	Public Relations
QC	Quantile Correlation
QCPM	Quantile Composite Path Modeling [R package]
QC-PM	Quantile Composite-based Path Modeling
QR	Quantile Regression
R	A software language and environment for statistical computing and graphics
REBUS-PLS	Response-based Procedure for Detecting Unit Segments in PLS
RegPLSc	Regularized PLSc
RGCCA	Regularized Generalized Canonical Correlation Analysis
RMS	Root Mean Square
RMSE	Root Mean Squared Error
RMSEA	Root Mean Square Error of Approximation
RMS_{theta}	Root Mean Square Error Correlation
Robust PLS	Algorithm for dealing with outliers in PLS
RQ	Research Question
SCM	Stereotype Content Model
SEM	Structural Equation Model
SEMinR	Building and Estimating Structural Equation Models (R Package)

SMAR	Standardized Mean Absolute Residual
SmartPLS 4	A Software with Graphical User Interface for PLS-SEM
SPR	Simpson's Paradox ratio
SRMR	Standardized Root Mean [Square] Residual
STDCR	Standardized Threshold Difference Count Ratio
STDSR	Standardized Threshold Difference Sum Ratio
TAM	Technology Acceptance Model
TOT	Trade-off Theory
ULS	Unweighted Least Squares
VIF	Variance Inflation Factor
WarpPLS 8	Nonlinear Structural Equation Modeling for PLS
XLSTAT-PLSPM	PLS Path Modeling—Statistical Software for Excel

Contents

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Hengky Latan currently serves as research director at the FTD Institute and senior researcher at HLC Consulting (Indonesia). He has authored over 15 books including *Covariance Structure Analysis* (CSA), *PLS-Path Modeling* (PLS-PM) and *Generalized Structure Component Analysis* (GSCA) for Structural Equation Modeling (SEM) approaches and several multivariate analysis books using IBM SPSS and Stata. He is also the Editor-in-Chief for the edited book on PLS-PM published by Springer (Cham). His current research addresses the business ethics, sustainability, human resource management, innovation, and quantitative methods. He has published over 50 articles, most of them in leading international journals such as the *Journal of Business Ethics*, *Human Resource Management Journal*, *International Journal of Production Economics*, *Ecological Economics*, *Technological Forecasting & Social Change*, *Journal of Business Research*, *Industrial Marketing Management*, *Technovation* and others. He has also been included in Stanford University's ranking of the 2% most cited scientists globally since 2021. He frequently publishes in FT50, CABS4, CNRS1 and FNEGE1 journals. According to Google Scholar, his works have been cited more than 15,000 times (H-Index = 46) in just eight years of his academic career.

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Part I
Basic Concepts and Extensions

Chapter 1
Introduction to the Partial Least Squares Path Modeling: Basic Concepts and Recent Methodological Enhancements

Hengky Latan, Joseph F. Hair Jr., Richard Noonan, and Misty Sabol

Abstract This chapter aims to provide a brief overview of the three primary structural equation modeling approaches, which include partial least squares-path modeling (PLS-PM), covariance-based structural equation modeling (CB-SEM), and generalized structure component analysis (GSCA). We also provide guidelines regarding the appropriate situation to apply each of the three SEM methods. In addition, we describe recent methodological developments in SEM, particularly the method of PLS-PM, as well as applications of selected essential features of PLS-PM. We identify these topics as essential emerging tools for PLS-PM scholars since increasingly their understanding and application will be required in research utilizing PLS-PM. In the end, we summarize our observations and conclusions regarding the evolving state of PLS-PM.

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1.1 Introduction

Social science researchers have a variety of analytical methods to obtain solutions to complex relationships between multiple latent variables, ensure rigor in their analysis, and facilitate replicability by subsequent scholars. Many researchers seeking a method to achieve these goals have increasingly turned to partial least squares path modeling (PLS-PM) (Hair et al., 2022, 2023; Latan & Ghozali, 2022; Mehmetoglu & Venturini, 2021). Others continue to rely on the traditional covariance-based structural equation modeling approach (CB-SEM) (Hoyle, 2023; Kline, 2023; Whittaker & Schumacker, 2022). At the same time, methodologists are developing new structural equation modeling approaches such as generalized structural component analysis (GSCA), which combine characteristics between PLS-PM and CB-SEM (Hwang & Takane, 2015; Latan, 2014).

To ensure these SEM methods are properly applied and interpreted, and applications take advantage of the most recent analytical extensions, it is important for researchers to become familiar with recent methodological advances. Research scholars need to expand their knowledge of alternative SEM approaches, features, and limitations. This chapter begins with an overview of the three primary structural equation modeling approaches, which include PLS-PM, CB-SEM, and GSCA. We also provide guidelines regarding the appropriate situation to apply each of the three SEM methods. The next section describes recent methodological developments in SEM, particularly the method of PLS-PM, as well as applications of selected essential features of PLS-PM. We identify the topics in this section as essential emerging tools for applied researchers since increasingly their understanding and application will be required in study utilizing PLS-PM. The final section summarizes our observations and conclusions regarding the evolving state of PLS-PM, more recently known as partial least squares structural equation modeling (PLS-SEM).

1.2 Overview of Three Primary SEM Methods

The partial least squares path modeling (PLS-PM) approach was proposed almost 60 years ago as a method to combine the analytical benefits of two multivariate data analysis techniques—principal components analysis (PCA) and multiple regression (MR). By combining the two techniques researchers could obtain solutions for single and multicomponent models, as well as canonical correlation for interdependent systems (Wold, 1966, 1981). Wold's generalized least squares algorithm was later extended to include latent and emergent variables in path models (Lohmöller, 1989; Wold, 1975, 1980a, 1982, 1985) and used in real-world applications for the first time (Noonan & Wold, 1977, 1980, 1982, 1983). On the other hand, partial least squares regression (PLS-R) designed to reduce the issue of multicollinearity in regression models was also created (Adelman & Lohmöller, 1994; Sanchez, 2013).

The PLS-R approach focused on optimizing the variance extracted from the independent variables while simultaneously maximizing the variance explained in the dependent variables, and enabled researchers to estimate models with more independent variables than observations in the data set (Geladi & Kowalski, 1986; Sanchez, 2013; Tobias, 1997).

Wold's (1982) generalized algorithm for obtaining PLS-PM solutions optimizes path model parameters for a set of equations. The method combines principal components analysis to evaluate the measurement models with structural model assessment via the ordinary (fixed-point) least squares (OLS) algorithm to estimate the relationships between the latent and composite variables (Wold, 1965). The resulting combined exploratory and confirmatory PLS-PM, initially referred to as "soft modeling," (Apel & Wold, 1982; Falk & Miller, 1992; Wold, 1980b) was designed to be a more flexible alternative to Jöreskog's (1973) covariance structure analysis, which requires rigorous assumptions to be met.

The covariance-based SEM (Jöreskog, 1973; Jöreskog et al., 2016) was the dominant SEM method for almost 30 years. In the past decade, however, applications of the composite-based SEM alternative (Lohmöller, 1989; Wold, 1989), referred to as partial least squares structural equation modeling (PLS-SEM), have grown exponentially. Researchers need to understand the fundamental differences between the two methods when deciding which approach is appropriate for their research. CB-SEM is primarily used for confirmation of an established theory (i.e., explanation) and testing cause-and-effect relationships. In contrast, PLS-PM is a prediction-oriented approach to SEM, initially applied primarily for exploratory research, but more recently proposed as appropriate for confirmatory research (Hair et al., 2020; Sarstedt et al., 2014; Schuberth et al., 2018) i.e., to test causal-predictive relationships. Two fundamental differences between these SEM methods are: (1) CB-SEM uses only common variance and is referred to as a common factor modeling approach, and (2) must achieve fit (i.e., goodness of fit indices—GOFI) between the observed covariance matrix and an estimated covariance matrix to confirm the theory (i.e., explanation). In contrast, PLS-SEM (1) uses total variance and is referred to a composite modeling approach, and (2) focuses on measurement and structural model optimization with the objective of maximizing prediction of the variance in the dependent variables (Hair et al., 2019b).

Based on this logic, PLS-PM offers the combination of simultaneously achieving multiple objectives, and being both confirmatory and predictive, provides a method for researchers to assess the predictive accuracy of their SEM models as well as develop meaningful, substantive causal explanations (Sarstedt et al., 2022). This concept is described by Gregor (2006, p. 626) as a combination of explanation and prediction theory, noting the approach "implies both understanding of underlying causes and prediction, as well as description of theoretical constructs and the relationships among them" (Gregor, 2006). Therefore, the PLS-SEM method is quite useful for many business research applications whose objectives are both testing a primitive theory (i.e., explanation for relationships that are not yet established) and developing recommendations for management practice (i.e., prediction).

A much more recent methodological SEM alternative is the generalized structured component analysis (GSCA), which relies on the alternating least squares (ALS) algorithm and optimizes a single criterion (Hwang & Takane, 2015; Latan, 2014). GSCA is a component-based structural equation modeling approach for analyzing complex inter-relationships between indicators and constructs. GSCA, as with PLS-SEM, relies on measurement and structural models that represent the relationships between the components and indicators. There are, however, meaningful differences in the two methods. GSCA specifies a third sub-model, referred to as a weighted relation model, that defines the components as weighted sums of their associated indicators. GSCA then combines the three sub-models into a single overall model (equation) that makes it possible to calculate a global optimization metric, similar to GOFI in the CB-SEM (Cho et al., 2023; Hwang & Takane, 2004; Latan, 2014). In contrast, PLS-SEM calculates a separate optimization criterion for the measurement models and the structural model. There are, however, other meaningful differences between GSCA and PLS-SEM. These include GSCA path models that can include circular relationships between the components (non-recursive relationships) while PLS-SEM structural relationships are considered recursive. Moreover, with GSCA it is possible for each indicator to be linked to multiple components (Hwang & Takane, 2015; Latan, 2014) while PLS-SEM indicators are linked to only one composite component (Hair et al., 2021).

To assist researchers in selecting the appropriate SEM method, we have developed a table that compares the advantages and limitations of these three approaches. Table 1.1 displays the comparison of methods. While the three SEM methods continue to evolve, we believe these guidelines represent the current thinking of methodological scholars.

1.3 Recent Developments in the PLS-PM/PLS-SEM Method

For almost 30 years after it was proposed by Wold (1966), the PLS-PM method received little attention (note: we call this the gestation period). Limited awareness was created by the availability of user-friendly PLS-Graph software (Chin, 2003) and some researchers began to recognize the method's potential and apply it in their research. But PLS-PM was not widely adopted until after Christian Ringle and colleagues introduced the SmartPLS software (Ringle et al., 2005, 2022). Following publication of the first overview article on PLS-SEM (Hair et al., 2011) and a comprehensive textbook (Hair et al., 2014), applications of the method grew exponentially.

Since that time numerous introductory articles on the PLS-SEM method have been published (Chin et al., 2003; Gudergan et al., 2008; Haenlein & Kaplan, 2004; Hair & Alamer, 2022; Nitzl & Chin, 2017; Tenenhaus et al., 2005). Moreover, in recent years PLS-SEM applications have also emerged in other disciplines, such

Table 1.1 Comparison of three primary SEM methods

Primary guidelines: choosing the appropriate structural equation modeling (SEM) method		
Partial Least Squares SEM (PLS-SEM)	Generalized Structured Component Analysis (GSCA)	Covariance-based SEM (CB-SEM)
1. Research purpose: both exploratory and confirmatory	1. Research purpose: both exploratory and confirmatory	1. Research purpose: confirmation of measurement and structural model theory (explanation)
2. Measurement models: estimation with composite modeling approach using total variance	2. Measurement models: estimation with composite modeling approach using total variance	2. Measurement models: estimation with common factor model using only common variance (covariances)
3. Research objective: prediction and inference to the population, particularly out-of-sample prediction, and when the goodness of fit indices (GOFI) are not mandated as assessment criteria	3. Research objective: prediction and inference to the population including out-of-sample prediction and when the goodness of fit indices (GOFI) are desirable as assessment criteria	3. Research objective: confirmation of the relationships between all variables and the assessment necessitates an acceptable overall measure of goodness of fit indices (GOFI)
4. Structural and/or measurement models are relatively complex	4. Structural and/or measurement models are relatively complex	4. Structural and/or measurement models are often relatively simple
5. Measurement philosophy: constructs that are specified as reflective and formative (i.e., component-based), which are represented by composites in the model estimation	5. Measurement philosophy: constructs that are specified as reflective and formative (i.e., component-based), which are represented by composites in the model estimation	5. Measurement philosophy: reflectively measured constructs derived based on the common factor model. Formatively measured constructs using causal indicators (i.e., multiple indicator multiple cause)

(continued)

Table 1.1 (continued)

Primary guidelines: choosing the appropriate structural equation modeling (SEM) method		
Partial Least Squares SEM (PLS-SEM)	Generalized Structured Component Analysis (GSCA)	Covariance-based SEM (CB-SEM)
6. Data is normally or nonnormally distributed, particularly when the data is skewed (e.g., heteroskedastic)	6. Data is normally and nonnormally distributed, particularly when the data is skewed (e.g., heteroskedastic)	6. Data is normally distributed and characterized by homoskedasticity. Nevertheless, in cases of non-normal data, it can be accommodated using asymptotically distribution free (ADF) or robust maximum likelihood estimators, but requires a considerably large sample size

Secondary guidelines: choosing the appropriate SEM method		
PLS-SEM	GSCA	CB-SEM
7. Smaller sample size is permissible if representative to entire population (e.g., business-to-business research involving small populations or through a census). Note: The adequacy of the sample size hinges on factors like model complexity, effect sizes, and the choice of algorithm (whether classic PLS or PLSc) and a wide variety of sizes could potentially be acceptable. Extremely small sample sizes (e.g., < 30 cases) are unacceptable in any scenario. Furthermore, when opting for the PLSc algorithm, it is imperative to have a relatively large sample size	7. Smaller sample size is permissible (e.g., business-to-business research involving small populations or through a census). Note: The adequacy of the sample size hinges on factors like model complexity, effect sizes and the choice of algorithm (i.e., GSCA, IGSCA or GSCAm) and a wide variety of sizes could potentially be acceptable. Extremely small sample sizes (e.g., < 30 cases) are unacceptable in any scenario. In addition, the selection of the GSCAm algorithm must use a relatively large sample size	7. Requires large sample size ($n > 250+$ cases); and preferably 500+ to generate robust GOFI metrics and undistorted parameter estimates. Employing it with small sample sizes (e.g., fewer than 100 cases) is not recommended
8. Scaling of responses is nominal (dummy variable) or ordinal, if correctly coded. Interval and ratio both OK	8. Scaling of responses is nominal (dummy variable) or ordinal, if correctly coded. Interval and ratio both OK	8. Scaling of responses is interval or ratio
9. Prediction improves when endogenous measurement models are less complex (i.e., have a smaller number of indicators) and use relatively large sample sizes	9. Prediction improves when endogenous measurement models are less complex (i.e., have a smaller number of indicators) and use relatively large sample sizes	9. Prediction is not a relevant criterion; statistical objective is optimization based on explanation of all model relationships simultaneously

(continued)

Table 1.1 (continued)

Secondary guidelines: choosing the appropriate SEM method

PLS-SEM	GSCA	CB-SEM
10. The research objective includes using latent variable scores in subsequent analyses (scores are determinate)	10. The research objective includes using latent variable scores in subsequent analyses (scores are determinate)	10. Latent variable scores are indeterminate and cannot be used in subsequent analyses
11. The structural model is estimated with a higher order construct that has only two first order constructs (LOCs). HOCs can be structured as second, third, fourth, or more levels	11. The structural model is estimated with a higher order construct that has only two first order constructs (LOCs). HOCs can be structured as second, third, fourth, or more levels	11. Higher order constructs (HOCs) are possible but must always have three or more indicators/LOCs to achieve model identification. HOCs can be structured as second, third, fourth, or more levels
12. Model relationships typically are recursive	12. OK for both recursive and nonrecursive relationships	12. OK for both recursive and nonrecursive relationships

as agriculture, engineering, environmental sciences and ecology, geography, and psychology (Sarstedt et al., 2022).

Quite a few methodological options have also emerged for PLS-PM in the past decade. These updates to PLS-SEM have extended the analytical capabilities well beyond CB-SEM, and increasingly there are situations where PLS-SEM is the preferred method instead of CB-SEM. Moreover, several of the analysis features of PLS-SEM are not possible with CB-SEM, including prediction with latent variable scores due to indeterminacy, and higher order constructs with only two first order constructs. Fortunately, user-friendly software programs have added these new features for executing PLS-SEM analyses. Recent releases include options for executing out-of-sample prediction (Shmueli et al., 2019), multi-group analysis (Sarstedt et al., 2011) invariance testing by means of the measurement invariance of composite models (MICOM) (Henseler et al., 2016), linear and non-linear moderation, continuous moderators (Fassott et al., 2016), confirmatory tetrad analysis (CTA) (Gudergan et al., 2008), prediction-oriented segmentation (PLS-POS) (Becker et al., 2013), composite-based structural modeling (Hair et al., 2017), confirmatory composite analysis (CCA) (Hair et al., 2020; Schuberth et al., 2018); cross-validated predictive ability test (CVPAT) (Liengaard et al., 2020), predictive model assessments (Sharma et al., 2023) and so forth. Editors and reviewers increasingly are requesting these analytical options and procedures so the ability to easily execute and interpret them is a benefit to researchers.

In planning future research, we urge researchers to consider the rapidly increasing PLS-SEM analytical possibilities when specifying their research design and selecting the method of structural equation modeling. As noted in the Editors Preface, numerous analytical tools have emerged since the first edition of this book in 2017.

1.4 Essential Emerging PLS-SEM Tools for Social Sciences Scholars

In this section we describe four PLS-SEM tools we believe social science scholars need to understand and apply in their research, where appropriate. These tools include mediation, moderation, moderated mediation, non-linear modeling, and out-of-sample prediction. There are clearly other very useful PLS-SEM tools, but we believe the ones we include are an essential foundation for advancing PLS-SEM as an increasingly meaningful analytical method.

1.4.1 Mediation

A recent review of mediation-focused research for the period 2016–2022 found more than 50% of the articles in top social science journals apply PLS-SEM for

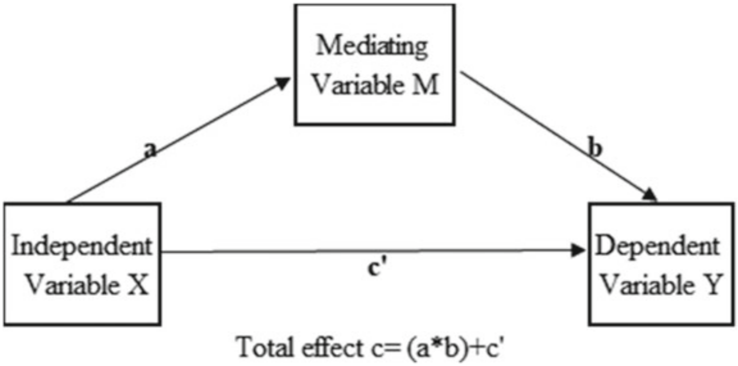


Fig. 1.1 Simple mediation model

assessing mediation models, thus confirming the popularity of PLS-SEM mediation modeling in empirical research (Sabol et al., 2023). Mediation analysis using PLS-SEM estimates all structural model relationships in a single analysis by running separate regressions of each outcome variable on its associated predictor variable (Iacobucci, 2008; Sarstedt et al., 2020a). A simple mediation model contains at least three variables: an independent variable (X), a mediator variable (M) and a dependent variable (Y). Figure 1.1 depicts the relationships between these three variables. A mediating effect is present when the indirect effect from variable X to Y is statistically significant. However, it's crucial for researchers to consider that this acceptance is contingent on the magnitude of the indirect effect size. If the obtained indirect effect size was exceedingly small (< 0.01), even if it was statistically significant ($p < 0.05$), the results were deemed inconsequential and should be rejected. In addition, to assess the total effect of mediation, the direct effect (from X to Y) is added to the indirect effect (X to M to Y). For a more detailed description of testing indirect effects in PLS, see Chap. 8 in this volume.

A primary strength of using PLS-SEM is the ability to assess multiple outcome variables at the same time and obtained complete estimation results without the need for other operations. This ability enables researchers to estimate direct and indirect effects of the entire model, while at the same time removing measurement error (unexplained variance), which is the explained variance subtracted from the total variance (Sarstedt et al., 2020a). Simultaneous assessment of all model relationships at the same time enables scholars to determine if and how much the estimated effect of an initial relationship parameter could impact the parameter estimate of a subsequent relationship (Hair et al., 2022; Legate et al., 2023). Another strength of using PLS-SEM for mediation analysis is the method calculates weighted construct scores which are more accurate than the unweighted sum scores used in the PROCESS approach (Sarstedt et al., 2020a). More specifically, using sum scores increases the likelihood of incorrectly measuring relationship parameters, which can impact the accuracy of mediation results (Rigdon et al., 2020). These benefits of the PLS-SEM method of assessing mediation make it the preferred approach for estimating mediation models.

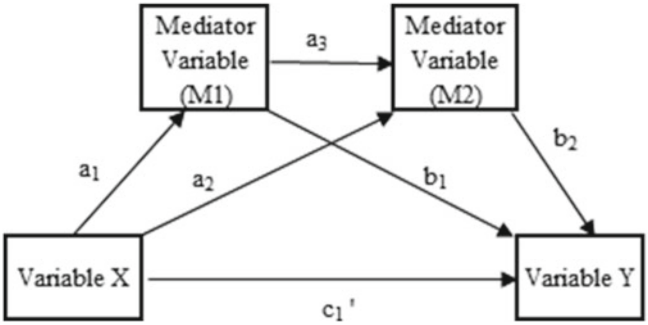


Fig. 1.2 Multiple mediation model

Figure 1.2 displays more than one mediator or multiple mediation models, an increasingly common approach in more complex PLS-SEM applications. The variables M_1 and M_2 are mediators. There are three mediated relationships to examine. One is X to M_1 to M_2 and then to the dependent variable Y. A second mediated relationship is X to M_1 and to the dependent variable Y. A third mediated relationship is X to M_2 and to the dependent variable Y. To obtain the total effect, therefore, you must add the three indirect effects to the direct effect to obtain the total effect.

1.4.2 Moderation

A moderation effect occurs when a third variable (W) changes the relationship between two other variables and thereby changes the strength or direction of the relationship (Hayes, 2018, 2022). Figure 1.3 displays a simple moderation model. Moderator variables can be categorical or continuous. Categorical moderator analysis enables researchers to evaluate observed heterogeneity in the data and identify the significantly different one between two or more groups (for example, differences in gender or race). Where meaningful differences are present multigroup analysis can be run to compare and profile the groups (Hair et al., 2019a; Latan & Ghozali, 2022). A primary strength of using PLS-SEM for moderation analysis is the ability to assess continuous moderating variables, which is not possible (or difficult due to feature limitations) when using CB-SEM (Hair et al., 2021, 2023; Latan, 2013). To determine whether a relationship is moderated, the statistical significance of the moderating effect is examined (Becker et al., 2023). When the analysis involves a continuous moderator variable the extent of moderation should also be examined using a simple slope analysis.

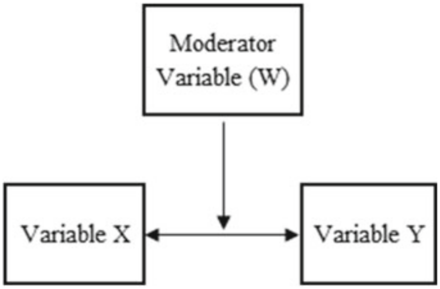


Fig. 1.3 Simple moderation model

1.4.3 Moderated Mediation

Moderated mediation combines mediation and moderation both in the same analysis. For example, Fig. 1.4 depicts the impact of including of a third mediation variable (M) between X and Y, and also a moderator variable (W) that potentially influences the relationship between X and Y, as well as between X and M. In other words, a moderated mediation analysis measures the indirect effect of the mediator at different values of a moderator. In a moderated mediation model in which only the direct effect (X to Y) is moderated, X exerts its effect on Y indirectly through M, independent of any other variable. At the same time, there also is a direct effect, with the magnitude of the direct effect depending on W making c' not a single number but instead a conditional function of W (Hayes, 2018, 2022). Therefore, if the indirect effect of X differs systematically as a function of W, we can say that the mediation of X's effect on Y by M is moderated by W—moderated mediation (Latan et al., 2019).

Recent research emphasizes the efficacy of PLS-SEM for combining mediating and moderating effects in a single analysis to estimate conditional mediation analysis (CoMe) (Cheah et al., 2021; Latan et al., 2019; Sarstedt et al., 2022). The CoME procedure simultaneously evaluates mediated and moderated relationships and enables researchers to improve their understanding of how relationships get stronger or weaker (the size and/or significance of the coefficient changes) and under which conditions this effect might take place. This improved understanding

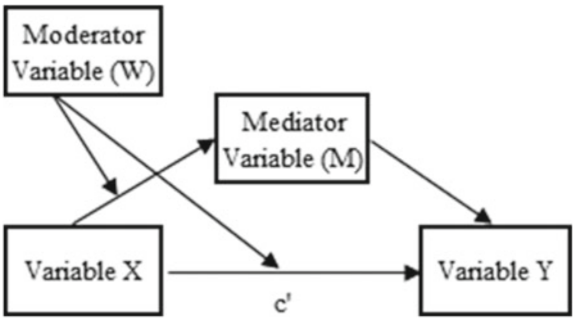


Fig. 1.4 Moderated mediation model

of relationships cannot be measured when mediation and moderation are tested independently (Richter et al., 2022), for example through PROCESS.

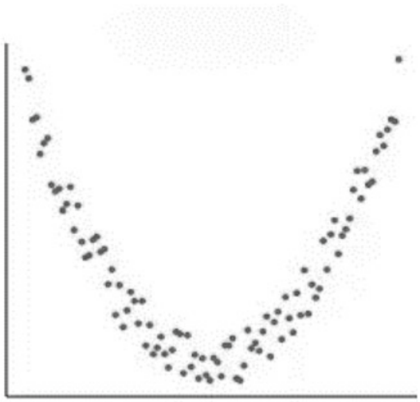
CoME analysis also enables mediation and moderation to examine how mediated relationships change as a function of context, boundaries, and/or individual differences (Hayes, 2018, 2022). Using PLS-SEM for estimating a CoMe model offers several advantages, including overcoming the limitations of separate sequential approaches, reducing inherent measurement error, and measuring the significance of the effect a moderator has on a mediated relationship (see Cheah et al., 2021, for additional details). CoMe analysis using PLS-SEM provides a better basis for researchers to draw more accurate conclusions, to advance theory, and to develop meaningful practical insights.

1.4.4 Non-linear SEM Solutions

As demonstrated in our review of conditional moderation the relationships between constructs in PLS-SEM can manifest in various forms, including, linear, non-linear, cubic and so on. In path modeling, linear relationships are depicted by straight lines while nonlinear and cubic relationships are represented by a curve when plotting the values of latent variables on a scatterplot (see Fig. 1.5). These curved lines represent either decreasing or increasing curved effects (often referred as U shaped or inverted-U-shaped) contingent on the level of the predictor variable. Another prevalent nonlinear relationship, at times termed an S-shaped (or inverse-S-shaped) relationship (Jaccard & Jacoby, 2020; Negrão et al., 2020).

A useful feature of PLS-SEM is that when estimating different forms of nonlinear model relationships, multi-item measures are composites of observed variables which reduces measurement error (Basco et al., 2022). As elucidated in Chap. 5 of this volume, all PLS software offers the capability to examine non-linear or quadratic relationships. For nonlinear effects the measurement error aspect is particularly important

Fig. 1.5 Plotting a nonlinear relationship (U shaped)



since the amount of error could impact the effect size metrics. Considering potential nonlinearities in model relationships enables researchers to avoid erroneous assumptions of linearity that could hide true relationships and underestimate model effects (Jaccard & Jacoby, 2020).

Researchers often assume the relationships between constructs are linear when estimating path models (Latan, 2018). This assumption should be tested, however, by assessing the significance of the quadratic effect of the predictor variable (Sarstedt et al., 2020b) and examine the effect sizes of the non-linear relationships tested (see Negrão et al., 2020 for exemplary application). The quadratic effect is comparable to an interaction term in moderation and can be regarded as a special case of moderation. This special case can be described as a relationship in which the predictor variable self-moderates the relationship between the predictor and dependent variables (in this case, X moderates the relationship between X and Y). In other words, the nonlinear interaction terms represent simple slopes that vary across respondents, just as the values of the predictor variables vary across respondents (Jaccard & Jacoby, 2020). A priori testing the nature (linear/nonlinear) of structural relationships between constructs in a SEM model is essential to ensure results interpretations are aligned with theory. Moreover, understanding the linearity or lack thereof in a PLS-SEM model is particularly important to confirm the robustness of structural model results in terms of nonlinear effects.

1.4.5 Out-of-Sample Prediction

In addition to the strengths of PLS-SEM discussed thus far, a distinguishing advantage of this method with CB-SEM and GSCA is prediction, including several user-friendly options to easily assess prediction. Shmueli (2010) and Shmueli et al. (2016) proposed out-of-sample prediction as a process to assess the ability to infer to the population, a more useful metric than the traditional in-sample metric of R^2. The process divides the initial sample into two groups—the analysis group and the holdout group (Hair & Sarstedt, 2021). The analysis group data is used to develop the parameters of the PLS model solution which are then applied to generate item and construct predictions at an observation level (Manley et al., 2021; Shmueli et al., 2019). The predictive power of a PLS-SEM model is then assessed using out-of-sample error prediction metrics such as the mean absolute error (MAE), the root mean square error (RMSE) and the misclassification error rate (MER).

The MAE is the average absolute difference between the prediction and actual observation. RMSE is the square root of the average of the squared differences between the prediction and actual observation. MER is the incorrect classification rate. Although three statistics measure the differences between predictions and observations, the RMSE is the preferred metric (or gold standard) because of how weights are assigned to errors (Hair et al., 2022).

Researchers should assess the prediction error related to the target construct by evaluating the Q^2_{predict} statistic. This statistic compares prediction errors in the path model against the simple mean predictions. If the Q^2 is positive, the prediction error of the PLS-SEM model provides better predictive performance than simply using the indicator mean values. Another approach to assess prediction errors utilizes a linear regression model (LM sum scores) as a benchmark for comparing predictions between the LM and PLS-SEM models using the RMSE statistic for each model. In this comparison if the RMSE errors of the PLS prediction are fewer than the benchmark LM errors, the predictive power of the PLS-SEM model is superior (see Shmueli et al., 2019, for additional details).

Systematic reviews regularly call for assessing and reporting advanced robustness tests to enable researchers to assess and convey the predictive capabilities of their SEM models (Becker et al., 2023; Latan, 2018). Unfortunately, up until now, researchers have frequently omitted holdout sample prediction procedures in their studies to validate the predictive performance of their models (Hair, 2022; Sabol et al., 2023). This omission might be attributed to the lack of accessible software tools for computing these metrics. As the most recent update for all PLS software (see Chap. 5 of this volume), only SmartPLS and cSEM offer options for computing these metrics. However, we hope further advancements in other PLS-SEM software will incorporate these metrics to address this limitation.

1.5 Observations and Conclusions

Overall, we recommend continuing to explore other important features of PLS we were not able to include in our descriptions. These include model comparisons executed using the cross-validated predictive ability test (CVPAT and its extensions), higher order constructs to reduce multicollinearity and to model complex multidimensional composites, observed heterogeneity modeling options such as measurement invariance of composites (MICOM), multigroup analysis (MCA), unobserved heterogeneity approaches such as finite mixture PLS (FIMIX-PLS), and PLS prediction-oriented segmentation (PLS-POS). While these tools have been available for several years, very few social science researchers using PLS-SEM have applied them in their analyses.

We also suggest that you explore other chapters within this book to gain insights into the application of various PLS-SEM features. Some valuable PLS-SEM features covered in the remaining chapters of this book include the following: quantile composite-based path models discussed in Chap. 2, assessing out-of-sample predictions using ordinal PLS and PLSc in Chap. 6, ridge PLS-SEM (similar to ridge regression) in Chap. 7, higher order constructs (HOCs) in Chap. 9, necessary condition analysis (NCA) in Chap. 10, PLS and archival data in Chap. 13, and importance performance map analysis (IPMA) in Chap. 14. In conclusion, we encourage you to delve into each of these chapters and contemplate how they can augment your analytical skills and contribute to your research endeavors.

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Chapter 2
Quantile Composite-Based Path Modeling with R: A Hands-on Guide

Cristina Davino, Pasquale Dolce, Giuseppe Lamberti, and Domenico Vistocco

Abstract The aim of the chapter is to provide step-by-step instructions to implement, estimate, and interpret a Quantile Composite-based Path Model, exploiting the `qcpm` package (https://rdrr.io/cran/qcpm/), freely available for the `R` software. The chapter encompasses both methodological aspects of this recent quantile approach to Partial Least Squares Path Modeling, and real data applications, so as to offer a comprehensive guide to the readers interested in the use of the method on their own data. All steps of a quantitative analysis, i.e., data loading, pre-processing, coefficient estimation and model validation are described showing the options and functionalities of the package along with the corresponding methodology.

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2.1 Introduction

Quantile Composite-based Path Modeling (QC–PM) is a recent advance in the field of Partial Least Squares Path Modeling (PLS–PM). It was proposed by Davino and Esposito Vinzi (2016), and then formalized by Dolce et al. (2021), which detailed the iterative procedure for parameter estimation, along with a methodological variation in the estimation phase of the outer model. QC–PM exploits potentialities of Quantile Regression (Koenker & Bassett, 1978; Davino et al., 2013; Furno & Vistocco, 2018) in exploring the dependence structure at places other than the expected value, namely at the conditional quantiles of the response. Therefore, QC–PM aims to provide a natural complement to PLS–PM, which focuses on the average effects, being based on standard least squares procedures.

In many contexts, exploring the impact of a set of drivers on the extreme parts of the distribution of the response variable may provide added value, being at times be the real target of interest. As an example, just consider contexts in which it is necessary to explore inequalities or, more generally, to handle heterogeneity in the distribution of the phenomenon of interest. This requirement becomes even more difficult to face when the goal is to measure a set of complex and multidimensional constructs, i.e., in cases where there is a structure of relationships between constructs that are not directly observable. The reader interested in the methodological details can refer to the papers previously published by the authors of the QC–PM (Dolce et al., 2021; Davino et al. 2020; Davino et al., 2017; Davino & Esposito Vinzi, 2016; Davino et al., 2014).

This chapter aims to detail the steps required to define, estimate and validate QC–PM through a real data example, using the R package **qcpm**, a library recently available on `CRAN`.[1] An empirical application is used to show the method in action and to complement the presentation of the methodology with guidelines to interpret results. Data comes from the Italian system of indicators on Equitable and Sustainable Well-Being (Benessere Equo e Sostenibile—BES) (ISTAT 2018) proposed by the National Institute of Statistics. They concern the relationships among three well-being domains (Education, Economic Well-Being, and Health) measured on Italian provinces. In particular, we focus here on the structural model proposed by Davino et al. (2020) to obtain the best predictions in a network of relationships.

The `qcpm` package, along with the main R functionalities, enables a complete analysis of results. Functions are available to customize each phase of the analysis, following the common approach of PLS–PM. The chapter is organized as follows: Sect. 2.2 briefly introduces QC–PM, Sect. 2.3 describes the data used in the empirical application, Sect. 2.4 details the steps required to perform a complete analysis using the `qcpm` package. In particular, the data preparation phase along with the exploratory analysis are carried out exploiting functionalities external to the `qcpm` package as reported in Sect. 2.4.1. The specification of the inner and outer models (Sect. 2.4.2) adopts the *lavaan* syntax (Rosseel, 2012). The same Sect. 2.4.2 offers guidelines to analyze and interpret loadings and path coefficients, while assessment is performed

[1] https://cran.r-project.org/web/packages/qcpm/index.html.

in Sect. 2.4.3. Finally, Sect. 2.4.4 provides useful complements to exploit `qcpm` output in different contexts, i.e., to obtain graphical representation of the results to use it as input of other methods or outside of R. Conclusions and discussion of further research developments to be explored are in Sect. 2.5.

2.2 Quantile Composite-Based Path Modeling in a Nutshell

QC–PM (Davino & Esposito Vinzi, 2016) introduces a quantile approach to the traditional PLS–PM (Wold, 1985; Esposito Vinzi et al., 2010; Hair et al., 2016). QC–PM exploits quantile regression (QR) (Koenker & Bassett, 1978; Koenker, 2005; Davino et al., 2013) to investigate changes in the relationships among constructs, and between constructs and observed variables, according to the analyzed quantiles of interest, and it can be considered a complement to PLS–PM, aiming to analyze the entire distribution of outcome variables.

QC–PM estimates the effects that predictors exert on the whole conditional distributions of the outcomes involved in path models and provides a comprehensive view on the structure of the relationships among the variables. Since PLS–PM is based on simple and multiple ordinary least squares (OLS) regressions, its coefficients focus on the conditional means of the dependent variables. However, in presence of heteroscedastic variances of the errors or highly skewed dependent variables, the estimates of coefficients may vary along the distribution of the dependent variables. In such cases, PLS–PM may give an incomplete picture of the relationships among variables. The quantile approach is instead able to model the location, scale, and shape of the responses. More precisely QR offers a complete view of a response variable providing a method for modeling the rates of changes at multiple points (conditional quantiles) of its distribution without requiring assumptions on the errors. A quantile regression approach can be exploited also when a monotone transformation of the response and/or the explanatory variables is advisable. Although different functional forms can be used, here we will deal only with simple linear regression models. For a basic introduction to QR the interested reader can refer to the Appendix in Dolce et al. (2021).

QC–PM shares with PLS–PM most of the theoretical and technical aspects. A comparison between the two algorithms is detailed in Dolce et al. (2021). Relationships among variables are illustrated using the path diagram, i.e., a diagram where observed variables and constructs are depicted by boxes and circles, respectively, interconnected with arrows used to represent directed dependencies among variables. In the same way as PLS–PM, QC–PM is based on two models: the measurement (outer) model, which relates observed variables to the constructs, and the structural (inner) model, which describes the strength and direction of relationships among the constructs. The QC–PM algorithm follows the same steps of the PLS–PM algorithm to estimate the model parameters. Firstly, the algorithm identifies a system of weights to estimate the constructs through an iterative process. Secondly, it estimates the coefficients which measure the strength of relationships between constructs (path coefficients), and the strength of relationships between each construct with its own set of observed variables (loadings). The main difference between QC–PM and PLS–PM is about the method used to estimate coefficients in each step of the algorithm. In fact, while PLS–PM exploits standard linear regression and Pearson correlation, QC–PM replaces them with quantile regression (Koenker & Bassett, 1978) and quantile correlation (Li et al., 2014). It is worth to recall that the interpretation of QR estimates is in line with other linear models: the intercept refers to the response value when all regressors are set to zero, each slope measures the rate of change in the response per a unit change in the value of the correspondent regressor, keeping all the others constant. The only difference with respect to standard linear model is about the interest in the conditional quantiles of the response, each QR set of coefficients (intercept and slopes) being associated to a different conditional quantile of the response. Therefore, quantile correlation is used to measure the sensitivity of a conditional quantile of a variable when the other variable changes.

In the following, we assume that our data are organized in K blocks of P_k variables ($k = 1, ..., K$), where each block identifies the set of manifest variables (MVs) related to a specific construct ξ. Denoting by x_{p_k} ($p_k = 1, ..., P_k$) the generic MV, and by ξ_k a generic construct, the model specification (outer and inner model) can be expressed through the following two equations:

$$x_{p_k} = \lambda_{p_k 0}(\tau) + \lambda_{p_k}(\tau)\xi_k + \epsilon_{p_k}(\tau) \tag{2.1}$$

$$\xi_{k'}(\tau) = \beta_{k'0}(\tau) + \sum_k \beta_{k'k}(\tau)\xi_k + \zeta_{k'}(\tau) \tag{2.2}$$

where $\tau \in (0, 1)$ represents the generic quantile of interest. Equation (2.1) specifies the outer model, $\lambda_{p_k 0}$ being a location parameter, λ_{p_k} the loading coefficient that captures the effect of ξ_k on x_{p_k}, and ϵ_{p_k} the outer error term. The inner model is instead formulated in Eq. (2.2), where $\beta_{k'0}$ is a location parameter, $\beta_{k'k}$ the path coefficient capturing the effects of the exploratory construct ξ_k on the dependent construct $\xi_{k'}$, and $\zeta_{k'}$ the inner error term.

Each construct ξ_k is defined by a weight vector $w(\tau)$, that it is computed through an iterative two-phase algorithm. Such an algorithm iterates between an inner and an outer approximation phase until convergence of the outer vectors is achieved, i.e., until the difference in the outer weights of two subsequent iterations is smaller than a predefined tolerance threshold.

In the inner phase, constructs are approximated as weighted aggregates of the adjacent constructs (two constructs are adjacent if they are connected in the inner model independently of the direction). The inner weights are defined through the quantile correlation values between constructs obtained at the previous step (this method corresponds to the factorial scheme of the classical PLS–PM). Another option (centroid scheme) exploits the sign of the quantile correlation to define the inner weight.

In the outer estimation phase, constructs are instead approximated through a normalized weighted aggregate of the corresponding manifest variables. Outer weights are computed through simple quantile regressions (mode A) or multiple quantile regression (mode B), again in line with PLS–PM.

Apart from the use of QR and quantile correlation, QC–PM differs from PLS–PM in the assessment measures of the model. In fact, the use of QR in the estimation process implies that standard PLS–PM assessment measures (Hair et al., 2019; Benitez et al., 2020) cannot be used. Therefore, specific QC–PM measures have been proposed (Davino & Esposito Vinzi, 2016; Dolce et al., 2021), starting from the $Pseudo - R^2$ (Koenker & Machado 1999), which simulates the role and interpretation of the R^2 in classical regression analysis. In detail, $Pseudo - R^2$ measures the contribution of the explicative variables to the explanation of the dependent variable, having the null model as reference model. Strictly speaking, $Pseudo - R^2$ compares the residual absolute sum of weighted differences for the selected model with the total absolute sum of weighted differences using a model with the only intercept. Therefore, $Pseudo - R^2$ can be considered an indicator of goodness of fit for the inner model, measuring the explanatory power of the independent constructs in expressing dependent constructs.

Concerning the outer model, communality and redundancy have been proposed as assessment measures (Davino et al., 2014; Dolce et al., 2021). Communality indicates the amount of the MVs' variance explained by the corresponding construct. It can be calculated both for each MV and for a block, using the average of communalities of each MV belonging to the block. Communality is calculated through the $Pseudo - R^2$ computed on each model that relates a MV to its own construct. Instead, the block communality for a specific block k of p_k variables is computed as:

$$communality_k(\tau) = \frac{1}{p_k} \sum Pseudo - R^2_{p_k}(\tau) \tag{2.3}$$

Redundancy measures the percentage of variance of manifest variables in a dependent block predicted from the corresponding explanatory constructs. Redundancy can be computed for each manifest variable of the dependent blocks, or for a whole dependent block averaging redundancies of the MVs in the block. Accordingly, these measures can be computed as:

$$redundancy_{p_{k'}}(\tau) = communality_{p_{k'}} \times Pseudo - R^2_{k'}(\tau)$$
$$redundancy_{k'}(\tau) = \frac{1}{p_{k'}} \sum p_{k'} redundancy_{p_{k'}}(\tau)$$

where $p_{k'}$ denotes the number of MVs of the block k'.

Therefore QC-PM provides estimates of the coefficients of the measurement and structural model, along with the previous assessment measures, for each quantile of interest. Inferential tools typical of quantile regression can be used to validate coefficients of the measurement model, while the assessment measures can be exploited to compare the quality of the internal and external models between different explored quantiles.

2.3 Data Description

In the following, we will use the well-being model proposed by Davino et al. (2020) to show the qcpm package in action. We refer the interested reader to the original paper for further details. In short, the model (see Fig. 2.1[2]) explores the relationship among three constructs: health (henceforth HEALTH), education and training (EDU), and economic well-being (ECOW), starting from a subset of indicators of the equitable and sustainable well-being report (BES) (ISTAT, 2018), produced by the Italian National Institute of Statistics. The model aims to analyze to what extent HEALTH of Italian citizens is affected by EDU and ECOW. In fact, evidences in literature showed that higher education offers more income opportunities, and promotes lower vulnerability to health risks (Mackenbach et al., 2008; Murtin et al., 2017; Petrelli et al., 2019). Accordingly, we hypothesize that: (1) the Education positively affects the Economic Well-Being; (2) the Education positively affects the Health of citizens; and (3) the Economic Well-Being positively affects the Health of citizens.

In summary, the simple well-being model has one main theoretical component: the target construct of interest—namely, HEALTH (endogenous construct)—and two well-being dimensions: EDU and ECOW (exogenous constructs), which are key determinants of the target construct. Each construct is quantified through a multiple set of indicators measured on the 110 Italian provinces and metropolitan cities. HEALTH is measured through three indicators: life expectancy at birth of females (HEALTH1) and males (HEALTH2), and infant mortality rate (HEALTH3). EDU is measured by seven indicators grouped into three categories: qualification (EDU1, EDU2), participation in education and long-life learning (EDU3, EDU4, EDU5), and competences (EDU6, EDU7). Finally, ECOW is measured by six indicators reflecting measures of income and wealth, and economic difficulties (labeled from ECOW1, to ECOW6). Note that some indicators were reversed for the analysis.

Table 2.1 summarizes the description of the indicators for the three constructs considered in the well-being model: first column lists the constructs, second column the corresponding indicators, third column their names as used in Davino et al. (2020) to facilitate cross-reference, and last column the description of the indicators. All the observed indicators are continuous variables (see Tables 3 and 4 in Davino et al. (2020) for details on the unit of measurement of each variable).

[2] The symbols used in Fig. 2.1 follow the symbolism proposed by Henseler (2021), which distinguishes reflective latent variables, represented using ovals, from composites, represented through hexagons.

Table 2.1 Constructs and indicators of the well-being model

Constructs	MV	Original name	Description
Education (EDU)	EDU1	O.2.2	People with at least upper secondary education level (25-64 years old)
	EDU2	O.2.3	People having completed tertiary education (30-34 years old)
	EDU3	O.2.4	First-time entry rate to university by cohort of upper secondary graduates
	EDU4	O.2.5_aa	People not in education, employment or training
	EDU5	O.2.6	Participation in long-life learning
	EDU6	O_2.7_2.8	Level of literacy and numeracy
	EDU7	O_2.7_2.8_AA	Gender differences in the level of numeracy and literacy
Economic well-being (ECOW)	ECOW1	O.4.1	Per capita disposable income
	ECOW2	O.4.4aa	Pensioners with low pension amount
	ECOW3	O.4.5	Per capita net wealth
	ECOW4	O.4.6aa	Rate of bad debts of the bank loans to families
	ECOW5	O.4.2	Average annual salary of employees
	ECOW6	O.4.3	Average annual amount of pension income per capita
Health (HEALTH)	HEALTH1	O.1.1F	Life expectancy at birth (females)
	HEALTH2	O.1.1M	Life expectancy at birth (males)
	HEALTH3	O.1.2.MEAN_aa	Infant mortality rate

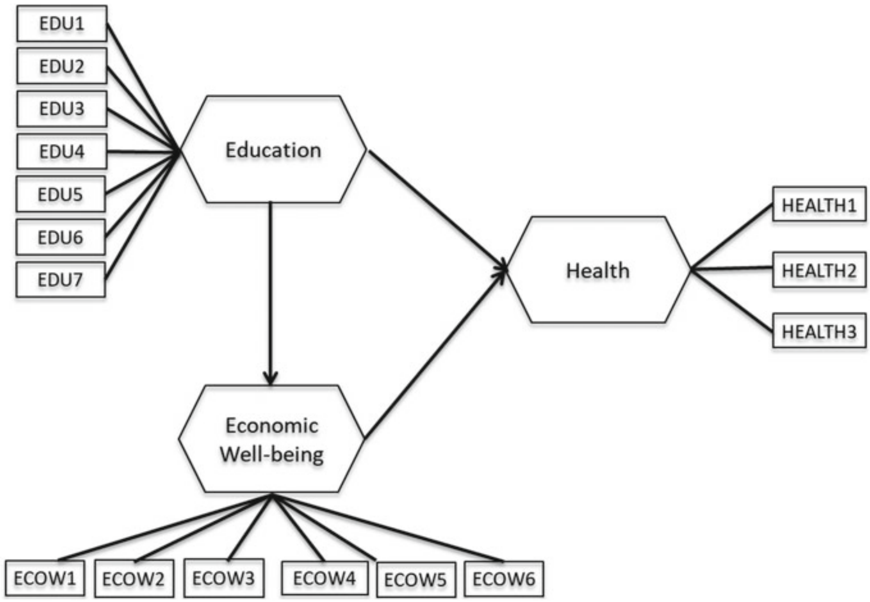


Fig. 2.1 A path model to explain health outcomes from education and economic well-being

2.4 Running QC–PM with R

The `qcpm`[3] package is available through the official `CRAN` repository (stable version) or the github repository (https://github.com) (development version). It can be installed using the item **Install packages** available in the menu **Packages** of the R Console, the button **Install** available in the toolbar of the **Packages** tab in RStudio, or using the command lines:

```
# to install the qcpm packages:
# from CRAN
install.packages("qcpm")
# from github
# note: the devtools package must be installed
devtools::install_github("glamb85/qcpm")
```

Technical details about the package (version number, authors, short description, dependencies, license, maintainer) are available through the `packageDescription` function, while the list of the functions and the links to their documentation are available using the standard `help` function:

[3] `qcpm` can be cited as: Lamberti et al. (2022). qcpm: Quantile Composite Path Modeling. Available at: https://CRAN.R-project.org/package=qcpm.

```
# to print the DESCRIPTION file of the package
packageDescription("qcpm")

# to access the help page with the list of the available functions
help(package = "qcpm")
```

2.4.1 Loading and Pre-processing of the Data

Once installed, it is helpful to load the package into memory to have a direct access to its contents (data and functions):

```
# load the qcpm library
library(qcpm)
```

The dataset described in Sect. 2.3 is directly available in R once `qcpm` is loaded in memory. A detailed description of the data is accessible through the `help` function:

```
# help page for the dataset province
help(province)
```

The `names` function prints the list of indicators in the dataset:

```
# list the names of the variables (indicators)
names(province)
```

```
 [1] "EDU1"    "EDU2"    "EDU3"    "EDU4"    "EDU5"    "EDU6"    "EDU7"
 [8] "ECOW1"   "ECOW2"   "ECOW3"   "ECOW4"   "ECOW5"   "ECOW6"   "HEALTH1"
[15] "HEALTH2" "HEALTH3"
```

There are several options available in R to plot and summarize data. In the following, we refer to the `tidyverse` (Grolemund & Wickham, 2016), a collection of `R` packages designed for a convenient and consistent approach to data analysis.

```
# you need to install the set of packages if not already installed
## install.packages("tidyverse")

# load the set of packages of the tidyverse
library(tidyverse)
```

It is possible to have a glance at all the indicators reshaping the data to a long format through the `pivot_longer` function:

```
# view the original dataset in the data viewer
View(province)
```

```
# reshape the table from wide to long format
province_long <- province %>%
  pivot_longer(cols = everything(),
               names_to = "var_name",
               values_to = "var_value")

# view the reshaped dataset (long format) in the data viewer
View(province)
```

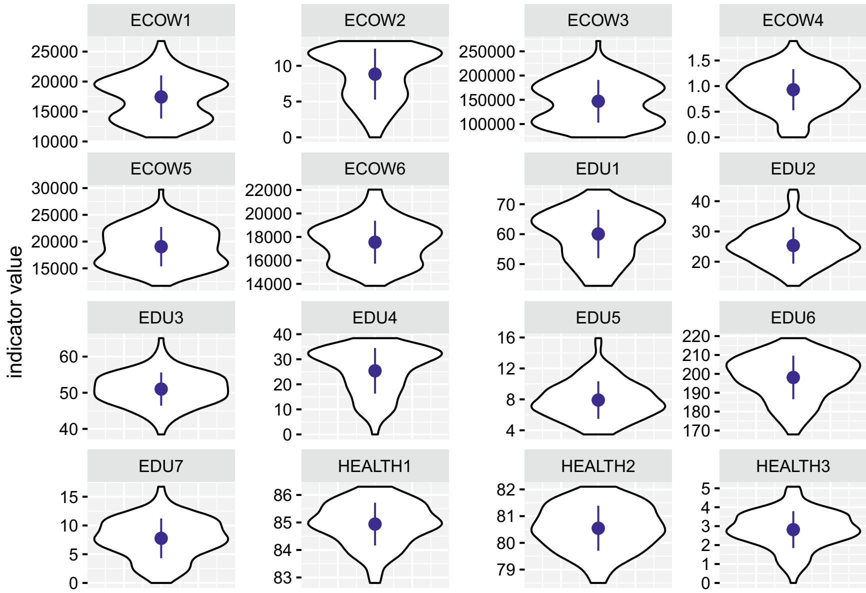
Starting from the table in long format and exploiting the two function `group_by` and `summarize`, it is immediate to compute means and standard deviations for all the variables in one shot:

```
# computing means and standard deviations exploiting data in long format
province_long %>%
  group_by(var_names) %>%
  summarize(var_avg = sprintf("%0.2f", mean(var_values)),
            var_sd = sprintf("%0.2f", sd(var_values)))
```

The reshaping of the table in long format is also convenient for easily obtaining plots using the `ggplot2` package, part of the `tidyverse`. This approach makes it possible to change only the geometric object `geom_*` to represent the same data using different type of plots. Here is the case of violin plots, as an example:

```
# function to compute average and average +- standard deviation
data_summary <- function(x) {
  m <- mean(x)
  ymin <- m-sd(x)
  ymax <- m+sd(x)
  return(c(y=m,ymin=ymin,ymax=ymax))
}

# violin plots of the indicators
ggplot(data =province_long,
       aes(x = 1, y = var_values)) +
  geom_violin() +
  stat_summary(fun.data=data_summary,
               col = "darkblue", show.legend = FALSE, size = 0.5) +
  xlab("") + ylab("indicator value") +
  facet_wrap(vars(var_names), scales = "free_y")
```



Violin plots (Hintze & Nelson, 1998) are a combination of a box plot and a density plot, realized rotating and placing symmetrically on each side two density plots. The length of the vertical axis of each graph allows to appreciate the range of the observed values while the shape highlights how values are distributed in terms of variability and skewness. The idea is to depict simultaneously the full distribution of a set of data, and the number of the data considered. Indeed, the height of each violin informs about the range of the values, while the position of the peak is provided by the width of the violin. The point inside each violin depicts the average value, and the segments are located at ± 1 standard deviation. Note that violin plots in different panels are not always comparable, as the variables have different units of measurement and scales. Except few cases, variables present high asymmetry and different shapes of the distribution.

The `tidyverse` approach is particularly convenient also for obtaining group summaries, in case data contains stratification variables. The `province` dataset contains only the indicators, and therefore we can go with the model specification. Section 2.4.4 shows the use of `tidyverse` to obtain graphical representations starting from the output provided by the **qcpm** package.

In case you need to standardize the columns, you can exploit the `scale` function available in base R, combining it with the `mutate` function available in the `tidyverse`. In particular, let suppose `data_wide` is the object containing the dataset in wide format, i.e., each indicator on a column, the following code can be exploited to standardize all the columns:

```
# standardize all the columns of a dataset
data_wide_scaled <- data_wide %>%
  mutate(.cols = across(everything(), .fns = scale))
```

2.4.2 Model Specification, Estimation, and Results

The main function of the **qcpm** package is `qcpm`, essential to implement the QC–PM model.

Models are defined using *lavaan* model syntax (Rosseel, 2012), where the ~ operator specifies the regression equations in the inner model, the =~ operator specifies the outer model in case Mode A is used for computing the outer weights, whereas the <~ operator must be used for Mode B.

Since in our example we use Mode A for the three constructs, the model specification is as follows:

```
# model specification
my_model<- "
          # reflective measurement (outer) model
          EDU =~ EDU1 + EDU2 + EDU3 + EDU4 + EDU5 + EDU6 + EDU7
          ECOW =~ ECOW1 + ECOW2 + ECOW3 + ECOW4 + ECOW5 + ECOW6
          HEALTH =~  HEALTH1 + HEALTH2 + HEALTH3

          # structural (inner) model
          ECOW ~ EDU
          HEALTH ~ EDU + ECOW

         "
```

The `qcpm` function requires at least 2 arguments: the model (`model`) and the dataset (`data`). Indeed, other arguments are set to convenient default values. If only the arguments `model` and `data` are specified, the `factorial` inner weighting scheme is used (`scheme = "factorial"`), the three quartiles are considered for the estimation (`tau = c(0.25, 0.5, 0.75)`)[4], and also used in the iterative procedure of QC–PM (`fix.quantile = FALSE`). The `centroid` weighting scheme can be also used as an alternative (`scheme = "centroid"`). In case invariance is an issue, the quantile used in the iterative procedure can be set to 0.5 by setting `fix.quantile = TRUE`. Loadings are estimated by default using quantile regression (`qcorr = FALSE`), quantile correlation can be used setting the argument to TRUE. The other two arguments (`tol`, and `maxiter`) are used to tune convergence.

[4] A focus on the three quartiles is a quite common choice in QR applications. It is worth to recall that it is theoretically possible to estimate infinite models at different quantiles. In practice, a fairly accurate approximation of the whole quantile process can be obtained using a dense grid of equally spaced quantiles in the unit interval (0, 1) (Davino et al., 2020). In real data applications, it is quite common to select a reduced number of quantiles according to the part of the conditional distribution the researcher is interested to explore.

```
# compute qcpm using the default values for the arguments
well_qcpm <- qcpm(model=my_model, data=province)
```

```
---------------------------------------------------------------------------
QC-PM: Quantile Composite-based Path Modeling
---------------------------------------------------------------------------
Quantile estimation: complete

Info models:
- Number of LV: 3
- Number of MV: 16
- LV modes:A A A
- LV scheme:  factorial

---------------------------------------------------------------------------
Info quantile:
Quantile not specided and fixed by default:
0.25 0.5 0.75

---------------------------------------------------------------------------
Use also:
- for general results datails use function:             summary()
- for assessment results datails use function:          assessment()
- for boostrap results datails use function:            boot()
- for reliability results of LV use function:           reliability()
---------------------------------------------------------------------------
```

The function qcpm returns an object of class qcpm, that is a special list storing the typical output of the model:

```
# class of the output object
class(well_qcpm)
```

```
[1] "qcpm"
```

```
# output stored in the output object
names(well_qcpm)
```

```
[1] "outer.weights"     "outer.loadings"
"path.coefficients" [4] "latent.scores"     "data"
"model"
```

The generic summary function can be exploited on the qcpm object to visualize the main results:

```
# print general results of the analysis
summary(well_qcpm)
```

```
----------------------------------------------------------------------
QC-PM:
general results
----------------------------------------------------------------------
quantile estimation: complete
----------------------------------------------------------------------
Results:
 - Outer Loading:
                   0.25    0.5   0.75
EDU-EDU1        0.9285 0.8852 0.8218
EDU-EDU2        0.8138 0.7931 0.7682
EDU-EDU3        0.6054 0.6221 0.6501
EDU-EDU4        0.8999 0.9554 0.9419
EDU-EDU5        0.6349 0.8142 0.8198
EDU-EDU6        0.7560 0.8540 0.8476
EDU-EDU7        0.7809 0.7651 0.7509
ECOW-ECOW1      0.9343 0.9664 1.0299
ECOW-ECOW2      0.9114 0.9174 0.9015
ECOW-ECOW3      0.8454 0.9101 1.0199
ECOW-ECOW4      0.8524 0.6772 0.7512
ECOW-ECOW5      0.9223 0.9230 0.9576
ECOW-ECOW6      0.8719 0.8772 0.8943
HEALTH-HEALTH1 0.9836 0.9088 0.9449
HEALTH-HEALTH2 0.9200 0.8837 0.8491
HEALTH-HEALTH3 0.6538 0.6067 0.2911

----------------------------------------------------------------------
 - Outer weights:
                   0.25    0.5   0.75
EDU-EDU1        0.2114 0.1748 0.1460
EDU-EDU2        0.1481 0.1842 0.1802
EDU-EDU3        0.1311 0.1302 0.1374
EDU-EDU4        0.2282 0.2069 0.1990
EDU-EDU5        0.1611 0.1746 0.1866
EDU-EDU6        0.1762 0.1834 0.2058
EDU-EDU7        0.1689 0.1760 0.1801
ECOW-ECOW1      0.2034 0.2036 0.2176
ECOW-ECOW2      0.2009 0.1968 0.2065
ECOW-ECOW3      0.1650 0.1778 0.1826
ECOW-ECOW4      0.1721 0.1410 0.1230
ECOW-ECOW5      0.1862 0.1945 0.1993
ECOW-ECOW6      0.1765 0.1852 0.1656
HEALTH-HEALTH1 0.4656 0.4606 0.5184
HEALTH-HEALTH2 0.4187 0.4633 0.4485
HEALTH-HEALTH3 0.3234 0.2641 0.1875

----------------------------------------------------------------------
 - Path coefficients:
                 0.25    0.5   0.75
EDU->ECOW     0.8837 0.8459 0.8734
EDU->HEALTH   0.7910 0.6857 0.4353
ECOW->HEALTH 0.0263 0.0741 0.2392

----------------------------------------------------------------------
```

The $ operator makes it possible to inspect the single components of the output object. The `outer.loadings` component stores the loadings:

```
# show qcpm loadings
well_qcpm$outer.loadings
```

```
                 0.25    0.5   0.75
EDU-EDU1       0.9285 0.8852 0.8218
EDU-EDU2       0.8138 0.7931 0.7682
EDU-EDU3       0.6054 0.6221 0.6501
EDU-EDU4       0.8999 0.9554 0.9419
EDU-EDU5       0.6349 0.8142 0.8198
EDU-EDU6       0.7560 0.8540 0.8476
EDU-EDU7       0.7809 0.7651 0.7509
ECOW-ECOW1     0.9343 0.9664 1.0299
ECOW-ECOW2     0.9114 0.9174 0.9015
ECOW-ECOW3     0.8454 0.9101 1.0199
ECOW-ECOW4     0.8524 0.6772 0.7512
ECOW-ECOW5     0.9223 0.9230 0.9576
ECOW-ECOW6     0.8719 0.8772 0.8943
HEALTH-HEALTH1 0.9836 0.9088 0.9449
HEALTH-HEALTH2 0.9200 0.8837 0.8491
HEALTH-HEALTH3 0.6538 0.6067 0.2911
```

For the considered data, loadings are very high and similar across quantiles except for few cases. Notice that for the HEALTH block, the MV HEALTH3 has low loading, the lowest coefficient equal to 0.29 being at quantile of 0.75. We decided to keep this MV in the model since theory suggests that it is relevant for the construct of interest. Moreover, all loadings are statistically significant (see Sect. 2.4.3).

We can evaluate the inner relationships by looking at the path coefficients estimates:

```
# show qcpm path coefficients
well_qcpm$path.coefficients
```

```
               0.25    0.5   0.75
EDU->ECOW    0.8837 0.8459 0.8734
EDU->HEALTH  0.7910 0.6857 0.4353
ECOW->HEALTH 0.0263 0.0741 0.2392
```

In general, EDU is the most relevant driver of HEALTH, but the effect is greater for low levels of HEALTH and decreases as the HEALTH level increases. Since health conditions are related to geographical location, this indicates that the effect of EDU on HEALTH increases moving from provinces with good health conditions to provinces with worse conditions. With regard to ECOW, QC–PM estimates confirm the same pattern for the effect of economic well-being: it has a relative high impact on HEALTH only for provinces with high health conditions.

It is helpful to recall that a reliable comparison among path coefficients estimates over quantiles is feasible only if measurement invariance in the outer model is established, i.e., loadings do not significantly change across quantiles. QC–PM still lacks a statistical test for measurement invariance, but we can apply a variant of QC–PM fixing the quantile to the median in the iterative procedure of the algorithm, in order to keep the outer weights fixed over quantiles. This approach is obtained setting to `TRUE` the `fix.quantile` argument of the `qcpm` function:

```
# apply qcpm fixing the median in theiterative procedure
well_qcpm_median <-qcpm(model=my_model,
                        data=province,fix.quantile = TRUE)
```

```
---------------------------------------------------------------------------
QC-PM: Quantile Composite-based Path Modeling
---------------------------------------------------------------------------
'fix.quantile == TRUE': tau is fixed to the median
in the parameters
    iterative estimation. Loadings, weights, and communality are admisible
    only for tau=0.5

Info models:
- Number of LV: 3
- Number of MV: 16
- LV modes:A A A
- LV scheme:  factorial

---------------------------------------------------------------------------
Info quantile:
Quantile not specided and fixed by default:
0.25 0.5 0.75

---------------------------------------------------------------------------
Use also:
- for general results datails use function:            summary()
- for assessment results datails use function:         assessment()
- for boostrap results datails use function:           boot()
- for reliability results of LV use function:          reliability()
---------------------------------------------------------------------------
```

Clearly, when `fix.quantile = TRUE`, loadings are estimated only for the median (tau=0.5):

```
# show qcpm loadings
well_qcpm_median$outer.loadings
```

```
                    0.5
EDU-EDU1        0.8852
EDU-EDU2        0.7931
EDU-EDU3        0.6221
EDU-EDU4        0.9554
EDU-EDU5        0.8142
EDU-EDU6        0.8540
EDU-EDU7        0.7651
ECOW-ECOW1      0.9664
ECOW-ECOW2      0.9174
ECOW-ECOW3      0.9101
ECOW-ECOW4      0.6772
ECOW-ECOW5      0.9230
ECOW-ECOW6      0.8772
HEALTH-HEALTH1 0.9088
HEALTH-HEALTH2 0.8837
HEALTH-HEALTH3 0.6067
```

By setting the argument `qcorr = TRUE`, loadings are estimated through quantile correlations (the default `qcorr = FALSE` exploits quantile regression):

```
# apply qcpm estimating loadingsthrough quantile correlations
well_qcpm_qcorr <- qcpm(model=my_model,data=province, qcorr = TRUE)
```

```
----------------------------------------------------------------------------
QC-PM: Quantile Composite-based Path Modeling
----------------------------------------------------------------------------
Quantile estimation: complete

Info models:
- Number of LV: 3
- Number of MV: 16
- LV modes:A A A
- LV scheme:  factorial

----------------------------------------------------------------------------
Info quantile:
Quantile not specided and fixed by default:
0.25 0.5 0.75

----------------------------------------------------------------------------
Use also:
- for general results datails use function:              summary()
- for assessment results datails use function:           assessment()
- for boostrap results datails use function:             boot()
- for reliability results of LV use function:            reliability()
----------------------------------------------------------------------------
```

```
# show qcpm loadings
well_qcpm_qcorr$outer.loadings
```

```
                  0.25    0.5   0.75
EDU-EDU1        0.7615 0.7361 0.5472
EDU-EDU2        0.7532 0.7112 0.5822
EDU-EDU3        0.4893 0.6325 0.4451
EDU-EDU4        0.7809 0.7458 0.5775
EDU-EDU5        0.6527 0.5002 0.4180
EDU-EDU6        0.8247 0.6878 0.4872
EDU-EDU7        0.7235 0.6379 0.4868
ECOW-ECOW1      0.7413 0.8703 0.6466
ECOW-ECOW2      0.7246 0.8138 0.5633
ECOW-ECOW3      0.7255 0.8262 0.5767
ECOW-ECOW4      0.5860 0.6363 0.5872
ECOW-ECOW5      0.6346 0.8010 0.6481
ECOW-ECOW6      0.7184 0.8060 0.6028
HEALTH-HEALTH1 0.6968 0.7539 0.6987
HEALTH-HEALTH2 0.6111 0.7346 0.6764
HEALTH-HEALTH3 0.5933 0.3991 0.2135
```

The use of quantile correlation provides loadings easier to interpret and to compare, since they take values in [0, 1].

In case the interest is on particular quantiles of the response, it is possible to exploit the argument `tau` of the `qcpm` function. For illustrative purposes, here is the case of the estimation for the median, along with two extreme quantiles:

```
# apply qcpm on a custom set of quantiles
well_qcpm_custom <- qcpm(model=my_model,data=province, tau=c(0.1, 0.5, 0.9))
```

```
---------------------------------------------------------------------------
QC-PM: Quantile Composite-based Path Modeling
---------------------------------------------------------------------------
Quantile estimation: complete

Info models:
- Number of LV: 3
- Number of MV: 16
- LV modes:A A A
- LV scheme:  factorial

---------------------------------------------------------------------------
Info quantile:
Quantile selected: 0.1
 Quantile selected: 0.5
 Quantile selected: 0.9

---------------------------------------------------------------------------
Use also:
- for general results datails use function:            summary()
- for assessment results datails use function:         assessment()
- for boostrap results datails use function:           boot()
- for reliability results of LV use function:          reliability()
---------------------------------------------------------------------------
```

The `summary` function can be used to display the main results.

2.4.3 Model Assessment and Validation

The final phase of the analysis concerns the assessment of the internal and external parts of the model. Inferential tools (confidence intervals and/or hypothesis testing) for loadings and path coefficients can be used. QC–PM, like quantile regression, provides separate estimates for each quantile of interest, and therefore the assessment phase is carried out separately for each quantile.

All the assessment measures, discussed in Davino et al. (2014) and Dolce et al. (2021), are based on the $Pseudo - R^2$, proposed by Koenker and Machado (1999).

Communality and redundancy measures of QC–PM cannot be directly compared with goodness-of-fit measures of PLS–PM, since the $Pseudo - R^2$ obtained in quantile regression cannot be compared with the R^2 of classical regressions. $Pseudo - R^2$ is the most common measure of fit in literature, although the debate on this topic is still open (Koenker & Machado, 1999; He & Zhu, 2003). A direct comparison between PLS-PM and QC-PM is not possible, likewise ordinary regression results are not directly comparable with QR results. However, assessment measures adapted to the QC-PM context are very useful for comparing the quality of the model and the results obtained at different quantiles.

The `assessment` function of the **qcpm** package provides a complete analysis for the validation of results:

```
# run qcpm assessment
well_assessment <- assessment(well_qcpm)
```

```
-------------------------------------------------------------------
QC-PM model
assesement: Cummunality, Ridondance, and Pseudo-R2
-------------------------------------------------------------------
```

The output object stores all the assessment measures useful to interpret and validate the results:

```
# components of the assessment output object
names(well_assessment)
```

```
[1] "Communality"       "Block_Communality"  "Redundancy"
[4] "Block_Redundancy"  "pseudo.R2"
```

With respect to the inner model, the amount of variability of the two endogenous constructs, ECOW and HEALTH, explained by their explanatory constructs, respectively, EDU for ECOW, ECOW, and EDU for HEALTH, is measured by the following pseudo R^2 results:

```
# show qcpm pseudo R2
well_assessment$pseudo.R2
```

```
       ECOW HEALTH
0.25 0.5065 0.3851
0.5  0.5502 0.2982
0.75 0.5073 0.2834
```

In interpreting these results, please bear in mind the above considerations about $Pseudo - R^2$. In addition, it is important to carry out a separate assessment for each quantile of interest. As an example, when considering HEALTH, it is useful to note that the explanatory power of its exogenous variables is greater in the group of provinces with the worst health conditions. Overall, the results are not particularly satisfactory for either constructs. A synthesis of the evaluations for the whole inner model can be obtained by averaging all the $Pseudo - R^2$.

The evaluation of endogenous blocks also covers the external part of the model through the `Redundancy` measures, expressing the percentage of the variance of the MVs in the endogenous blocks, ECOW and HEALTH, predicted from such explanatory constructs:

```
# show redundancy measures
well_assessment$Redundancy
```

```
                  0.25    0.5   0.75
ECOW-ECOW1      0.4012 0.4408 0.3999
ECOW-ECOW2      0.3068 0.3308 0.2587
ECOW-ECOW3      0.3267 0.3715 0.3155
ECOW-ECOW4      0.2048 0.1984 0.1665
ECOW-ECOW5      0.2918 0.3525 0.3173
ECOW-ECOW6      0.3221 0.3353 0.2742
HEALTH-HEALTH1 0.2563 0.1986 0.1913
HEALTH-HEALTH2 0.1992 0.1812 0.1775
HEALTH-HEALTH3 0.1114 0.0476 0.0146
```

Results reveal a low ability of HEALTH to explain the variability of its outcome MVs for high quantiles, while for ECOW the best performance is in the center of the distribution ($\tau = 0.5$). The averages of the MV redundancies of the two endogenous blocks confirm these trends:

```
# show redundancy measures for the blocks
well_assessment$Block_Redundancy
```

```
       ECOW HEALTH
0.25 0.3089 0.1889
0.5  0.3382 0.1425
0.75 0.2887 0.1278
```

The communality values for each block, related to each MV and to the whole block, are stored in the `Communality` and `Block_Communality`, respectively:

```
# show communality measures
well_assessment$Communality
```

```
                   0.25    0.5   0.75
EDU-EDU1         0.5416 0.5346 0.4746
EDU-EDU2         0.4773 0.4690 0.4562
EDU-EDU3         0.2422 0.2679 0.2444
EDU-EDU4         0.6499 0.5895 0.4752
EDU-EDU5         0.3801 0.3433 0.2668
EDU-EDU6         0.4900 0.4790 0.4666
EDU-EDU7         0.4282 0.3690 0.3449
ECOW-ECOW1       0.7921 0.8012 0.7884
ECOW-ECOW2       0.6058 0.6013 0.5100
ECOW-ECOW3       0.6450 0.6753 0.6220
ECOW-ECOW4       0.4043 0.3606 0.3282
ECOW-ECOW5       0.5761 0.6407 0.6254
ECOW-ECOW6       0.6359 0.6094 0.5406
HEALTH-HEALTH1 0.6655 0.6660 0.6750
HEALTH-HEALTH2 0.5174 0.6078 0.6264
HEALTH-HEALTH3 0.2892 0.1596 0.0515
```

```
well_assessment$Block_Communality
```

```
        EDU   ECOW HEALTH
0.25 0.4585 0.6099 0.4907
0.5  0.4360 0.6148 0.4778
0.75 0.3898 0.5691 0.4510
```

Even if in most cases the amount of variability explained by each LV is low, it is interesting to note the variability across the quantiles, and the presence of quantiles where the measurement model assessment is better. Overall, the ECOW block shows more satisfactory results. However, for all the three blocks the quality of the outer model decreases as the quantile of interest increases.

Finally, it is important to recall that `fix.quantile=TRUE` can be used in the function `qcpm` to fix the quantile in the outer step of the iterative algorithm equal to the median. Clearly, in such a case, the function returns communalities only for the quantile 0.5.

Statistical significance of loadings and path coefficients can be carried out using a classical two tailed *t*-test (Koenker & Machado, 1999; Kocherginsky et al., 2005) where, following one of the most widely used approaches for inference in quantile regression, standard errors are estimated through bootstrap. The package **`qcpm`** uses the *xy-pair* method, or *design matrix bootstrap* (Parzen et al., 1994). Model parameters are estimated through the average of the bootstrap values. The standard error of the vector of bootstrap estimates represents an estimate of the QR standard error used for confidence intervals and hypothesis testing.

From a technical point of view, standard errors are computed by exploiting the bootstrap method implemented in the `tidy.rq` function of the **`broom`** package (Robinson et al., 2022):

```
# bootstraping qcpm
well_boot <- boot(well_qcpm)
```

```
----------------------------------------------------------------------
QC-PM model inference: loadings and path coefficients significance
----------------------------------------------------------------------
```

The output object stores all the bootstrap estimate measures to validate the results:

```
# components stored in the output object
names(well_boot)
```

```
[1] "boot.loadings" "boot.path"
```

```
# bootstrap results for loadings
well_boot$boot.loadings
```

```
$`0.25`
               Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU-EDU1         0.9285     0.0543 17.1013        0    0.8209      1.0361
EDU-EDU2         0.8138     0.0789 10.3145        0    0.6574      0.9702
EDU-EDU3         0.6054     0.1022  5.9238        0    0.4028      0.8079
EDU-EDU4         0.8999     0.0436 20.6550        0    0.8135      0.9862
EDU-EDU5         0.6349     0.0644  9.8618        0    0.5073      0.7625
EDU-EDU6         0.7560     0.0970  7.7911        0    0.5637      0.9483
EDU-EDU7         0.7809     0.0633 12.3378        0    0.6554      0.9064
ECOW-ECOW1       0.9343     0.0193 48.3569        0    0.8960      0.9726
ECOW-ECOW2       0.9114     0.0679 13.4275        0    0.7768      1.0459
ECOW-ECOW3       0.8454     0.0545 15.5010        0    0.7373      0.9535
ECOW-ECOW4       0.8524     0.0933  9.1396        0    0.6675      1.0372
ECOW-ECOW5       0.9223     0.0768 12.0157        0    0.7702      1.0744
ECOW-ECOW6       0.8719     0.0413 21.0896        0    0.7899      0.9538
HEALTH-HEALTH1   0.9836     0.0671 14.6559        0    0.8506      1.1167
HEALTH-HEALTH2   0.9200     0.0609 15.1014        0    0.7992      1.0407
HEALTH-HEALTH3   0.6538     0.0919  7.1128        0    0.4716      0.8361

$`0.5`
               Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU-EDU1         0.8852     0.0474 18.6609        0    0.7912      0.9792
EDU-EDU2         0.7931     0.0695 11.4064        0    0.6553      0.9309
EDU-EDU3         0.6221     0.0942  6.6046        0    0.4354      0.8089
EDU-EDU4         0.9554     0.0587 16.2663        0    0.8389      1.0718
EDU-EDU5         0.8142     0.0727 11.1978        0    0.6700      0.9583
EDU-EDU6         0.8540     0.0654 13.0634        0    0.7244      0.9836
EDU-EDU7         0.7651     0.1004  7.6212        0    0.5661      0.9641
ECOW-ECOW1       0.9664     0.0326 29.6071        0    0.9017      1.0311
ECOW-ECOW2       0.9174     0.0741 12.3782        0    0.7705      1.0643
ECOW-ECOW3       0.9101     0.0426 21.3593        0    0.8256      0.9945
ECOW-ECOW4       0.6772     0.0753  8.9907        0    0.5279      0.8265
ECOW-ECOW5       0.9230     0.0425 21.7298        0    0.8388      1.0072
ECOW-ECOW6       0.8772     0.0405 21.6601        0    0.7969      0.9575
HEALTH-HEALTH1   0.9088     0.0336 27.0622        0    0.8422      0.9754
HEALTH-HEALTH2   0.8837     0.0392 22.5153        0    0.8059      0.9615
HEALTH-HEALTH3   0.6067     0.1147  5.2883        0    0.3793      0.8341

$`0.75`
               Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU-EDU1         0.8218     0.0512 16.0522   0.0000    0.7203      0.9233
EDU-EDU2         0.7682     0.0707 10.8719   0.0000    0.6282      0.9083
EDU-EDU3         0.6501     0.0889  7.3089   0.0000    0.4738      0.8264
EDU-EDU4         0.9419     0.0923 10.2018   0.0000    0.7589      1.1249
EDU-EDU5         0.8198     0.1156  7.0921   0.0000    0.5907      1.0490
EDU-EDU6         0.8476     0.0463 18.2892   0.0000    0.7557      0.9394
EDU-EDU7         0.7509     0.0947  7.9289   0.0000    0.5632      0.9387
ECOW-ECOW1       1.0299     0.0279 36.8711   0.0000    0.9745      1.0853
ECOW-ECOW2       0.9015     0.0476 18.9583   0.0000    0.8073      0.9958
ECOW-ECOW3       1.0199     0.0538 18.9514   0.0000    0.9132      1.1265
ECOW-ECOW4       0.7512     0.0945  7.9505   0.0000    0.5639      0.9384
ECOW-ECOW5       0.9576     0.0660 14.5016   0.0000    0.8267      1.0884
ECOW-ECOW6       0.8943     0.0526 17.0043   0.0000    0.7900      0.9985
HEALTH-HEALTH1   0.9449     0.0424 22.2644   0.0000    0.8608      1.0290
HEALTH-HEALTH2   0.8491     0.0483 17.5889   0.0000    0.7534      0.9447
HEALTH-HEALTH3   0.2911     0.1414  2.0586   0.0419    0.0108      0.5715
```

```
# bootstrap results for path coefficients
well_boot$boot.path
```

```
$`0.25`
             Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU->ECOW      0.8837     0.0577 15.3063    0.000    0.7693      0.9982
EDU->HEALTH    0.7910     0.1528  5.1752    0.000    0.4880      1.0940
ECOW->HEALTH   0.0263     0.1423  0.1845    0.854   -0.2559      0.3084

$`0.5`
             Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU->ECOW      0.8459     0.0631 13.4115   0.0000    0.7209      0.9710
EDU->HEALTH    0.6857     0.2643  2.5943   0.0108    0.1617      1.2097
ECOW->HEALTH   0.0741     0.2374  0.3122   0.7555   -0.3966      0.5448

$`0.75`
             Estimate Std. Error t value Pr(>|t|) low 0.95% upper 0.95%
EDU->ECOW      0.8734     0.0505 17.2839   0.0000    0.7732      0.9736
EDU->HEALTH    0.4353     0.1681  2.5898   0.0109    0.1021      0.7685
ECOW->HEALTH   0.2392     0.1559  1.5346   0.1278   -0.0698      0.5483
```

For all the quantiles of interest, the loadings are significantly different from zero. However in the inner part of the model, the impact of ECOW on HEALTH is never significant.

A more rigorous approach would require the use of bootstrap in the iterative model estimation algorithm to jointly obtain the estimation and validation of loading and path coefficients (Hair et al., 2016). This limitation of the current inference procedure will be overcome in the next versions of the package.

2.4.4 Post-processing: Graphs and Result Exporting

The output of QC–PM can be visualized using base `R` graphics. Here we exploit the `ggplot2` system, part of the `tidyverse`. To this end, the objects of **`qcpm`**, typically stored in `matrix` objects, must be converted in `data.frame` or `tibble`. Here is a convenient approach applied on the path coefficients:

```
# transform qcpm path coefficients into a dataframe moving the rownames to a column
path_coef <-well_qcpm$path.coefficients%>%
  as.data.frame() %>%
  rownames_to_column(var = "path")
# print the resulting object
path_coef
```

```
          path   0.25    0.5   0.75
1    EDU->ECOW 0.8837 0.8459 0.8734
2  EDU->HEALTH 0.7910 0.6857 0.4353
3 ECOW->HEALTH 0.0263 0.0741 0.2392
```

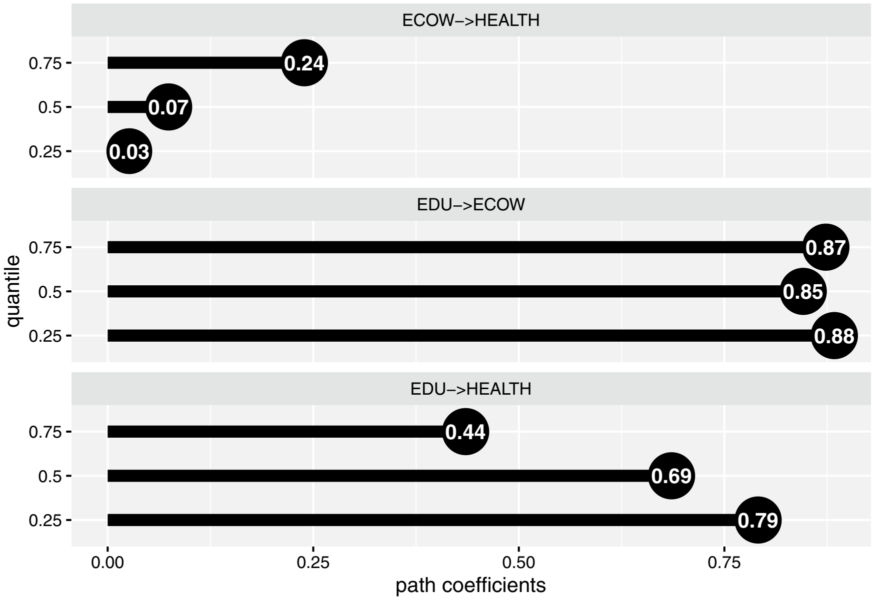
For most of the plot, data must be reshaped in long format through the `pivot_wider` function:

```
# reshape the tibble of path coefficients to long format
path_coef_long <- path_coef%>%
  pivot_longer(cols = -path, names_to = "quantile", values_to = "values")
# print an extract of the resulting object
path_coef_long
```

```
# A tibble: 9 x 3
  path         quantile values
  <chr>        <chr>     <dbl>
1 EDU->ECOW    0.25      0.884
2 EDU->ECOW    0.5       0.846
3 EDU->ECOW    0.75      0.873
4 EDU->HEALTH  0.25      0.791
5 EDU->HEALTH  0.5       0.686
6 EDU->HEALTH  0.75      0.435
7 ECOW->HEALTH 0.25      0.0263
8 ECOW->HEALTH 0.5       0.0741
9 ECOW->HEALTH 0.75      0.239
```

Once reshaped, the path coefficients can be used to obtain an illustrative graphical representation, showing the importance of each coefficient in the QC–PM model:

```
# plot path coefficients through ad hoc bar plot
  ggplot(data = path_coef_long,
         aes(x = quantile, y = values)) +
  geom_segment(aes(x = quantile, xend = quantile,
                   y = 0, yend = values),
               size = 3) +
  geom_point(size = 11, alpha = 1) +
  geom_text(aes(label = round(values, 2)),
            position = position_dodge(width = 1),
            vjust = +0.5, size = 3.8, color = "white", fontface = "bold") +
            ylab("path coefficients") +
            coord_flip() +
            facet_wrap(vars(path), ncol = 1)
```



Each panel of the plot represents a different path coefficient effect. From the top to the bottom, we have the representation of the effect of ECOW on HEALTH (first panel), EDU on ECOW (second panel) and finally, EDU on HEALTH (third panel). The quantiles are shown on the ordinates (in our case 0.25, 0.50, 0.75) while the length of each bar is proportional to the path coefficients. The exact values of these coefficients are shown in the circumference.

A similar approach can be used to represent the loadings. However, here is useful to add an additional column to the `tibble` object to denote the blocks, so to easily obtain a representation for each block. The function `separate` can be added to the previous pipeline to this end:

```
# transform qcpm loadings into a data frame moving the rownames to a column
# and adding a column for denoting the blocks
  loadings_coef<-well_qcpm$outer.loadings%>%
  as.data.frame() %>%
  rownames_to_column(var = "loadings") %>%
  separate(col = loadings, into = c("block", "indicator"))
# print the resulting object
loadings_coef
```

```
    block indicator   0.25    0.5   0.75
1     EDU      EDU1 0.9285 0.8852 0.8218
2     EDU      EDU2 0.8138 0.7931 0.7682
3     EDU      EDU3 0.6054 0.6221 0.6501
4     EDU      EDU4 0.8999 0.9554 0.9419
5     EDU      EDU5 0.6349 0.8142 0.8198
6     EDU      EDU6 0.7560 0.8540 0.8476
7     EDU      EDU7 0.7809 0.7651 0.7509
8    ECOW     ECOW1 0.9343 0.9664 1.0299
9    ECOW     ECOW2 0.9114 0.9174 0.9015
10   ECOW     ECOW3 0.8454 0.9101 1.0199
11   ECOW     ECOW4 0.8524 0.6772 0.7512
12   ECOW     ECOW5 0.9223 0.9230 0.9576
13   ECOW     ECOW6 0.8719 0.8772 0.8943
14 HEALTH   HEALTH1 0.9836 0.9088 0.9449
15 HEALTH   HEALTH2 0.9200 0.8837 0.8491
16 HEALTH   HEALTH3 0.6538 0.6067 0.2911
```

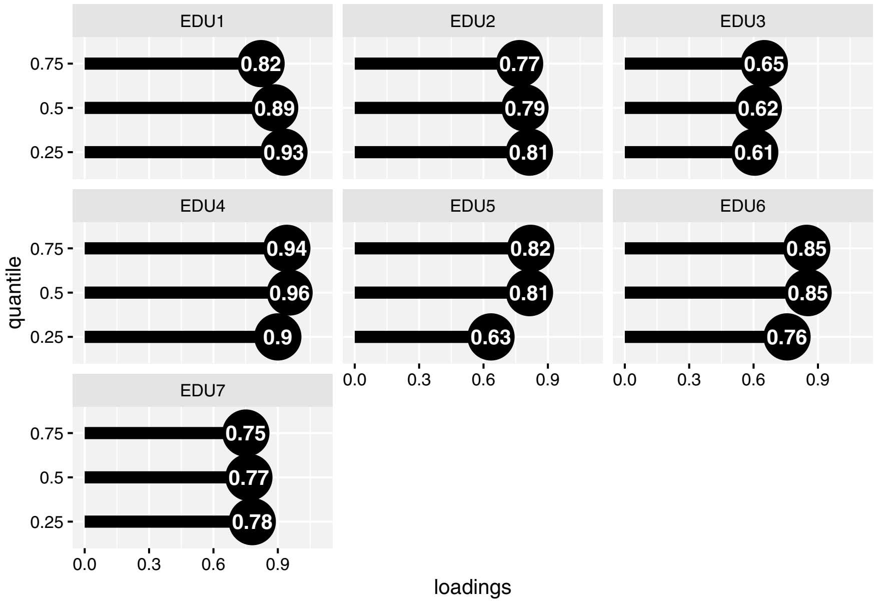
The resulting object can be reshaped in long format to prepare it for graphical representations:

```r
# reshape the tibble of loadings in long format
loadings_long <- loadings_coef%>%
  pivot_longer(cols = c(-block, -indicator),
               names_to = "quantile",
               values_to = "values")
# print an extract of the resulting object
loadings_long
```

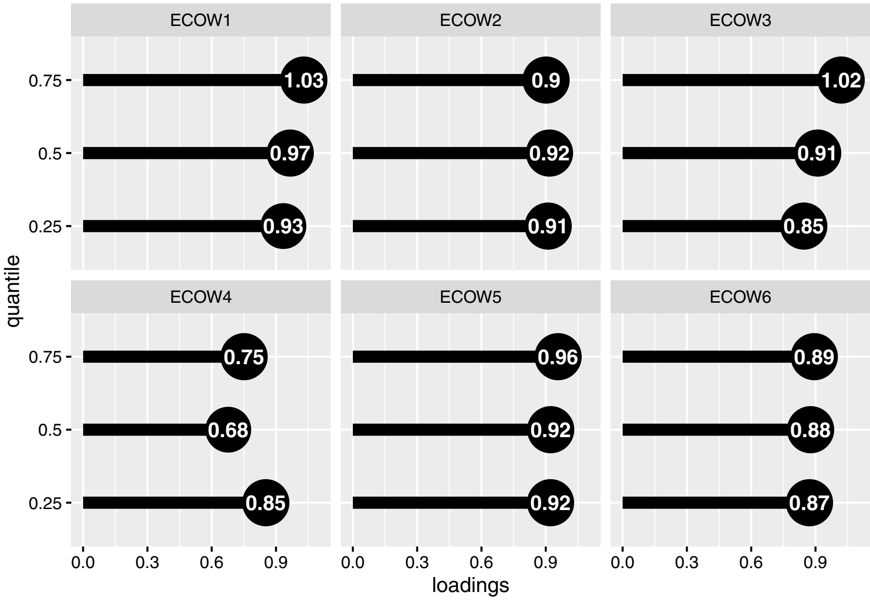
```
# A tibble: 48 x 4
   block indicator quantile values
   <chr> <chr>     <chr>     <dbl>
 1 EDU   EDU1      0.25      0.928
 2 EDU   EDU1      0.5       0.885
 3 EDU   EDU1      0.75      0.822
 4 EDU   EDU2      0.25      0.814
 5 EDU   EDU2      0.5       0.793
 6 EDU   EDU2      0.75      0.768
 7 EDU   EDU3      0.25      0.605
 8 EDU   EDU3      0.5       0.622
 9 EDU   EDU3      0.75      0.650
10 EDU   EDU4      0.25      0.900
# ... with 38 more rows
```

The `block` column can then be exploited to filter the loadings related to the block of interest. Here is the case of EDU block:

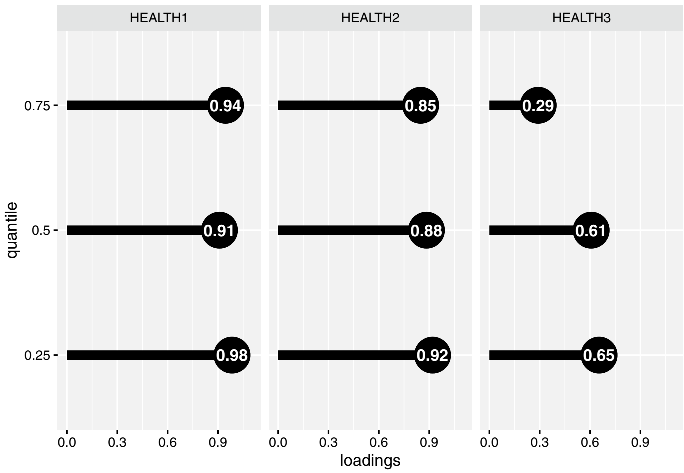
```
# filter the loadings of EDU block and represent them through ad hoc barplots
ggplot(data = filter(loadings_long, block== "EDU"),
       aes(x = quantile, y = values)) +
  geom_segment(aes(x = quantile, xend = quantile,
                   y = 0, yend = values), size=3) +
  geom_point(size=11, alpha=1) +
  geom_text(aes(label = round(values, 2)),
            position = position_dodge(width = 1),
            vjust = +0.5, size = 3.8, color = "white", fontface = "bold") +
  ylim(0, 1.1) +
  coord_flip() +
  xlab("quantile") + ylab("loadings") +
  facet_wrap(~ indicator, nrow = 3)
```



The following plot can be easily obtained by setting the filtering criterion for block equal to ECOW in the previous chunk of code (`block == "ECOW"`):



Finally, here is the representation for the loadings of HEALTH block:



2.5 Concluding Remarks

In this manuscript, we described how to perform QC–PM with R, using the **qcpm** package. As an empirical example, we used data from the Italian system of indicators on Equitable and Sustainable Well-Being (ISTAT, 2018) proposed by the National Institute of Statistics, focusing on three well-being domains (Education, Economic

Well-Being and Health) measured on Italian provinces. We also showed that some graphical tools may support the users in exploring their data before and after the model estimation. The proposed model was simple, but **qcpm** package can easily be used to estimate more complex path models. Since QC–PM does not pose on any distributional assumptions and does not have closed-form solutions for standard errors: bootstrap or jackknife resampling procedures should be used to compute the inferential quantities of interest. Currently, the **qcpm** package does not contain a statistical test for measurement invariance, when the quantile in the outer step of the iterative algorithm is not fixed to the median.

Future releases of the **qcpm** package will include: (1) an integrated bootstrapping resampling procedure in QC–PM to estimate standard errors for statistical tests, critical quantiles and confidence intervals, (2) a statistical test of measurement invariance of composites, (3) a new parameter to introduce moderating effects for dealing with observed heterogeneity among observations, and (4) a specific methods to visualize model data.

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Chapter 3
Use of Partial Least Squares Path Modeling Within and Across Business Disciplines

Stacie Petter and Yasamin Hadavi

Abstract The acceptance and application of PLS-PM vary dramatically across business disciplines. Some business disciplines, such as marketing and information systems, have used PLS-PM for decades. Other disciplines, such as accounting, have been slower at incorporating path models and PLS-PM in their research studies. The differences in adoption of PLS-PM across business disciplines can be confusing for authors interested in applying, using, and reporting the PLS-PM results in published research within their own discipline or across business disciplines. To address this concern, this chapter reviews the use and application of PLS-PM in *Financial Times* (FT50) journals. Our results identify the prevalence of PLS-PM use within and across business disciplines. This chapter reviews the rationales provided by authors for their use of PLS-PM within and across business disciplines, discusses questionable and appropriate rationales for PLS-PM, and offers guidance for authors intending to publish articles using PLS-PM.

3.1 Introduction

A century ago, a geneticist developed path modeling to examine how factors cause variation in hypothesized outcomes. Scholars developed and applied path modeling techniques in the social sciences decades later (e.g., Jöreskog, 1969; Wold, 1966). By the 1980s, a few scholars in business disciplines applied these techniques (i.e., partial least square path modeling (PLS-PM) and covariance-based structural equation modeling (CB-SEM)) to test hypotheses (Fornell & Bookstein, 1982). Unlike CB-SEM, which focuses on confirmatory approaches for model testing, Wold (1985)

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envisioned PLS-PM to enable scholars to discover new theories by engaging with the data and the PLS-PM process. Other scholars have highlighted the value of PLS-PM to examine the predictive performance of research models (e.g., Chin et al., 2020; Sarstedt et al., 2021; Shmueli et al., 2016).

After PLS-PM was introduced to the marketing discipline in the early 1980s, articles using PLS-PM to analyze hypotheses within path-based models appeared in other business disciplines, such as management (e.g., Cool et al., 1989) and information systems (e.g., Amoroso & Cheney, 1991). Figure 3.1 shows the number of articles using PLS-PM as an analysis technique to assess path models within *Financial Times* 50 (FT50) journal articles between 1980 and 2020. The adoption rate was low among business journals until the 2000s, when approximately ten articles using PLS-PM were published per year. By 2006, the number of articles using PLS-PM began rising steadily and peaked in 2013 with 46 articles published in a year. Between 2014 and 2020, the number of articles using PLS-PM has a decreasing trendline.

Some business disciplines, such as information systems, have adopted PLS-PM broadly, but other business disciplines have been more measured or slower to publish articles using PLS-PM as an analysis technique. Some scholars within specific business disciplines have sought to advance PLS-PM, for example, by explaining how to use PLS-PM for complex models with moderators (e.g., Chin et al., 2003) or higher order constructs (e.g., Becker et al., 2012). However, as some scholars continued with the application of PLS-PM within business disciplines, other scholars have expressed concerns with the partial least squares algorithm (e.g., Rönkkö et al., 2016) and its application for small sample sizes (e.g., Goodhue et al., 2012), interaction effects (e.g., Goodhue et al., 2007), and hypothesis testing (e.g., Evermann & Rönkkö, 2023; Rönkkö & Evermann, 2013). Other scholars have supported the use of PLS-PM to analyze measurement and structural models in certain settings but have encouraged researchers to use caution when analyzing, interpreting, and reporting results (e.g., Petter & Hadavi, 2021; Richter et al., 2016).

Authors frequently justify the use of PLS-PM based on characteristics of the data (e.g., small sample size, non-normal data) or the research model (e.g., formative measurement, moderators). Editors of the *Journal of Operations Management,* a premier journal within the FT50 journal list, published an editorial expressing their concerns about various research methods and criteria. Within their editorial, Guide and Ketokivi (2015) stated that they were desk rejecting nearly all articles using PLS-PM because "Most of the time, use of PLS is (incorrectly) justified" for many reasons (p. vii). These concerns associated with the poor justification for PLS-PM are still relevant as authors continue to use poor rationales for PLS-PM (e.g., Petter & Hadavi, 2021; Richter et al., 2016) or fail to understand the methodological implications associated with using PLS-PM (e.g., Evermann and Rönkkö, 2023).[1]

Many methodological studies explaining PLS-PM, advancing the technique, or providing guidance to authors are published within discipline-specific journals. For

[1] Providing a full description of the PLS-PM method and its proper application and use is beyond the scope of this book chapter. We refer readers to the many books, journal articles, and websites explaining the PLS-PM methodology and the interpretation of its results.

example, there are discipline-specific reviews about the prevalence of the use of PLS-PM and guidance for reporting results within the areas of marketing (Hair et al., 2012b), accounting (Nitzl, 2016), entrepreneurship (Manley et al., 2021), hospitality and tourism (Ali et al., 2018; do Valle & Assaker 2016; Usakli & Kucukergin, 2018), human resource management (Ringle et al., 2020), information systems (Hair et al., 2017a; Ringle et al., 2012), international business (Richter et al., 2016), knowledge management (Cepeda-Carrion et al., 2018), operations management (Bayonne et al., 2020; Peng & Lai, 2012), supply chain management (Kaufmann & Gaeckler, 2015), and strategic management (Hair et al., 2012a). While much of the guidance and findings are similar across disciplines, authors who are not familiar with these articles outside of their discipline may not be aware of more recent recommendations and articles regarding PLS-PM.

Since prior reviews of PLS-PM articles focus on research published within a single discipline, this chapter first identifies the frequency of PLS-PM use within FT50 journals over time. Then, we analyze more recent publications in FT50 journals from 2015 to 2020 that use PLS-PM to identify differences in justifications for its approach across business disciplines. As we review our findings, we provide suggestions for authors using PLS-PM to help them provide more robust justifications for using PLS-PM, regardless of their discipline.

3.2 Frequency of PLS-PM Use in Financial Times Journals

To identify how frequently authors use PLS-PM in FT50 journals, one author performed full-text searches for keywords related to PLS-PM for each journal in the FT50 list using the following keywords: “partial least squares” or “PLS.” Any research article found during this search was retained for further consideration (i.e., 1,124 articles). The earliest article identified within our dataset was from 1982 (i.e., Fornell & Bookstein, 1982). Next, both authors reviewed the article to determine if PLS-PM was used to analyze data within the article. This step revealed multiple articles that were not relevant to this study. For example, articles were excluded if “PLS” was used as an abbreviation for another term (e.g., Abedifar et al., 2013), the authors did not analyze data using PLS-PM (e.g., Chenhall, 2005; Hughes et al., 1986), or the article discussed PLS-PM as a methodology (Dijkstra & Henseler, 2015). After this stage, 674 articles were retained for additional review.

Next, both authors further reviewed the application and use of PLS-PM within the manuscript. Upon closer review, some articles used PLS-PM to analyze the measurement model or a specific construct; however, PLS-PM was not used to assess the structural model (e.g., Chatterjee & Ravichandran, 2013). Other studies may have analyzed a structural model using PLS-PM, but the analysis was performed as a robustness check or supplementary analysis in conjunction with another form of structural equation modeling (e.g., Tiwana & Keil, 2009). If the authors did not describe their analysis using PLS-PM, the article was excluded from our literature review (e.g., Patel et al., 2012). This final review yielded 604 articles. Appendix A

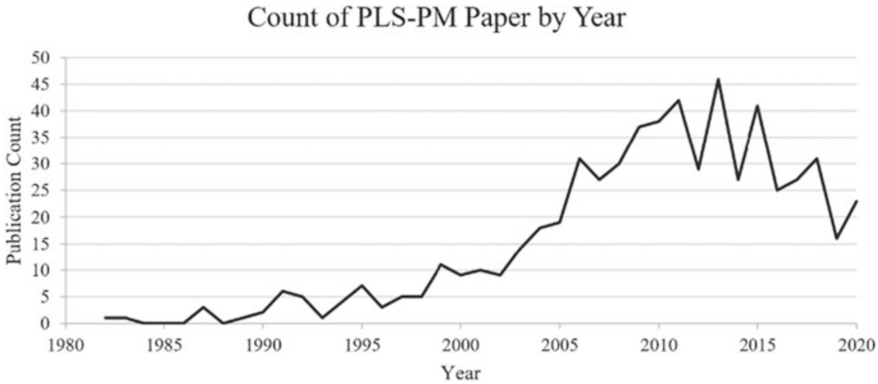


Fig. 3.1 Number of FT50 articles using PLS-PM by year

explains how each journal was classified into a discipline, lists the FT50 journals by discipline, and identifies the number of PLS-PM articles published in each journal from 1982 to 2020.

Figure 3.2 identifies the number of articles using PLS-PM in FT50 articles by discipline (see Fig. 3.2). No articles in economics or finance FT50 journals published articles using PLS-PM through 2020. The three information systems journals in the FT50 journal list published nearly half (i.e., 46.7%) of the 604 articles using PLS-PM. General business (17.5%), marketing (12.3%), and management (11.3%) published more articles using PLS-PM compared to other disciplines.

While Fig. 3.1 (see Introduction) identifies the number of papers in FT50 journals using PLS-PM to analyze path models each year, we also wanted to identify if the rate of publications using PLS-PM was similar across business disciplines. Figure 3.3 shows the number of FT50 articles published using PLS-PM over time by discipline over 5-year increments, beginning in 1981 and ending in 2020.

The information systems discipline has a sharp increase in the number of publications between 1996 and 2010; however, the number of articles using PLS-PM declines in the last two periods, with a marked decrease in the final period (i.e., 2016–2020). Some disciplines tend to have a consistent number of publications throughout the reporting periods (e.g., accounting, entrepreneurship). General business shows a strong increase throughout the entire period, and it is the only discipline to have an increase in the number of publications using PLS-PM in the final period (i.e., 2016–2020). Other disciplines show a decline in the number of PLS-PM publications in the final reporting period. The most severe downturn in the last reporting period occurred within operations management (i.e., from 18 articles in 2011–2015 to 2 articles in 2016–2020).

Comparing Figs. 3.1 and 3.3, the number of PLS-PM articles in FT50 journals trended downward after 2013. Some journal editors published editorials about their concerns related to PLS-PM as an analysis technique (e.g., Browning & de Treville, 2018; Guide & Ketokivi, 2015). Other editors-in-chief of FT50 journals encouraged

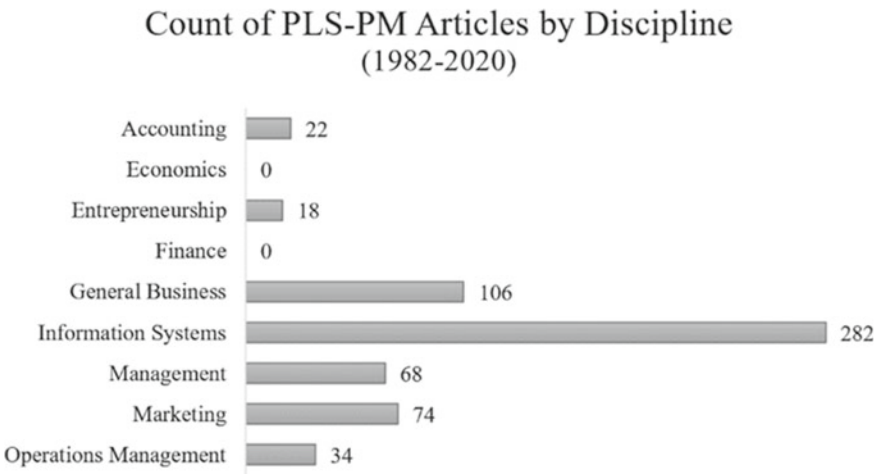
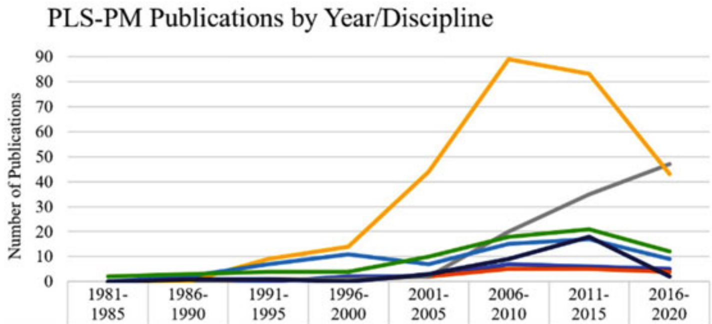


Fig. 3.2 Number of PLS-PM articles by discipline



	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2020
Accounting	0	0	0	2	2	7	6	5
Entrepreneurship	0	0	1	1	2	5	5	4
General Business	0	0	1	1	2	20	35	47
Information Systems	0	0	9	14	44	89	83	43
Management	0	2	7	11	7	15	17	9
Marketing	2	3	4	4	10	18	21	12
Operations Management	0	1	1	0	3	9	18	2

Fig. 3.3 Number of PLS-PM publications by year and discipline

their editorial boards to be more critical of articles using PLS-PM by raising the standards required for publication, calling for rejection of articles using PLS-PM, and asking authors to use alternative analysis techniques. The only business discipline with a steady increase in the number of PLS-PM articles published is general business. Nearly all of these articles are published in the *Journal of Business Ethics.*

The decline in the number of articles using PLS-PM findings in this review contrasts with most discipline-specific reviews of PLS-PM use. Many discipline-specific reviews note their fields are publishing *more* articles using PLS-PM. For example, entrepreneurship (Manley et al., 2021), operations management (Bayonne et al., 2020), and knowledge management (Cepeda-Carrion et al., 2018) have noted an increase in the number of articles using PLS-PM in their respective discipline-specific journals. Each of the discipline-specific review articles tended to review many journals within the discipline, with ranging levels of quality. Yet, in the FT50 subset of journals, the use of PLS-PM is *declining*, except in general business (and specifically the *Journal of Business Ethics).* As authors consider publishing outlets, it would be appropriate to note that even if the use of PLS-PM is increasing within their discipline, many FT50 journals have published fewer PLS-PM articles in recent years.

3.3 Rationale for PLS-PM Use in Financial Times Journals

Since recommendations for PLS-PM are constantly evolving and multiple articles have appeared across business disciplines related to the use of PLS-PM, we focused our analysis on more recently published articles using PLS-PM published in FT50 journals. We analyzed the 163 articles using PLS-PM for path analysis published in 2015–2020. Of the 163 articles using PLS-PM to analyze a structural model in 2015–2020, most articles appeared in the information systems (39%) and the general business (34%) disciplines. Table 3.1 identifies the number of articles we analyzed across each discipline that used PLS-PM each year.

We used a similar coding approach as other discipline-specific PLS-PM review articles, such as Ringle et al. (2012) and Ali et al. (2018). We recorded attributes of the measurement model, structural model, dataset, measurement model assessment, structural model assessment, and the rationale provided by the authors for using PLS-PM. To ensure consistency, the two authors reviewed and recorded the attributes of the

Table 3.1 Number of PLS-PM articles by year and discipline (2015–2020)

Discipline	2015	2016	2017	2018	2019	2020	Total
Accounting	1	0	1	1	1	1	5
Entrepreneurship	0	1	1	2	0	0	4
General business	7	6	3	14	8	17	55
Information systems	22	8	15	9	5	5	64
Management	3	2	4	2	0	1	12
Marketing	5	6	4	2	0	0	17
Operations management	4	2	0	0	0	0	6
Total	42	25	28	30	14	24	163

same ten articles. We examined our results and reconciled any discrepancies. Through this exercise, we clarified our terminology and processes. Then, each author independently coded approximately half of the remaining articles. The authors discussed and reviewed some articles jointly when questions arose. When an article described and analyzed multiple research models using PLS-PM within the same paper, we recorded information about the most complex model (based on the number of structural and measurement model components).

To analyze the 163 articles that applied PLS-PM in 2015–2020, we first examined the rationale offered by authors for using PLS-PM for their study. We identified general categories for authors' rationale for using PLS-PM based on prior literature (e.g., Ali et al., 2018; Petter & Hadavi, 2021; Ringle et al., 2012) and created new categories based on our review of the findings. After considering the rationales for using PLS-PM provided by authors, we performed additional analyses of the articles published in 2015–2020 within FT50 journals to identify additional insights for authors. Most papers using PLS-PM provided at least one rationale for using PLS-PM for analyzing their structural model. Table 3.2 shows the frequency of each rationale for PLS-PM by discipline.

All articles in entrepreneurship and operations management provided at least one rationale for their use of PLS-PM. However, 32 articles across the remaining disciplines did not justify their use of PLS-PM. The business disciplines least likely to provide a rationale for PLS-PM use include information systems and general business. Given the widespread use of PLS-PM in these two fields, authors publishing in information systems or general business FT50 journals may not perceive a need to justify their use of PLS-PM. However, scholars across disciplines have called for authors to provide one or more clearly stated and appropriate rationales for using PLS-PM (e.g., Petter & Hadavi, 2021; Richter et al., 2016; Usakli & Kucukergin, 2018).

Among the articles that provided a rationale for using PLS-PM, authors identified, on average, 2.5 reasons for using PLS-PM. The most common reasons authors used to justify the use of PLS-PM was the ability of PLS-PM to accommodate smaller sample sizes, non-normal data, and complex models, which may include moderators, mediators, formative measures, or multidimensional constructs. Many authors specifically discussed the value of PLS-PM as a tool for theory development, performing exploratory research, or prediction. As described below, some of these rationales are problematic as reasons to justify the use of PLS-PM. The following subsections highlight concerns and offer recommendations associated with the most common rationales for using PLS-PM within FT50 journals.

3.3.1 Problematic Rationale: Small Sample Size

Nearly one-third of articles using PLS-PM in FT50 journals published between 2015 and 2020 justified the use of PLS-PM due to the technique's purported ability to support small sample sizes. While information systems rarely used small sample size

Table 3.2 Frequency of rationale by discipline

Rationale	Acc (5)	Ent (4)	GB (55)	IS (64)	Mgt (12)	Mkt (17)	Ops (6)	Total
Fewer data assumptions	0	0	3	5	2	0	0	10
Non-normal data	2	2	21	8	5	5	1	44
Small sample size	3	2	23	6	10	6	2	52
Fewer model assumptions	0	0	4	7	0	2	0	13
Model complexity	0	2	19	11	3	6	3	44
Moderator analysis	0	0	5	8	0	2	2	17
Mediator analysis	0	0	5	1	0	4	2	12
Formative measures	1	1	7	16	0	4	0	29
Theory development	0	2	8	13	2	4	0	29
Exploratory research	0	0	13	11	4	2	1	31
Theory testing	0	0	3	0	0	0	0	3
Prediction	1	2	7	4	2	4	1	21
Other	0	1	11	7	1	1	0	21
Not mentioned	1	0	11	17	1	2	0	32
Total	8	12	140	114	30	42	12	358

Acc = Accounting; Ent = Entrepreneurship; GB = General Business; IS = Information Systems; Mgt = Management; Mkt = Marketing; Ops = Operations Management; number of articles using PLS-PM within discipline identified in parentheses

as a justification for PLS-PM (9%), other disciplines, such as management (83%), accounting (60%), entrepreneurship (50%), and general business (42%) have a larger percentage of articles relying on this rationale.

Table 3.3 provides descriptive statistics of sample sizes by discipline for articles that reported the sample size. Some articles performed multiple studies with PLS-PM, and for our analysis purposes, we recorded the smallest sample within each paper. Two articles did not identify the sample size used for PLS-PM. General business and information systems have the highest mean sample size.

Table 3.4 shows the number of articles using PLS-PM with sample sizes in various ranges (i.e., very small, small, medium, large, and very large). About half of the articles using PLS-PM (87 of 163) used very small or small sample sizes. We also

Table 3.3 Descriptive statistics of sample size by discipline

Discipline	# Articles	Mean	Std Dev	Range
Accounting	5	158.0	85.0	77–290
Entrepreneurship	4	377.3	395.5	47–951
General business	54	560.8	1,003.6	52–6,000
Information systems	63	411.5	419.6	21–2,276
Management	12	243.5	336.1	67–1,289
Marketing	17	263.1	176.8	97–773
Operations management	6	197.5	116.7	68–392
Overall	161	416.7	657.3	21–6,000

Table 3.4 Number of articles by sample size and discipline

Discipline	NR	<100	101–250	251–500	501–1000	1001+	Total
Accounting	0	2	2	1	0	0	5
Entrepreneurship	0	1	1	1	1	0	4
General business	1	5	17	23	3	6	55
Info systems	1	7	26	10	15	5	64
Management	0	3	7	1	0	1	12
Marketing	0	3	8	4	2	0	17
Ops management	0	2	3	1	0	0	6
Overall	2	23	64	41	21	12	163

found examples of studies in which the sample size is extremely small (i.e., $n < 50$). Every business discipline that has published articles using PLS-PM has published at least one article with a sample size less than 100. Several disciplines have published one or more articles using PLS-PM with sample sizes greater than 1,000.

Most of the articles with very small sample sizes (i.e., less than 100) mentioned the benefits of PLS-PM at smaller sample sizes, and over one-third of articles with small samples (i.e., $100 < n < 250$) stated small sample size as a reason to use PLS-PM. Interestingly, one article with a large sample size (i.e., $501 < n < 1000$) mentioned the benefits of using PLS-PM as being "robust to both small and large samples" (Harmeling et al., 2015, p. 53).

Justifying the use of PLS-PM based on sample size is problematic, and multiple scholars have called for authors to stop using sample size to justify the use of PLS-PM (e.g., Ali et al., 2018; Bayonne et al., 2020; Hair et al., 2013; Rigdon, 2016). While "PLS can be applied in many instances of small samples when other methods fail" (Henseler et al., 2014, p. 199), authors should recognize the limitations associated with small sample sizes. "No statistical method—including PLS-SEM—can offset a badly designed sample" (Sarstedt et al., 2021, p. 14). Among the articles using

Table 3.5 Number of articles performing power calculations

Discipline (# articles)	Not reported	A priori data collection	Post Hoc data collection	Total
Accounting (5)	5	0	0	5
Entrepreneurship (4)	4	0	0	4
General business (55)	47	0	8	55
Info systems (64)	55	5	4	64
Management (12)	11	0	1	12
Marketing (17)	16	0	1	17
Ops management (6)	5	0	1	6
Overall (163)	143	5	15	163

PLS-PM published in FT50 journals between 2015 and 2020, 23 articles (14.3%) had sample sizes less than 100.

Scholars reviewing the use of PLS-PM across disciplines have identified the lack of minimum sample size calculations or power analysis among authors using PLS-PM (e.g., Ali et al., 2018; Henseler et al., 2014; Kaufmann & Gaeckler, 2015; Nitzl, 2016; Ringle et al., 2012, 2020). Scholars have developed methods to perform power analysis or determine a minimum sample size when using PLS-PM, such as G-Power or other calculation methods (e.g., Aguirre-Urreta & Rönkkö, 2015; Kock & Hadaya, 2018). However, few FT50 articles we analyzed performed a power analysis or minimum sample size calculation before or after data collection. Only five articles (3%) reported conducting sample size calculations or performing a power analysis a priori to data collection. An additional 15 articles (9.2%) performed some form of post hoc statistical power calculations. Table 3.5 shows the number of articles by discipline performing power calculations a priori or post hoc to data collection.

Of the 20 articles in our analysis performing a power analysis or minimum sample size calculation a priori or post hoc data collection, 9 of those articles appeared in information systems journals. However, even with the higher numbers of articles performing power calculations within information systems, these nine articles only comprise 14% of all information systems articles we analyzed. The eight articles performing power calculations post hoc data collection within general business only comprise 14.5% of all articles using PLS-PM within that discipline. Regardless of the statistical technique, authors should continue to heed the many calls of scholars to calculate and report minimum sample size or power calculations to aid in the interpretation of nonsignificant results.

3.3.2 Problematic Rationale: Data Normality

Another common rationale to use PLS-PM within FT50 articles is the claim that PLS-PM accommodates non-normal data (i.e., 26.9% of studies). Authors publishing articles in entrepreneurship, management, accounting, and general business FT50 journals disproportionately rely upon non-normal data as a rationale for PLS-PM. Information systems authors are less likely to rely on this rationale.

Scholars have repeatedly warned authors that non-normal samples can increase bias (Hair et al., 2012b) and can reduce the model's statistical power (Bayonne et al., 2020) when the sample size is small and the degree of non-normality is high. Scholars have cautioned that non-normality is one of several faulty premises often used to justify PLS-PM and should be avoided (Rigdon, 2016). Furthermore, some authors imply that PLS-PM is the only statistical technique that can accommodate non-normal data, which is not an accurate assertion.[2]

While PLS-PM can be more tolerant of non-normal data compared to some statistical methods, scholars have repeatedly called for authors to test and report on the normality of their data (e.g., Bayonne et al., 2020; Hair et al., 2012a, 2012b; Kaufmann & Gaeckler, 2015; Kock & Hadaya, 2018; Richter et al., 2016; Ringle et al., 2012). Among the articles we analyzed, authors of only 16 of the 163 articles (9.8%) assessed and reported the skewness or kurtosis of their data. The percentage of authors reporting normality statistics among FT50 journals is consistent or only slightly better than many other discipline-specific reviews of PLS-PM use. Reviews of PLS-PM use in human resource management (Ringle et al., 2020) and strategic management (Hair et al., 2012b) found no authors reported normality statistics. Reviews in the following disciplines report that authors reported skewness or kurtosis in 10% or fewer articles: accounting (Nitzl, 2016), information systems (Ringle et al., 2012), international business (Richter et al., 2016), marketing (Hair et al., 2012b). Disciplines with higher reporting rates for normality statistics among discipline-specific reviews included operations management at 11% (Bayonne et al., 2020) and hospitality at 25% (Ali et al., 2018).

Within FT50 journals, of the 44 articles stating PLS-PM was used for its ability to accommodate non-normal data, only 11 reported normality statistics (e.g., skewness and kurtosis). Five articles provided information about the normality of the data analyzed, even though non-normal data was not a stated reason for using PLS-PM. Table 3.6 shows the number of studies by discipline that cited PLS-PM's ability to analyze non-normal data, the number of studies stating this justification that analyzed their data for non-normality, and the number of studies that analyzed data for non-normality even though non-normality was not a stated reason for using PLS-PM.

Operations management was the only business discipline in our sample in which the authors justified using PLS-PM because their data was non-normal and then reported statistics assessing the normality of their data (de Vries et al., 2016). All other disciplines had articles stating that PLS-PM was beneficial due to its ability to handle non-normal data. Yet, the authors failed to report if their data was indeed non-normal. We urge authors to avoid using certain rationales for PLS that have been deemed problematic for justifying PLS-PM use, such as small sample size and non-normal data (Gefen et al., 2011; Rigdon, 2016; Rönkkö et al., 2016).

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[2] In addition to non-parametric tests, some CB-SEM tools provide test statistics for non-normal data.

Table 3.6 Number of articles justifying PLS-PM based on non-normality and assessment of non-normality

Discipline	# Articles with non-normal rationale	# Articles (with rationale) assessing normality	# Articles (without rationale) assessing normality
Accounting	2	0	0
Entrepreneurship	2	1	0
General business	21	4	1
Info systems	8	2	3
Management	5	0	0
Marketing	5	3	1
Ops management	1	1	0
Overall	44	11	5

3.3.3 Questionable Rationale: Model Complexity

3.3.3.1 Measurement Model Complexity

Many studies justified the use of PLS-PM because of the complexity of their measurement model, such as formative measures or multidimensional constructs. Specifically, 29 articles mentioned formative measures as a rationale for using PLS-PM. Table 3.7 identifies the number of articles with certain forms of measurement model complexity: formative measures or multidimensional constructs.

While PLS-PM can be useful for certain forms of measurement model complexity, authors should be thoughtful when using model complexity as a reason for justifying the use of PLS-PM. Sometimes authors' explanation for using PLS-PM implies that this is the only statistical technique that can appropriately address certain forms of measurement model complexity, such as formative measurement or multidimensional constructs. However, other techniques, such as CB-SEM can sometimes be

Table 3.7 Number of articles with specific types of measurement model complexity

Discipline (# Articles)	Formative measures	Multidimensional constructs
Accounting (5)	1	2
Entrepreneurship (4)	1	1
General business (55)	8	15
Info systems (64)	22	22
Management (12)	2	4
Marketing (17)	5	6
Ops management (6)	2	0
Overall (163)	41	45

used when constructs use formative measures or are multidimensional (Gefen et al., 2011; Petter et al., 2007).

As authors consider their choice of measurement and structural model analysis tool, it is important to understand the differences in assumptions between PLS-PM and CB-SEM related to the measurement and composition of constructs. CB-SEM assumes a common factor model, while PLS-PM assumes a composite model.[3] The differences between a common factor model and a composite model can create confusion for many authors, particularly if trying to compare model results across PLS-PM and CB-SEM (Hair et al., 2017b; Henseler et al., 2014; Rigdon et al., 2017).

Further complicating the discussion for authors using PLS-PM is the discussion surrounding consistent PLS (Dijkstra, 2014), sometimes referred to as PLSc. PLSc claims to correct for potential bias that can occur among structural path coefficients when the measurement model contains reflectively measured constructs (Dijkstra & Henseler, 2015). Some scholars advocate the use of PLSc when the research model contains one or more reflectively measured constructs (Ali et al., 2018; Cepeda-Carrion et al., 2018; Evermann and Rönkkö, 2023). Yet, others argue that PLSc contains assumptions more consistent with common factor models in CB-SEM and has a more limited (or even no) role within PLS-PM (e.g., Hair et al., 2017a). Within our review of FT50 journals, only nine articles used the PLSc algorithm (six in general business, two in marketing, and one in entrepreneurship).

Some scholars have advocated for authors to use confirmatory tetrad analysis within PLS-PM to identify if constructs are better measured reflectively (i.e., Mode A) or formatively (i.e., Mode B) (Hair et al., 2012b, 2017a).[4] Other scholars have expressed concerns about using an empirical approach (as opposed to conceptual or theoretical approaches) to specify the relationship between constructs and items (Jarvis et al., 2012; Petter et al., 2012). In our review of FT50 journals, three articles used confirmatory tetrad analysis to provide support for the measurement model (i.e., specification of reflectively versus formatively measured constructs).

Among the FT50 journal articles analyzed for this study, many authors justified using PLS-PM due to the presence of multidimensional constructs within their measurement model (27.6%). However, the modeling of multidimensional constructs within PLS-PM is not straightforward. In CB-SEM, authors can model the lower and higher order dimensions within the measurement model as part of a larger, structural model, assuming the model is identified (Petter et al., 2007). Although PLS-PM has different requirements for model identification, authors must still make adjustments

[3] Refer to Henseler et al. (2014) for a detailed description of the differences in common factor and composite models.

[4] Originally, confirmatory tetrad analysis was developed to discover additional causal relationships within the data in the context of CB-SEM (Glymour et al., 1987). Bollen and Ting (2000) later discussed how to use confirmatory tetrad analysis to test if variables in the model are causal (i.e., formative) or effect (i.e., reflective) indicators. Gudergan et al. (2008) further extended this work to PLS-PM by explaining how authors could explore and confirm the specification of the measurement model (i.e., formative vs. reflective items).

to the measurement model when using multidimensional constructs by using alternative measurement modeling approaches, such as the repeated measure, two-stage, or hybrid approach (Becker et al., 2012; Ringle et al., 2012; Wetzels et al., 2009).

We caution authors justifying using PLS-PM due to measurement model complexity. Some authors lack an understanding of common factor versus composite models and how these assumptions vary when using CB-SEM and PLS-PM. Some disciplines and scholars are engaged in debates regarding the use of PLSc, which makes this algorithm controversial within some disciplines. Other scholars have differing opinions regarding if formative measures should be evaluated empirically through confirmatory tetrad analysis or theoretically. Finally, there are known concerns and questions regarding modeling multidimensional constructs using PLS-PM. PLS-PM eliminates certain problems that may occur when using CB-SEM (e.g., model identification); however, there are still challenges that arise when using PLS-PM with complex measurement models.

3.3.3.2 Structural Model Complexity

Prior discipline-specific reviews comparing structural models analyzed using CB-SEM to PLS-PM have noted that PLS-PM models tend to be more complex with more constructs and items (Richter et al., 2016; Ringle et al., 2012). In our review of recently published FT50 articles, many authors justify their use of PLS-PM by stating that their structural model has complex elements, such as mediators or moderators (see Table 3.8).

Our review found that some disciplines, and even some journals within given disciplines, embraced more complex models than others. For example, articles using PLS-PM in *MIS Quarterly* (information systems) had on average 9 constructs, 29 items, and 11 hypothesized relationships between constructs. In contrast, PLS-PM papers published in the *Journal of Business Ethics* had structural models with on

Table 3.8 Number of articles with specific types of structural model complexity

Discipline (# articles)	Moderator analysis	Mediator analysis
Accounting (5)	3	3
Entrepreneurship (4)	2	2
General business (55)	29	19
Information systems (64)	35	30
Management (12)	8	6
Marketing (17)	12	9
Operations management (6)	3	3
Overall (163)	92	72

average 6 constructs, 27 items, and 6 hypothesized relationships. Across all business disciplines, at least half of the articles using PLS-PM incorporate moderator or mediator analysis.

Within the FT50 articles analyzed, 60 articles (36.8%) examined moderators. Some authors included moderators or interaction effects as part of their structural model (e.g., Bedford et al., 2019; James et al., 2017; Yu et al., 2015). Other authors performed a moderator analysis to examine possible heterogeneity across groups, such as industry or culture (e.g., Hajli, 2018; Udo et al., 2016). While scholars across business disciplines have advocated for the use of FIMIX to identify unobserved heterogeneity (e.g., Hair et al., 2017a; Richter et al., 2016; Ringle et al., 2020; Usakli & Kucukergin, 2018), only four articles within the FT50 articles reported using FIMIX. Beyond FIMIX, authors can use other approaches to identify observed or unobserved heterogeneity (e.g., Qureshi & Compeau, 2009; Sarstedt et al., 2011) and measurement invariance using PLS-PM (e.g., Henseler et al., 2016a).

Scholars have encouraged authors using PLS-PM to use more contemporary approaches to assess mediation, such as Zhao et al. (2010), as opposed to Baron and Kenny's method (1986) or the Sobel test for mediation (e.g., Ali et al., 2018; Cepeda-Carrion et al., 2018; Henseler et al., 2016b). In the review of FT50 journals, mediation was analyzed using a range of approaches, including those identified by Baron and Kenny (1986), Preacher and Hayes (2008), Zhao et al. (2010), among others.

Authors should choose and justify PLS-PM because "the technique is consistent with the type of model they intend to estimate" (Rigdon et al., 2017, p. 12) and not simply because PLS-PM is perceived as being easier to use PLS-PM for more complex structural models. Authors using PLS-PM can avoid limitations that often arise when developing complex models in CB-SEM, such as identification, convergence, or Heywood cases (Hair et al., 2012b; Petter & Hadavi, 2021). Therefore, authors have more freedom to develop more complex structural models when using PLS-PM. The challenge remains for authors to avoid creating complex models that may overfit the data or lack parsimony. Regardless of the model's complexity, authors must ensure that their use of PLS-PM is consistent with their research intentions and goals.

3.3.4 Appropriate Rationale: Model Assessment

Many articles identified that one reason for using PLS-PM was to assess a model for the purpose of theory testing, exploratory research, theory development, or prediction. Table 3.9 identifies the number of articles by discipline that used these rationales.

Theory testing was rarely cited as a reason for using PLS-PM, with only articles in the general business discipline offering this rationale. While some scholars have argued that PLS-PM can be appropriate for null hypothesis testing (consistent with

Table 3.9 Number of articles using PLS-PM for different forms of model assessment

Discipline (# Articles)	Theory testing	Exploratory research	Theory development	Prediction
Accounting (5)	0	0	0	1
Entrepreneurship (4)	0	0	2	2
General business (55)	3	13	8	7
Information systems (64)	0	11	13	4
Management (12)	0	4	2	2
Marketing (17)	0	2	4	4
Operations management (6)	0	1	0	1
Overall (163)	3	31	29	21

theory testing) (e.g., Henseler et al., 2014), others have discouraged theory testing as a rationale for PLS-PM (e.g., Rönkkö & Evermann, 2013).

One rationale for PLS-PM that is consistent with Wold's (1985) vision for PLS-PM is to use the technique for exploratory research or theory development. Over one-third (36.8%) of FT50 journal articles stated they used PLS-PM to study less theoretically developed phenomena by engaging in exploratory research or theory development. Half of the articles in management journals (50%) offered one of these two reasons for using PLS-PM. Within general business, information systems, and marketing, about one-third of the articles (38.1%, 37.5%, and 35.3%, respectively) stated one of these two reasons for using PLS-PM.

PLS-PM was also developed to examine the predictive relevance of a model (Wold, 1985). Yet, a small proportion of articles (12.8%) within FT50 journals stated they used PLS-PM to assess the predictive ability of the model. The approaches for assessing the predictive ability of a PLS-PM model are well explained in multiple papers (e.g., Liengaard et al., 2021; Shmueli et al., 2016). Discipline-specific review articles have long advocated for assessing the predictive relevance of measurement models using measures other than R^2. Only a few articles within FT50 journals used more robust methods to assess the predictive nature of the model. In fact, most authors relied on reporting q^2 or Q^2 for prediction, which is not as robust of a predictive measure as other techniques (e.g., Chin et al., 2020; Shmueli et al., 2016). Table 3.10 identifies the number of articles by discipline that provided prediction as a rationale for PLS-PM and the number of articles that attempted to assess the prediction ability of their model using a technique other than R^2 (i.e., q^2, Q^2, or other more advanced and robust predictive analysis techniques).

Of the few articles that stated PLS-PM was used for prediction, less than half assessed the predictive nature of the model. Some disciplines were more consistent in assessing prediction than others. FT50 articles in general business, entrepreneurship,

Table 3.10 Number of articles citing prediction as a rationale and assessing prediction

Discipline (# articles)	Prediction rationale	Assessed prediction
Accounting (5)	1	0
Entrepreneurship (4)	2	1
General business (55)	7	5
Information systems (64)	4	0
Management (12)	2	1
Marketing (17)	4	2
Operations management (6)	1	1
Overall (163)	21	10

management, and marketing were more likely to assess the predictive validity of the model using techniques other than R^2. Information systems have the most opportunity for improvement, with none of the four studies providing measures for predictive validity beyond R^2.

Although PLS-PM was developed to support the evaluation of models in exploratory or predictive settings, many authors do not use these reasons to justify their use of PLS-PM in recent FT50 journal articles. Some suggest that the bias among journals toward confirmatory models can discourage researchers from using this justification for PLS-PM (Henseler et al., 2014). Scholars have called for editors and reviewers to avoid encouraging authors conducting exploratory research to present their research using a confirmatory approach (Richter et al., 2016). Some scholars assert that there is insufficient evidence for this claim and guidance to authors about how to use PLS-PM for exploration and prediction (Rönkkö et al., 2016). While much controversy remains surrounding the role of PLS-PM as an analysis technique, several discipline-specific reviews encourage justifying the use of PLS-PM based on the research question or intended purpose of the research study (as opposed to the sample or research model characteristics) (e.g., Cepeda-Carrion et al., 2018; Nitzl, 2016; Richter et al., 2016).

3.4 The Future of PLS-PM Use in Business Disciplines

There are ongoing discussions about the role of PLS-PM in business disciplines occurring within specific disciplines, such as information systems (Evermann & Rönkkö, 2023; Goodhue et al., 2023; Kock, 2023; Russo & Stol, 2023; Sharma et al., 2023). Within specific disciplines, scholars have provided specific recommendations or engaged in discussions related to methodological developments associated with PLS-PM, such as consistent PLS algorithms (e.g., Dijkstra & Henseler, 2015; Hair et al., 2017a) or general concerns about the use of PLS-PM (e.g., Browning & de Treville, 2018; Guide & Ketokivi 2015; Rönkkö et al., 2016). Several articles examine the rationale and practices associated with PLS-PM use among articles published across journals within a specific discipline. However, there is limited information about the use of PLS-PM among premier journals within specific disciplines (e.g., Hair et al., 2017a; Usakli & Kucukergin, 2018), much less an examination of rationales in premier journals across business disciplines.

This analysis reveals some new insights not observed in discipline-specific reviews. For example, many discipline-specific reviews found that the popularity and publication of articles using PLS-PM are increasing (e.g., Bayonne et al., 2020; Cepeda-Carrion et al., 2018; Manley et al., 2021; Richter et al., 2016). However, our analysis finds that the publication of articles using PLS-PM within FT50 journals is decreasing, except in general business (and specifically the *Journal of Business Ethics*). Some editorials in FT50 journals have publicly discouraged PLS-PM (Browning & de Treville, 2018; Guide & Ketokivi 2015), while other FT50 journals have adopted editorial policies limiting the use of PLS-PM through the review process. The controversy around PLS-PM within some business disciplines could encourage authors to use different analytical tools or publish results obtained using PLS-PM in non-FT50 journals.

Another finding from this analysis is that even within the most elite journals within business disciplines, many authors are still using rationales for PLS-PM that have long been identified as problematic. The continued justification for using PLS-PM due to data characteristics, such as small sample size or non-normality, is concerning. Many discipline-specific reviews and other PLS-PM methodology articles have pleaded with authors to avoid using these rationales, but still, these justifications for PLS-PM are still being used by many authors. Richter et al. (2016) encourage authors to make the decision to use PLS-PM due to the "study's research purpose and the related theoretical and empirical basis" and go on to state that "Sample and measurement characteristics—such as sample size, distributional assumptions, measurement type, and scale—should be secondary selection criteria" (p. 394). However, as noted from our review of recently published FT50 articles, authors often use inappropriate rationales for PLS-PM. Consistent with many scholars cited in this article who have performed discipline-specific reviews, we continue to encourage authors to abandon the problematic and questionable rationales for PLS-PM described in this chapter based on the sample and data characteristics, such as small sample size and data non-normality. More compelling rationales are those that are consistent with PLS-PM's original intentions (e.g., exploratory or predictive analysis).

As authors seek to publish articles using PLS-PM, there are different schools of thought on how to justify the use of PLS-PM. Peng and Lai (2012) encourage authors in operations management "consider PLS when CBSEM is unobtainable due to the violations of some key CBSEM assumptions (e.g., sample sizes and sample distribution) or model identification problems" (p. 478). Kaufmann and Gaeckler (2015) offer supply chain management authors similar advice. We caution authors from perceiving PLS-PM and CB-SEM as interchangeable analysis techniques and encourage the use of PLS-PM when the measurement or structural model is better represented by the composite model (as opposed to a common factor model) (Evermann and Rönkkö, 2023; Henseler et al., 2014; Rigdon et al., 2017; Sarstedt et al., 2016). Alternative justifications are for authors to consider the strengths and original intentions of PLS-PM and consider if PLS-PM is consistent with the goals of their research question. PLS-PM was intended for research questions that are "simultaneously data-rich and theory-primitive" (Wold, 1985, p. 589) or include predictive elements (Henseler et al., 2014; Wold, 1985). When authors use PLS-PM for exploratory research, theory development, or prediction, authors should also ensure that their discussion of the research model and findings are consistent with the rationale (Richter et al., 2016). For example, if PLS-PM is used for prediction, then authors should provide appropriate measures of predictive validity using appropriate in-sample and out-of-sample prediction methods (e.g., Manley et al., 2021; Shmueli & Koppius, 2011; Shmueli et al., 2016). Authors using PLS-PM for exploratory research can be more transparent about exploratory analyses performed as part of their theorizing with the data. Providing details through appendices or online supplements about the various measurement and structural models tested beyond the final reported results can enable readers to understand more about the entire research process and the final results. If journal editors and reviewers would enable scholars to be more candid about exploratory data analysis, this could address calls for research transparency (Burton-Jones et al., 2021) and replication (Hair et al., 2012a).

Although not a focus of this review of recently published FT50 articles, we noted that many authors fail to report information about their analysis (e.g., software used, number of bootstrapping samples, sign change, number of tails). Furthermore, only 11 papers recently published in FT50 journals report confidence intervals, and only two provide bias-corrected and accelerated (BCa) confidence intervals. Many scholars have called for more reporting on these elements (Ali et al., 2018; Cepeda-Carrion et al., 2018; Hair et al., 2017a; Nitzl, 2016; Peng & Lai, 2012; Richter et al., 2016; Ringle et al., 2012, 2020), yet many of these details are not provided by authors. There is still room for improvement for authors using PLS-PM to report more information about their measurement models, algorithm choices, and findings within FT50 journals.

3.5 Conclusions

This chapter examines business disciplines broadly to identify the frequency and applications of PLS-PM. By examining the frequency of PLS-PM use across business disciplines within the FT50 journal list, authors can identify the prevalence of PLS-PM in selected journals within each major business discipline. Our analysis identifies reasons why scholars use PLS-PM within and across business disciplines and explains some of the problematic justifications for using PLS-PM.

Although we would like to be as comprehensive as possible, we recognize our literature review has limitations. First, to conduct our search of articles for our literature review, we performed full-text searches of articles within each journal for terms such as "PLS" or "partial least squares" from multiple databases. Since we did not perform a manual search, some articles using PLS-PM may be missing from our analysis because they were not searchable or used different terms to describe the same technique. Second, many articles we coded are quite complex with multiple studies, samples, or research models. As a result, we had to make choices to minimize the complexity of the lengthy and difficult coding effort. We encourage readers to embrace our results as a representative sample of studies using PLS-PM in selected journals across business disciplines. Finally, this article does not provide a comprehensive list of all recommendations related to using PLS-PM but rather focuses on issues we noted in our analysis arising based on authors' rationales for using PLS-PM as an analysis technique. We provided insights on a subset of ongoing methodological discussions across business disciplines related to PLS-PM. While not discussed in this chapter, we did note that most articles across disciplines reported correlation matrices, measurement items, and reliability statistics (e.g., composite reliability or Cronbach's alpha). Yet, beyond our discussion, there is still room for improvement in reporting additional aspects of PLS-PM results, such as construct validity, effect size (beyond R^2), and bias-corrected and accelerated (BCa) confidence intervals in FT50 journals across business disciplines.

Many scholars have discouraged the use of PLS-PM as an analysis technique within business disciplines (e.g., Goodhue et al., 2023; Rönkkö et al., 2016), while others have provided argumentation to encourage the use of PLS-PM (e.g., Hair et al., 2011). Some scholars take a more measured approach to inform authors about the methodological considerations related to using PLS-PM, but these often appear in discipline-specific journals (Evermann & Rönkkö, 2023; Rigdon et al., 2017). Some scholars who value PLS-PM as an analysis technique have urged caution or have provided recommendations to encourage authors to take a more measured approach to using the technique (Gefen et al., 2011; Nitzl, 2016; Ringle et al., 2012). Since many of these articles are published in specific disciplines, it may be challenging for authors to stay abreast of best practices using PLS-PM. Furthermore, the differing recommendations and guidelines provided across disciplines can make it more difficult for authors to know how best to proceed with their analysis. The information provided in this chapter provides authors with more appropriate reasons for justifying the use of PLS-PM within and across business disciplines.

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Chapter 4
Statistical and Psychometric Properties of Three Weighting Schemes of the PLS-SEM Methodology

Ke-Hai Yuan and Zhiyong Zhang

Abstract Structural equation modeling (SEM) is a widely used technique for studies involving latent constructs. While covariance-based SEM (CB-SEM) permits estimating the regression relationship among latent constructs, the parameters governing this relationship do not apply to that among the scored values of the constructs, which are needed for prediction, classification and/or diagnosis of individuals/participants. In contrast, the partial-least-squares approach to SEM (PLS-SEM) first obtains weighted composites for each case and then estimates the structural relationship among the composites. Consequently, PLS-SEM is a preferred method in predicting and/or classifying individuals. Nevertheless, properties of PLS-SEM still depend on how the composites are formulated. Herman Wold proposed to use mode A to compute the scores for constructs with reflective indicators. However, Yuan and Deng recently showed that composites under mode B enjoy better psychometric properties. The authors thus proposed a structured transformation from mode A to mode B, denoted as mode B_A. This chapter further studies properties of the three modes of PLS-SEM. Analytical and numerical results show that (1) Mode A does not possess any solid statistical or psychometric properties, (2) Mode B possesses good theoretical properties but is over sensitive to sampling errors, and (3) Mode B_A possesses good theoretical properties as well as numerical stability. The performances of the three modes are also illustrated with two real data examples.

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4.1 Introduction

Structural equation modeling (SEM) and path analysis with weighted composites are among the most widely used methods in social and behavioral sciences. The two distinguished classes of methods are integrated in the so-called partial-least-squares approach to structural equation modeling (PLS-SEM). Based on the measurement and structural model, PLS-SEM first obtains weighted composites[1] to act as proxies to the latent variables, and then to estimate the structural model by regression analysis with the weighted composites. To differentiate the conventional SEM methodology from PLS-SEM, the former is often called covariance-based SEM (CB-SEM). The most well-known feature of CB-SEM is its capability of separating measurement errors from latent constructs. This feature facilitates consistent parameter estimates as well as test statistics and fit indexes for evaluating the goodness-of-fit of the overall model structure. In contrast, PLS-SEM or regression analysis with weighted composites directly estimates the relationship among the scored values of the composites and has the strength of maximizing the predictive roles of the exogenous variables on the endogenous variables according to the principle of LS regression (Boardman et al., 1981; Cho et al., 2022a, 2023; Hair et al., 2017; Wold, 1980). Still, the properties of PLS-SEM closely depend on how the weights of the composites are computed. Wold (1980, 1982) proposed two algorithms to compute the weights, termed as modes A and B, respectively. Yuan and Deng (2021) introduced a new mode, termed as mode B_A, and Sect. 4.4 of this chapter provides a detailed description of this mode. The purpose of this chapter is to systematically study the properties of the three weighting schemes, including statistical properties of scale invariance and scale-inverse equivariance when the scales of the observed variables change, as well as the psychometric properties of measurement reliability of the resulting composites. These properties will be obtained analytically and illustrated via numerical and real-data examples. To fully understand the performances of the three modes in operation, we will also discuss the sensitivity of the weights with imperfect data.

It is well-known that the scales of latent variables have to be fixed in order for the SEM model to be identified (see e.g., Loehlin & Beaujean, 2017). For a dependent latent variable, this is typically done by fixing one of the loadings of its indicators at 1.0. For an independent latent variable, this can be done by fixing either its variance at 1.0 or one of the loadings of its indicators at 1.0. The choices among the loadings are arbitrary and so is the value of 1.0. Although the overall model structure of the observed variables remains the same regardless of how the scale of each latent variable is fixed, the values of the parameters in the measurement and structural models depend on these choices. This implies that particular population values of the model parameters under CB-SEM are artificial. In parallel, the scales of the composites under PLS-SEM also need to be determined. This is typically done by fixing the variance of each composite at 1.0. While such a choice has become the

[1] Throughout the chapter, a weighted composite or composite-score is a weighted sum of the observed values of items that are designed to measure a latent construct.

norm in the field, one can also choose a different set of values for the scales of the composites without affecting any substantive aspect of the model. In particular, we can always choose the scales of the latent variables or those of the composites so that the two methods have identical values of path coefficients (see e.g., Devlieger et al., 2016; Skrondal & Laake, 2001; Yuan & Deng, 2021). Consequently, we will not compare parameter estimates of PLS-SEM against those of CB-SEM in this chapter. Instead, we will focus on the properties of the weights and the resulting composites under the three modes of the PLS-SEM methodology. The properties of the resulting parameter estimates under each mode will also be examined when the scales of the observed variables change. Because the formulations of composites and the efficiency of parameter estimates under PLS-SEM are totally determined by the weights of the items, our study of weights not only clarifies the pros and cons of the different modes of the methodology but also facilitates better understanding of other approaches of path analysis with weighted composites.

Although CB-SEM has the advantage in yielding consistent estimates of path coefficients, the parameters are for characterizing the relationship among latent variables that represent the population distribution, and all individuals/participants are equivalent under such a relationship. In practice when scored values of composites are used for prediction or diagnosis, individuals are no longer equivalent. An individual with greater scores is expected to perform better on the criterion variable, and such a relationship is directly characterized by the regression model with the composite-scores. In particular, the regression model with LS estimates still yields the best (i.e., smallest mean-squared error) linear unbiased predictor for a future value even when predictors contain measurement errors (see Fuller, 1987, p. 75). However, not all weighted composites are equivalent in prediction. The values of R^2 as well as the relative errors of the estimated regression coefficients depend on the measurement reliabilities of the composites (Yuan & Fang, 2022), which further depend on the formulation of the weights.

By focusing on models with reflective indicators, we will discuss the following aspects of the weights of composites in this chapter: The measurement reliability of the resulting composites; the reactions of the weights, the composites and the resulting regression coefficients to scale change of the observed variables; sensitivity of the weights to model misspecification, negative weights and negative estimates of error variances (Heywood cases). Numerical and real-data examples will be used in the analysis. Because PLS-SEM is relatively new to researchers in social and behavioral sciences, we will give a brief introduction to the methodology by pointing out some of its distinctive features.

The reason for us to mainly consider models with reflective indicators is because weights of composites for formative indicators are not determined by the indicators themselves but by their relationships with indicators of other latent variables or composites (Treiblmaier et al., 2011). Also, with formative indicators, the concept of measurement reliability may not apply since the indicators may not contain measurement errors nor do they need to share anything in common. In addition, our discussion of model misspecification is via the traditional factor model, not the composite models as described in Dijkstra (2017), Cho and Choi (2020), and Hwang et al. (2020). Furthermore, the analytical results on weights obtained by Dijkstra (1983) only hold for models with reflective indicators, and they will be further studied in this chapter. But our results on scale invariance and scale-inverse equivariance also apply to formative indicators and composite models, as will be further discussed in the concluding section.

A useful preface for following the development of this chapter is that PLS-SEM mode B does not have to stick to models with formative indicators, although such a match was recommended by Wold (1980, 1982). Actually, the analytical results by both Dijkstra (1983) and Schneeweiss (1993) include applying mode B to models with reflective indicators. This chapter presents additional theoretical advantages of mode B for models with reflective indicators, and they are shared by mode B_A at the level of population.

4.2 Two Distinctive Features of PLS-SEM and the Environmental Variable

While PLS-SEM is essentially path analysis with weighted composites (Hair et al., 2017; Henseler, 2021), the method is self-contained with its own algorithms for computing the composites and conducting parameter estimation of the structural model. Consider the path diagram in Fig. 4.1, where there are four latent variables ξ_1, ξ_2, η_1, η_2 and twelve reflective indicators, and the indicators of each latent variable are referred to as a block. There are no correlated errors nor cross loadings in Fig. 4.1. That is, each indicator only loads on the single latent variable of its block.

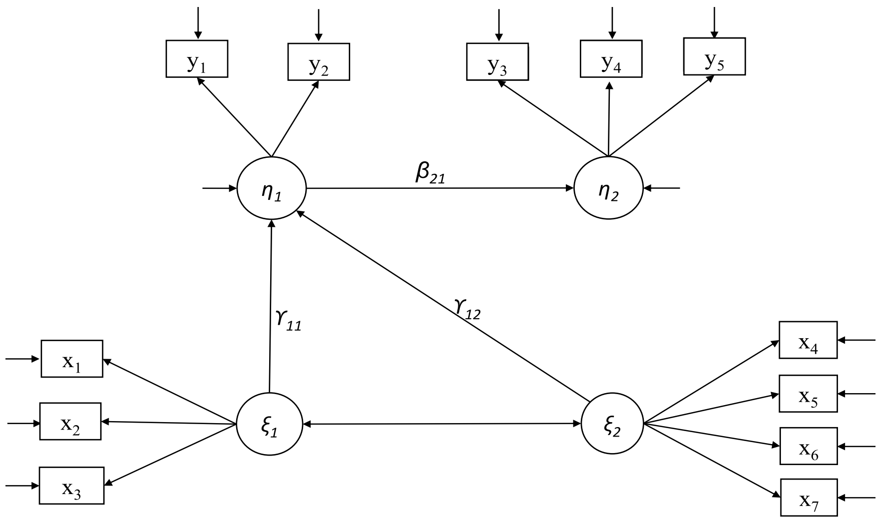

Fig. 4.1 A model with four latent variables and twelve indicators

Such a property is commonly termed as *unidimensionality* in measurement, which is a distinctive feature of PLS-SEM. Although unidimensionality is not necessary under CB-SEM, the property is very desirable because it facilitates theory testing and development as well as assessment and evaluation (e.g., reliability, validity, interpretability) (see e.g., Anderson & Gerbing, 1988). However, the model will be misspecified when either cross loadings or error covariances exist in the population. Even if CB-SEM permits the inclusion of cross loadings and/or correlated errors, model misspecification[2] cannot be avoided in practice (MacCallum, 2003), which will cause biased parameter estimates under both CB-SEM and PLS-SEM. We will discuss the effects of misspecified models on the different weighting schemes of the PLS-SEM methodology in a later section, based on recent results by Yuan et al. (2023). Effects of misspecified models on parameter estimates under CB-SEM can be found in Yuan et al. (2003).

Another distinctive feature of PLS-SEM is the way in *counting direct connections*, which is needed in the algorithms for computing the weights. In Fig. 4.1, ξ_1 is directly connected with η_1; ξ_2 is directly connected with η_1; η_1 is directly connected with ξ_1, ξ_2, and η_2; and η_2 is directly connected with η_1. However, the two-way arrow between ξ_1 and ξ_2 is not considered as a direct connection under PLS-SEM. Such a way of counting connections generates weighted composites by which the corresponding indicators partially maximize their predictive relationships (Boardman et al., 1981). The maximum relationship is operated by LS regression via the so-called *environmental variable*, which plays the role of being the representative of the directly connected constructs (Schneeweiss, 1993). In Fig. 4.1, the environmental variable of ξ_1 is $\bar{\xi}_1 = c_{\xi_1\eta_1}\eta_1$, where $c_{\xi_1\eta_1}$ can be the sign of the correlation between ξ_1 and η_1 or the correlation itself. Similarly, the environmental variable of η_1 is $\bar{\eta}_1 = c_{\eta_1\xi_1}\xi_1 + c_{\eta_1\xi_2}\xi_2 + c_{\eta_1\eta_2}\eta_2$, where each c can be either the sign of the correlation (termed as the centroid scheme) or the value of the correlation itself (termed as the factorial scheme). Thus, the environmental variable of a focal latent variable is a linear combination of the latent variables that are directly connected to the focal latent variable. In operation, when the latent variables are approximated by scored values of composites, environment variables will become the corresponding linear combinations of the composites. As to be described in the following section, weights of indicators are obtained by LS regression, which maximizes the linear relationship of each indicator with the corresponding environmental variable.

As noted earlier, composites do not have natural scales. They need to be assigned and are of an arbitrary nature. In PLS-SEM, this is done by scaling the weights for each block of indicators so that the resulting composite has a variance of 1.0. Also, for variables with a single connection, the value of the coefficient (c) in the environmental variable is cancelled due to standardization.

[2] Regardless of reflective or formative indicators, a model is misspecified whenever the model-implied covariance matrix does not equal the population covariance matrix of all the involved indicators. Modeling truly formative indicators as reflective or vice versa is expected to cause a discrepancy between the model-implied covariance matrix and its population counterpart.

4.3 PLS-SEM Modes A and B

PLS-SEM methodology consists of two stages. Weights of composites are computed in the first stage via an iterative process, and regression analysis with the weighted composites is conducted in the second stage. Consider the model in Fig. 4.1, let the initial composite for each latent variable be the simple average of its block of indicators, and followed by a standardization so that the sample variance of each composite is 1.0. The corresponding environmental variables are obtained when the constructs are replaced by their composites, where the coefficients c are also computed according to the correlations of the corresponding composites. Under mode A, weights of x_1 to x_3 are updated by the LS regression coefficient of each of the indicators on the environmental variable $\bar{\xi}_1$ (simple regression), and weights of x_1 to x_3 under mode B are updated by the LS regression coefficients of the environmental variable $\bar{\xi}_1$ on x_1, x_2 and x_3 (multiple regression). Weights of indicators in the other blocks are updated in parallel by the LS regression coefficients via the corresponding environmental variables. The updated weights of each block are proportionally rescaled so that the corresponding composite has a sample variance of 1.0. The environmental variables are then updated via the updated composites, which completes a cycle of iteration in estimating the weights. The iteration process continues with the updated environmental variables until the weights for all the blocks of indicators are stabilized, and the corresponding composites are consequently obtained. These weighted composites represent the constructs in conducting path analysis at stage 2. Although stage 2 can be done via fitting the sample covariance matrix of the composites by the structural model using different methods for covariance structure analysis (e.g., ML, LS, GLS), PLS-SEM uses separate LS regression to estimate the path coefficients for each endogenous construct (Wold, 1980, 1982), which is easy to carry out.

Conventionally, mode A has been recommended for models with reflective indicators and mode B for models with formative indicators (Wold, 1980, 1982). While such recommendations are followed in software[3] and textbooks (Hair et al., 2017), they are based on intuition rather than justified by statistical or psychometric theory. In particular, Yuan and Deng (2021) showed that, when applying mode B to reflective indicators, the method is asymptotically equivalent to regression analysis using Bartlett-factor scores (BFS). They also showed that regression-factor scores[4] are equivalent to Bartlett-factor scores in conducting regression analysis. Note that BFSs attain the maximum reliability among all weighted composites (see e.g., Bentler, 1968; Yuan & Bentler, 2002). The results in Yuan and Deng (2021) imply that composites under PLS-SEM mode B attain the maximum reliability asymptotically. Because more reliable composites correspond to more efficient estimates of regression coefficients

[3] A reviewer noted that software SmartPLS automatically assumes that indicators are reflective when mode A is chosen, and are formative when mode B is chosen.

[4] Note that regression-factor scores can be separately computed for each block of indicators or collectively computed for all the blocks of indicators. It is the separately computed regression-factor scores that are equivalent/proportional to the BFSs, which remain the same whether collectively or separately computed.

and greater R^2 values (Cochran, 1970; Yuan & Fang, 2022), mode B is theoretically more preferred than mode A for estimating models with reflective indicators.

We use numerical examples to show the theoretical advantage of mode B. For a block of indicators, let the variance of the latent factor be 1.0, $\boldsymbol{\lambda}$ be the vector of factor loadings, and $\boldsymbol{\Psi}$ be the diagonal matrix of error variances. Then the covariance matrix of the block of indicators is given by $\boldsymbol{\Sigma} = \boldsymbol{\lambda}\boldsymbol{\lambda}' + \boldsymbol{\Psi}$. The equivalence between BFS regression and PLS-SEM model B was based on the results in Dijkstra (1983) and Schneeweiss (1993), who showed that the weight vector under mode A is proportional to $\boldsymbol{\lambda}$ and that under mode B is proportional to $\boldsymbol{\Sigma}^{-1}\boldsymbol{\lambda}$. Let's use $\mathbf{w}_a$ and $\mathbf{w}_b$ to denote the weights under the two modes. The results in Dijkstra (1983), Schneeweiss (1993) and Yuan and Deng (2021) imply that $\mathbf{w}_a = c_a\boldsymbol{\lambda}$ and $\mathbf{w}_b = c_b\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda}$, where c_a and c_b are scalars so that the corresponding composites have a variance of 1.0. Table 4.1 contains four examples and each has three items. The population factor loadings λ_j and error variances ψ_{jj} for the first three examples are exact, while those for the fourth example are rounded. The reliabilities are computed according to the population factor loadings and error variances, where ρ_j is the reliability of the jth item, ω is the reliability of the equally weighted composite (EWC), ρ_A and ρ_B are respectively the reliabilities of composites under PLS-SEM modes A and B. With the variance of the latent variable in each example being 1.0, we have $\rho_j = \lambda_j^2/(\lambda_j^2 + \psi_{jj})$. The formulas for computing ρ_A and ρ_B were given by Yuan and Deng (2021), and that for computing ω was given by McDonald (1999), and was often called Dillon-Goldstein's ρ in the PLS-SEM literature (see Esposito Vinzi et al., 2010).

Table 4.1 Reliabilities of three composites with examples: ω is the reliability of equally weighted composite, ρ_A and ρ_B are the reliabilities of composites under PLS-SEM modes A and B, respectively

	Variable	Population θ		Reliability			
		λ_j	ψ_{jj}	ρ_j	ω	ρ_A	ρ_B
Example 1	x_1	0.400	0.840	0.160	0.597	0.666	0.697
	x_2	0.500	0.750	0.250			
	x_3	0.800	0.360	0.640			
Example 2	x_1	0.350	0.8775	0.123	0.562	0.695	0.746
	x_2	0.400	0.8400	0.160			
	x_3	0.850	0.2775	0.723			
Example 3	x_1	0.400	0.500	0.242	0.579	0.570	0.581
	x_2	0.500	0.700	0.263			
	x_3	0.800	0.900	0.416			
Example 4	x_1	0.492	0.758	0.242	0.567	0.578	0.581
	x_2	0.513	0.737	0.263			
	x_3	0.645	0.584	0.416			

Note Items in Example 4 are obtained by the standardization of those in Example 3. The population values of the parameters for Examples 1–3 are exact while those for Example 4 are rounded

In Example 1, the variance of each item is 1.0. The EWC has a reliability of 0.597 but the reliability of x_3 is 0.640. All the items in Example 2 also have variances at 1.0, and the reliability of x_3 is 0.723. Both the EWC and the weighted composite under PLS-SEM mode A are less reliable than the single item x_3. In Example 3, the items are not standardized. The weighted composite under mode A is less reliable than the EWC. The items in Example 4 are obtained by standardizing those in Example 3. The results of Examples 3 and 4 show that ω and ρ_A are scale dependent, while ρ_B is scale invariant. We will present analytical results regarding the properties of different modes under scale-transformation in a later section.

Based on Monte Carlo results Henseler et al. (2014, p. 190) stated "PLS Mode A outperforms the best indicator across all model constellations, providing support for the capability of PLS to reduce measurement error." Results in Table 4.1 suggest that the comparison of reliabilities among composites under mode A, EWCs, and individual indicators depends on conditions. When a block of indicators contains an item with rather larger reliability than the rest of the items, then it is hard for the composite under mode A or the EWC to be more reliable, as is the case in Example 2. When factor loadings and error variances are close to proportional, the reliability of the EWC is close to maximum while composites under PLS-SEM mode A can be less reliable. This is the case in Example 3. In general, if items with larger loadings have even larger error variances, then composites under mode A will be less reliable than equally weighted composites (see Yuan et al., 2020). But the composite under mode B reaches the maximum reliability regardless of the reliabilities of the individual items, although sampling errors may have a negative effect on the estimated weights of the mode. We will further discuss the sensitivity of mode B to sampling and model specification errors in the following sections.

Note that for simplicity we only considered models with a single construct in this section. The conclusions with the four examples also hold for models with more latent constructs.

4.4 PLS-SEM Mode $\mathbf{B_A}$

While PLS-SEM mode B yields composites with maximum reliability at the level of population, Dijkstra and Henseler (2015a) noted that mode A is numerically more stable. An example with a real dataset in Yuan and Deng (2021) showed that weights of some individual items under PLS-SEM mode B are negative. For the same dataset, all the individual weights under PLS-SEM mode A and all the factor loadings under CB-SEM are positive. Because negative weights are not logically acceptable for positively worded items, PLS-SEM mode B has problems in operation. In order to have weighted composites that enjoy the statistical/psychometric properties of mode B while the method also performs as stable as mode A numerically, Yuan and Deng (2021) proposed a procedure to transform the weights under mode A to weights that are asymptotically equivalent to those under mode B, or a transformed mode $\mathrm{B_A}$.

Let $\hat{\mathbf{w}}_a = (\hat{w}_{a1}, \hat{w}_{a2}, \ldots, \hat{w}_{ap})'$ be the estimated weights under mode A and $\mathbf{S}$ be the sample covariance matrix of a given block that has p indicators. The transformed mode is obtained via fitting the sample covariance matrix $\mathbf{S}$ by the one-factor model

$$\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \phi \hat{\mathbf{w}}_a \hat{\mathbf{w}}_a' + \boldsymbol{\Psi}, \tag{4.1}$$

where ϕ plays the role of factor variance, $\hat{\mathbf{w}}_a$ plays the role of factor loadings, $\boldsymbol{\Psi} = \text{diag}(\psi_{11}, \psi_{22}, \ldots, \psi_{pp})$ is a diagonal matrix of the unexplained variances, and $\boldsymbol{\theta} = (\phi, \psi_{11}, \psi_{22}, \ldots, \psi_{pp})'$ contains $(p + 1)$ free parameters. The model in Eq. (4.1) can be estimated by normal-distribution-based maximum likelihood (NML) or least-squares (LS). Appendix E of Yuan and Deng (2021) contains the development of the LS solutions, which are given by

$$\hat{\phi} = (\hat{\mathbf{w}}_a' \mathbf{S} \hat{\mathbf{w}}_a - \sum_{j=1}^{p} \hat{w}_{aj} s_{jj}) / [(\sum_{j=1}^{p} \hat{w}_{aj})^2 - \sum_{j=1}^{p} \hat{w}_{aj}^4] \ \text{and} \ \hat{\psi}_{jj} = s_{jj} - \hat{\phi} \hat{w}_{aj}^2, \tag{4.2}$$

where s_{jj} is the jth diagonal element of the sample covariance matrix $\mathbf{S}$.
With the estimates in (4.2), the estimated weights $\hat{\mathbf{w}}_{b_a} = (\hat{w}_{b_a 1}, \hat{w}_{b_a 2}, \ldots, \hat{w}_{b_a p})'$ under PLS-SEM mode B_A are given by

$$\hat{w}_{b_a j} = c_{b_a} \hat{\psi}_{jj}^{-1} \hat{w}_{aj}, \ \ j = 1, 2, \ldots, p,$$

where c_{b_a} is a scalar so that the weighted composite under model B_A has a sample variance of 1.0.

Because $\hat{\mathbf{w}}_a$ converges in probability to $\mathbf{w}_a = c_a \boldsymbol{\lambda}$ and $\mathbf{S}$ converges to $\boldsymbol{\Sigma} = \boldsymbol{\lambda}\boldsymbol{\lambda}' + \boldsymbol{\Psi}$, the LS estimates $\hat{\psi}_{jj}$ in Eq. (4.2) converge to ψ_{jj}. Consequently, $\hat{\mathbf{w}}_{b_a}$ converges to $\mathbf{w}_b = c_b \boldsymbol{\Psi}^{-1} \boldsymbol{\lambda}$. Thus, the weights under PLS-SEM mode B_A are asymptotically equivalent to those under PLS-SEM mode B as well as to those of the corresponding Bartlett-factor score. The resulting composites under mode B_A also enjoy the same theoretical properties as composites under mode B or the Bartlett-factor scores.

As for estimating any other factor models in factor analysis, the estimates $\hat{\psi}_{jj}$ in Eq. (4.2) can be negative (Heywood case). In such a case, we can replace the negative estimate by $\tilde{\psi}_{jj} = 0.05$ (or another small number) and adjust the value of $\hat{w}_{aj}$ via

$$\tilde{w}_{aj}^2 = (s_{jj} - \tilde{\psi}_{jj}) / \hat{\phi},$$

yielding

$$\tilde{w}_{b_a j} = c_{b_a} \tilde{\psi}_{jj}^{-1} \tilde{w}_{aj}.$$

The adjusted $\tilde{w}_{aj}$ is to keep $\hat{\phi} \tilde{w}_{aj}^2 + \tilde{\psi}_{jj} = s_{jj}$. One can also only adjust the value of $\hat{\psi}_{jj} < 0$ to a small positive number without adjusting the value of $\hat{\mathbf{w}}_a$.

With correctly specified models, Heywood cases are mostly due to a small sample size together with small population values of ψ_{jj}. Model misspecification and/or data contamination are also responsible for Heywood cases in practice. Thus, negative estimates of error variances can offer additional information about the model, the data, and/or the population, and they should be regarded as an opportunity rather than a bad luck.

The literature of PLS-SEM repeatedly claims that the methodology has solved the issue of negative estimates of error variances (e.g., Chin, 1998; Henseler, 2021, p. 162). This is because the estimand of error variance under PLS-SEM is different from that under CB-SEM, and the former includes both measurement and prediction errors. In contrast, the ψ_{jj}s in Eq. (4.1) only represent the variances of measurement errors, assuming no unique factors nor systematic errors in the model. Regardless of whether there exist measurement errors, LS regression never yields a negative estimate of prediction-error variance.

4.5 Scale Invariance and Scale-Inverse Equivariance

We have shown in Sect. 4.3 that composites under mode A may not be as reliable as a single indicator. In this section we will examine two additional statistical properties of the three modes, *scale invariance* and *scale-inverse equivariance*. These are fundamental because they describe how parameters react when the scales of the observed variables change. In particular, we will show that PLS-SEM mode A is scale dependent, and the use of standardized variables is to hide the issue of scale dependency of the method rather than having the issue solved. In contrast, weights under PLS-SEM mode B and mode B_A are scale-inverse equivariant and the resulting composites and regression coefficients are scale invariant. For simplicity, we will present the analytical results by a one-factor model and numerical illustration by a two-factor model. The results also hold for more complex models, as will be shown in Sect. 4.7 via real-data examples.

4.5.1 Analytical Results

Let $\mathbf{x}$ be a vector of mean-centered random variables representing a block of indicators. Suppose $\mathbf{x}$ follows a one-factor model with $\mathbf{x} = \boldsymbol{\lambda}\xi + \boldsymbol{\varepsilon}$ and

$$\text{Cov}(\mathbf{x}) = \boldsymbol{\Sigma} = \boldsymbol{\lambda}\boldsymbol{\lambda}' + \boldsymbol{\Psi},$$

where $\text{Var}(\xi) = 1$ for model identification and $\boldsymbol{\Psi} = \text{Cov}(\boldsymbol{\varepsilon})$ is a diagonal matrix. Dijkstra (1983) and Schneeweiss (1993) showed that weights under PLS-SEM mode A are proportional to $\boldsymbol{\lambda}$. That is,

$$\mathbf{w}_{ax} = c_{ax}\boldsymbol{\lambda}, \quad \text{with} \quad c_{ax} = (\boldsymbol{\lambda}'\boldsymbol{\Sigma}\boldsymbol{\lambda})^{-1/2}. \tag{4.3}$$

The corresponding composite is given by

$$\hat{\xi}_{ax} = \mathbf{w}'_{ax}\mathbf{x} = c_{ax}\boldsymbol{\lambda}'\mathbf{x}. \tag{4.4}$$

Let $\mathbf{D} = \mathrm{diag}(d_1, d_2, \ldots, d_p)$ be a diagonal matrix with $d_j > 0$. When the variables in $\mathbf{x}$ are scaled according to $\mathbf{y} = \mathbf{D}\mathbf{x}$, then the covariance matrix of $\mathbf{y}$ and weights under PLS-SEM mode A respectively become

$$\mathrm{Cov}(\mathbf{y}) = \mathbf{D}\boldsymbol{\Sigma}\mathbf{D} = \mathbf{D}\boldsymbol{\lambda}\boldsymbol{\lambda}'\mathbf{D} + \mathbf{D}\boldsymbol{\Psi}\mathbf{D} \;\; \text{and} \;\; \mathbf{w}_{ay} = c_{ay}\mathbf{D}\boldsymbol{\lambda}, \tag{4.5}$$

where $c_{ay} = (\boldsymbol{\lambda}'\mathbf{D}^2\boldsymbol{\Sigma}\mathbf{D}^2\boldsymbol{\lambda})^{-1/2}$. The composite corresponding to $\mathbf{y}$ is given by

$$\hat{\xi}_{ay} = \mathbf{w}'_{ay}\mathbf{y} = c_{ay}\boldsymbol{\lambda}'\mathbf{D}\mathbf{y} = c_{ay}\boldsymbol{\lambda}'\mathbf{D}^2\mathbf{x}. \tag{4.6}$$

Thus, both the weights $\mathbf{w}_a$ and the composite $\hat{\xi}_a$ depend on the scales of the indicators. Equation (4.5) indicates that $\mathbf{w}_a$ is *scale equivariant*. That is, each weight is transformed the same way as the corresponding indicator. However, Eq. (4.6) indicates that the values of the d_js are squared in the resulting $\hat{\xi}_{ay}$, which is very undesirable.

The procedure of standardization corresponds to $\mathbf{D} = \mathrm{diag}(1/\sigma_1, 1/\sigma_2, \ldots, 1/\sigma_p)$, where σ_j is the standard deviation of the jth indicator of the block. The results in Eqs. (4.3)–(4.6) show that working with standardized variables does not make mode A a scale-free method.

Dijkstra (1983) and Schneeweiss (1993) also showed that, when applying PLS-SEM mode B to a correctly specified model with reflective indicators, the resulting $\mathbf{w}_b$ is proportional to $\boldsymbol{\Sigma}^{-1}\boldsymbol{\lambda}$. Via an analytical expression for $\boldsymbol{\Sigma}^{-1}$, Yuan and Deng (2021) showed that $\mathbf{w}_b$ can be equivalently expressed as

$$\mathbf{w}_{bx} = c_{bx}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda}, \quad \text{with} \;\; c_{bx} = (\boldsymbol{\lambda}'\boldsymbol{\Psi}^{-1}\boldsymbol{\Sigma}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda})^{-1/2}.$$

The corresponding composite is given by $\hat{\xi}_{bx} = \mathbf{w}'_{bx}\mathbf{x} = c_{bx}\boldsymbol{\lambda}'\boldsymbol{\Psi}^{-1}\mathbf{x}$. Since the error variances of $\mathbf{y}$ are given by the diagonal of $\mathbf{D}\boldsymbol{\Psi}\mathbf{D}$, applying the above formula to the scale-transformed variables we have

$$\mathbf{w}_{by} = c_{by}(\mathbf{D}\boldsymbol{\Psi}\mathbf{D})^{-1}\mathbf{D}\boldsymbol{\lambda} = c_{by}\mathbf{D}^{-1}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda} \;\; \text{and} \;\; \hat{\xi}_{by} = \mathbf{w}'_{by}\mathbf{y} = c_{by}(\mathbf{D}^{-1}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda})'\mathbf{y} = c_{by}\boldsymbol{\lambda}'\boldsymbol{\Psi}^{-1}\mathbf{x},$$

where c_{by} is a scalar such that $\mathrm{Var}(\hat{\xi}_{by}) = 1$. Clearly, $c_{by} = c_{bx}$ and $\hat{\xi}_{by} = \hat{\xi}_{bx}$. Thus, the weights in $\mathbf{w}_b$ are *scale-inverse equivariant* and the composite $\hat{\xi}_b$ is *scale invariant*. These properties imply that PLS-SEM mode B will yield the same regression coefficients whether standardized variables or raw measurements are used in the analysis.

At the population level, the weight vector corresponding to the mode $\mathrm{B_A}$ is given by

$$\mathbf{w}_{b_a} = c_{b_a}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda},$$

where c_{b_a} is a constant such that $\mathbf{w}'_{b_a}\boldsymbol{\Sigma}\mathbf{w}_{b_a} = 1$, which implies $c_{b_a} = c_b$. When the variables in $\mathbf{x}$ are rescaled according to $\mathbf{y} = \mathbf{D}\mathbf{x}$, the resulting $\boldsymbol{\Sigma}_y = \mathrm{Cov}(\mathbf{y})$ and the weight vector for $\mathbf{y}$ under mode A are given by Eq. (4.5). Then the population counterpart of the $\boldsymbol{\Psi}$ in Eq. (4.1) becomes $\boldsymbol{\Psi}_y = \mathbf{D}\boldsymbol{\Psi}\mathbf{D}$. Thus, the weight vector under the mode $\mathrm{B_A}$ for the transformed variables is given by $\mathbf{w}_{b_a} = c_{b_a}\boldsymbol{\Psi}_y^{-1}(\mathbf{D}\boldsymbol{\lambda}) = c_{b_a}\mathbf{D}^{-1}\boldsymbol{\Psi}^{-1}\boldsymbol{\lambda}$, which is the same as $\mathbf{w}_b$. Therefore, weights under the mode $\mathrm{B_A}$ are scale-inverse equivariant, and the corresponding composite $\hat{\xi}_{b_a}$ as well as the regression coefficients are scale invariant.

4.5.2 Numerical Results

We use an example to illustrate the different properties of the three modes numerically. Figure 4.2 represents a model with 2 latent constructs and 7 indicators. Let the population values of the parameters be given by $\boldsymbol{\lambda}_x = (0.80, 1.00, 1.20)'$, $\boldsymbol{\lambda}_y = (1.00, 1.20, 0.80, 1.50)'$, $\gamma = 0.70$, $\phi = \mathrm{Var}(\xi) = 1.00$, and $\sigma_\zeta^2 = \mathrm{Var}(\zeta) = 0.40$. The matrices of the error variances are $\boldsymbol{\Psi}_x = \mathrm{diag}(0.55, 0.60, 0.40)$ and $\boldsymbol{\Psi}_y = \mathrm{diag}(0.58, 0.65, 0.60, 0.40)$. The resulting population covariance matrix $\boldsymbol{\Sigma}$ of the 7 indicators is given in Table 4.8 of Appendix 1.

Applying the PLS-SEM modes A, $\mathrm{B_A}$, and B to this population covariance matrix yields three population weight vectors, respectively. They are reported in the left panel of Table 4.2a and are denoted as $\mathbf{w}_\sigma$. When each of the 7 variables is standardized, we have a corresponding correlation matrix $\mathbf{P}$. Applying the three modes of PLS-SEM to this correlation matrix yields three different weight vectors, and they are in the middle panel of Table 4.2a. The three vectors in the right panel are obtained by applying $\mathbf{D}_\sigma\mathbf{w}_\sigma$ to each of the vector on the left panel, where $\mathbf{D}_\sigma$ is the diagonal matrix consisting of the population standard deviations of the 7 indicators. For both modes B and $\mathrm{B_A}$, there exists $\mathbf{D}_\sigma\mathbf{w}_\sigma = \mathbf{w}_\rho$ or $\mathbf{w}_\sigma = \mathbf{D}_\sigma^{-1}\mathbf{w}_\rho$, verifying the scale-inverse equivariance properties of the two modes. However, the weight vectors under mode A clearly do not enjoy such a property. In addition, modes B and $\mathrm{B_A}$ yield identical weight vectors in each case, which verifies that mode $\mathrm{B_A}$ is asymptotically equivalent to mode B, and both yield composites with maximal reliability.

Table 4.2b contains the parameters of the regression models $\eta_w = \gamma_w\xi_w + e_w$ corresponding to the three modes under the population covariances and correlations, where η_w and ξ_w are the weighted composites and γ_w is the corresponding regression

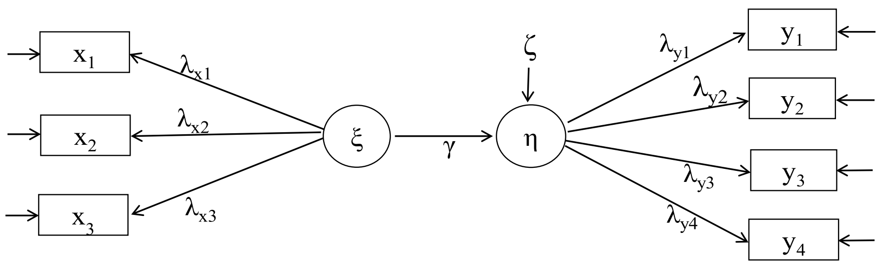

Fig. 4.2 A model with two latent variables and seven indicators

Table 4.2 (a) Population values of the weights of PLS-SEM modes A, B_A and B under the analyses of the covariances σ_{ij} ($\mathbf{w}_\sigma$), the correlations ρ_{ij} ($\mathbf{w}_\rho$), and by transformation ($\mathbf{D}_\sigma \mathbf{w}_\sigma$)

Weight	Modeling $\boldsymbol{\Sigma}$ ($\mathbf{w}_\sigma$)			Modeling $\mathbf{P}$ ($\mathbf{w}_\rho$)			$\mathbf{D}_\sigma \mathbf{w}_\sigma$		
	A	B_A	B	A	B_A	B	A	B_A	B
w_{x1}	0.241	0.210	0.210	0.348	0.230	0.230	0.263	0.230	0.230
w_{x2}	0.301	0.241	0.241	0.375	0.305	0.305	0.381	0.305	0.305
w_{x3}	0.362	0.434	0.434	0.420	0.589	0.589	0.490	0.589	0.589
w_{y1}	0.189	0.163	0.163	0.283	0.198	0.198	0.229	0.198	0.198
w_{y2}	0.226	0.175	0.175	0.296	0.243	0.243	0.315	0.243	0.243
w_{y3}	0.151	0.126	0.126	0.254	0.137	0.137	0.163	0.137	0.137
w_{y4}	0.283	0.356	0.356	0.332	0.551	0.551	0.439	0.551	0.551

(b) Population values for the regression models corresponding to the three modes of PLS-SEM under the analyses of the covariances σ_{ij} ($\boldsymbol{\theta}_\sigma$), and the correlations ρ_{ij} ($\boldsymbol{\theta}_\rho$)

Parameter	$\boldsymbol{\theta}_\sigma$			$\boldsymbol{\theta}_\rho$		
	A	B_A	B	A	B_A	B
γ_w	0.653	0.656	0.656	0.646	0.656	0.656
σ_w^2	0.573	0.569	0.569	0.583	0.569	0.569
$\mathcal{R}_w^2$	0.427	0.431	0.431	0.417	0.431	0.431

Note $\mathbf{P}$ is the population correlation matrix; $\mathbf{D}_\sigma$ is a diagonal matrix whose diagonal elements are the square root of the diagonal elements of $\boldsymbol{\Sigma}$; and $\mathcal{R}_w^2$ is the population counterpart of R^2

coefficient. The results in Table 4.2b show that the regression coefficient γ_w, the error variance $\sigma_w^2 = \mathrm{Var}(e_w)$, and the coefficient of determination $\mathcal{R}_w^2$ (population R-square) are scale invariant under both modes B and B_A. But the parameters under mode A do not possess such a property.

4.5.3 Sample Results

For the population covariance matrix $\boldsymbol{\Sigma}$ (Table 4.8) that generated the results in Table 4.2, a sample of size N=100 is drawn from the normal population $N(\mathbf{0}, \boldsymbol{\Sigma})$. The SAS IML program that generated the sample as well as the 100×7 data matrix are available at www3.nd.edu/~kyuan/PLS-SEM_property . The code of the SAS program is also provided in Appendix 2 for reference, and the sample covariance matrix of this sample is given in Table 4.9 of Appendix 1. Table 4.3 contains the results of applying modes A, B_A and B to this sample. Parallel to Table 4.2, the estimated weights corresponding to modeling the sample covariances ($\mathbf{S}$) and sample correlations ($\mathbf{R}$) are denoted by $\hat{\mathbf{w}}_s$ and $\hat{\mathbf{w}}_r$, respectively; and the transformed weights are obtained by $\mathbf{D}_s \hat{\mathbf{w}}_s$, where $\mathbf{D}_s$ is a diagonal matrix whose diagonal elements are

Table 4.3 (a) Estimated weights of PLS-SEM modes A, B_A and B under the analyses of the sample covariances s_{ij} ($\hat{\mathbf{w}}_s$), the sample correlations r_{ij} ($\hat{\mathbf{w}}_r$), and by transformation ($\mathbf{D}_s\hat{\mathbf{w}}_s$)

Weight	Modeling $\mathbf{S}$ ($\hat{\mathbf{w}}_s$)			Modeling $\mathbf{R}$ ($\hat{\mathbf{w}}_r$)			$\mathbf{D}_s\hat{\mathbf{w}}_s$		
	A	B_A	B	A	B_A	B	A	B_A	B
$\hat{w}_{x1}$	0.245	0.192	0.211	0.345	0.226	0.262	0.304	0.239	0.262
$\hat{w}_{x2}$	0.256	0.217	0.194	0.357	0.280	0.246	0.325	0.275	0.246
$\hat{w}_{x3}$	0.315	0.390	0.393	0.385	0.570	0.568	0.456	0.563	0.568
$\hat{w}_{y1}$	0.126	0.034	0.200	0.199	0.030	0.239	0.151	0.040	0.239
$\hat{w}_{y2}$	0.239	0.123	−0.223	0.336	0.122	−0.297	0.318	0.163	−0.297
$\hat{w}_{y3}$	0.180	0.059	−0.126	0.271	0.056	−0.158	0.224	0.074	−0.158
$\hat{w}_{y4}$	0.320	0.528	−0.526	0.395	0.856	−0.801	0.487	0.805	−0.801

(b) Estimates for the regression models corresponding to the three modes of PLS-SEM under the analyses of the sample covariances s_{ij} (θ_s) and the sample correlations r_{ij} (θ_r)

Parameter est	$\hat{\boldsymbol{\theta}}_s$			$\hat{\boldsymbol{\theta}}_r$		
	A	B_A	B	A	B_A	B
$\hat{\gamma}_w$	0.649	0.667	−0.686	0.634	0.666	−0.686
$\hat{\sigma}_w^2$	0.584	0.560	0.534	0.604	0.562	0.534
R_w^2	0.422	0.446	0.471	0.402	0.443	0.471

Note $\mathbf{D}_s$ is a diagonal matrix whose diagonal elements are the square root of the diagonal elements of $\mathbf{S}$

given by the square roots of those of $\mathbf{S}$. The estimates of the model parameters for $\hat{\eta}_w = \gamma_w\hat{\xi}_w + e_w$ are also reported in Table 4.3.

As expected, estimates under PLS-SEM mode A do not possess the property of scale-inverse invariance nor scale invariance when the scales of the indicators change. The estimated weights under mode B are scale-inverse equivariant and the estimated regression parameters are scale invariant. But three of the four weights for the y-indicators by mode B are negative. Note that we let the first element of each weight vector be positive in iteratively computing the weights. If we had let $\hat{w}_{y1}$ under mode B be negative, then $\hat{w}_{y2}$, $\hat{w}_{y3}$ and $\hat{w}_{y4}$ would be positive as would $\hat{\gamma}_w$.

The results in Table 4.3 imply that weights under mode B_A do not possess the property of scale-inverse equivariance nor the parameter estimates possess that of scale invariance with finite samples. This is because the sampling errors in the estimated weight $\hat{\mathbf{w}}_a$ and those in $\mathbf{S}$ affect the estimates of the error variances in Eq. (4.2). In particular, weights under mode B_A are obtained by transforming those under mode A. When the model in Eq. (4.1) does not fit the sample covariance matrix $\mathbf{S}$ perfectly, the effect of sampling errors is carried to weights under mode B_A. However, compared to the different weights under mode A, the elements of $\hat{\mathbf{w}}_r$ and $\mathbf{D}_s\hat{\mathbf{w}}_s$ under mode B_A are much closer to each other. This is because weights under mode B_A are asymptotically scale-inverse equivariant and estimates of regression parameters are asymptotically scale invariant.

The values of the R^2 in Tables 4.2 and 4.3 show that, while modes B and B_A are asymptotically equivalent, the former yields a greater R^2 value at the sample level. In contrast, mode A has the smallest R^2 in both the population and the sample.

Because our focus is PLS-SEM, we did not formally discuss the invariance or equivariance properties of regression analysis with equally weighted composites (EWC) in this section. Although EWC regression is widely used in practice and was recommended against PLS-SEM by some authors (e.g., Rönkkö et al., 2023), the results of EWC regression are neither scale invariant nor scale equivariant nor scale-inverse equivariant. The reliabilities of EWCs are also scale dependent. Parallel to PLS-SEM mode A, the use of standardized items or standardized composites under EWC regression is to avoid addressing the issues of scale dependency of the method. We will use an example to illustrate such facts in a later section.

4.6 Sensitivity of Weights to Misspecified Models

Results in the previous section and those in Yuan and Deng (2021) indicate that mode B can yield negative weights although the mode has theoretical advantages. This section discusses the sensitivity of different modes to model misspecification for the purpose of better understanding the empirical behaviors of the different modes. Detailed analysis on the sensitivity of weights to model misspecification was given in Yuan et al. (2023), and we only briefly summarize the results here.

A latent-variable model typically includes measurement model and structural model. Yuan et al. (2023) only considered misspecification in the measurement model, mostly because the measurement model under PLS-SEM is rather restricted. In contrast, the structural model under PLS-SEM can be specified as saturated. Thus, we also only consider misspecified measurement models in this chapter, which may mistakenly exclude three types of parameters: (1) within-block error covariances, (2) between-block error covariances, and (3) cross loadings. Our discussion will be for the three types of misspecification. For simplicity, we will only discuss the case with two latent variables. But the conclusions equally hold for models with more latent constructs, as to be illustrated via an empirical example in the next section. Interested readers are referred to Yuan et al. (2023) for a comprehensive study.

Consider the model in Fig. 4.2, which has seven measurement errors and seven factor loadings. Each error might be correlated with the errors of its own block or of the other block. Each indicator might also load on the latent variable of the other block. When the PLS-SEM mode is clear from the context, we will use $\mathbf{w}_x$ and $\mathbf{w}_y$ to represent the vectors of weights corresponding to the blocks $\mathbf{x}$ and $\mathbf{y}$, respectively. Since the scales of the weighted composites are arbitrary, we will focus on the relative change of the weights using their counterparts under the correctly specified model as the reference. In particular, we will regard the weights as not affected if they are proportional to their counterparts under the correctly specified model (i.e., no cross loadings nor correlated errors in the population). Because the order of the indicators within each block is arbitrary, the conclusions obtained for a particular indicator also apply to other indicators of the same nature within the same block.

4.6.1 PLS-SEM Mode A

Within-block error covariance

When x_1 and x_2 in Fig. 4.2 have correlated errors, neither the weight vector $\mathbf{w}_x$ nor the weight vector $\mathbf{w}_y$ under the mode A of PLS-SEM is affected. Each vector is still proportional to that of the correctly specified model, i.e., the vector of factor loadings of the respective block. Parallel results hold when y_2 and y_3 in Fig. 4.2 have correlated errors. That is, within-block correlated errors do not affect the weights under PLS-SEM mode A.

Between-block error covariance

When x_3 and y_4 in Fig. 4.2 have correlated errors, only the individual weights of x_3 and y_4 are affected. The other elements of $\mathbf{w}_x$ and $\mathbf{w}_y$ under mode A are still proportional to their respective factor loadings. If there is a 3rd latent variable with a block of reflective indicators, the weight vector for this block will not be affected by the error correlations between the other two blocks.

Cross loading

In Fig. 4.2 when x_1 has a nonzero loading on η, only the weight for x_1 in $\mathbf{w}_x$ is affected. The weights for the other indicators in the block $\mathbf{x}$ are still proportional to their respective factor loadings. The weight vector $\mathbf{w}_y$ is not affected. In parallel, the existence of a cross loading of y_4 on ξ in Fig. 4.2 only affects the weight of y_4 in $\mathbf{w}_y$. The other elements of $\mathbf{w}_y$ as well as the whole vector $\mathbf{w}_x$ are still proportional to their respective factor loadings.

4.6.2 PLS-SEM Mode B

Within-block error covariance

When y_3 and y_4 in Fig. 4.2 have correlated errors, the weights for y_3 and y_4 in $\mathbf{w}_y$ are affected. The other weights within the block are still proportional to their respective factor loadings. The weight vector $\mathbf{w}_x$ is not affected. Parallel results hold when errors in the block $\mathbf{x}$ are correlated. That is, within-block error covariances only affect the individual weights of the involved items. They do not affect the weights for the other items within the same block nor any of the weights of a different block.

Between-block error covariance

When x_3 and y_4 in Fig. 4.2 have correlated errors, only the individual weights of x_3 and y_4 are affected. The other elements of $\mathbf{w}_x$ and $\mathbf{w}_y$ under mode B are still proportional to their counterparts under the correctly specified model (i.e., the vector of factor loading multiplied by the precision matrix of the block). If there is a 3rd latent variable with a block of reflective indicators, the weight vector for this block will not be affected by the error covariances between the other two blocks.

Cross loading

When x_1 has a nonzero loading on η in Fig. 4.2, only the weight for x_1 in $\mathbf{w}_x$ is affected. The weights for the other indicators in the block $\mathbf{x}$ are still proportional to their counterparts under the correctly specified model. The weight vector $\mathbf{w}_y$ is still proportional to the vector of factor loadings multiplied by the precision matrix of the block $\mathbf{y}$. In parallel, the existence of a cross loading of y_4 on ξ in Fig. 4.2 only affects the weight of y_4 in $\mathbf{w}_y$, and the other elements of $\mathbf{w}_y$ are still proportional to their counterparts under a correctly specified model, and so is the whole vector $\mathbf{w}_x$.

4.6.3 PLS-SEM Mode $\mathrm{B_A}$

Within-block error covariance

When x_1 and x_2 in Fig. 4.2 have correlated errors, the one-factor model in Eq. (4.1) is misspecified. To account for the need of fitting the covariances of the indicators, the factor variance (the parameter ϕ) in Eq. (4.1) has to take a different value from that of the correctly specified model, and so do the error variances. Consequently, any error covariances within the block $\mathbf{x}$ will affect all the elements of $\mathbf{w}_x$ under the mode $\mathrm{B_A}$. However, error covariances within the block $\mathbf{x}$ do not affect the weight vector $\mathbf{w}_y$. Parallel results hold when $\mathbf{y}$ has within-block error covariances. That is, within-block error covariances only affect the weight vector of the corresponding block. They do not affect the weights of a different block.

Between-block error covariance

When x_3 and y_4 in Fig. 4.2 have correlated errors, all the elements of $\mathbf{w}_x$ and $\mathbf{w}_y$ are affected under the mode $\mathrm{B_A}$. This is because a change in a single element of the weight vector under mode A will affect the communalities of all the indicators in $\mathbf{x}$ via the change of the factor variance (the parameter ϕ) when Eq. (4.1) is estimated. They together cause all the elements of $\mathbf{w}_x$ and $\mathbf{w}_y$ under mode $\mathrm{B_A}$ to change. However, if there is a 3rd latent variable with a block of reflective indicators, the weight vector for this block will not be affected by the error covariances between the other two blocks.

Cross loading

When x_1 has a nonzero loading on η in Fig. 4.2, the change in weight of x_1 under mode A will affect the values of the communalities of all the indicators in $\mathbf{x}$ via the change of the factor variance (the parameter ϕ in Eq. 4.1). They further cause changes in all the elements of $\mathbf{w}_x$ under the mode $\mathrm{B_A}$. However, the vector $\mathbf{w}_y$ under mode $\mathrm{B_A}$ is not affected by the existence of a cross loading of x_1 on η.

We only discussed whether the weights will change or remain intact when an extra association in the population exists. The size of the change also varies between the different modes. In particular, mode B tends to have the largest change and is very sensitive to the existence of cross loadings, although more elements of the weights under mode $\mathrm{B_A}$ are affected (Yuan et al., 2023). Because model misspecification and sampling errors are empirically confounded, the results in this section explain why some weights under mode B in Table 4.3 are negative although the two-factor model is a correct model.

4.7 Two Real Data Examples

This section contains two examples, and the purpose is to illustrate the properties of the PLS-SEM methodology presented in the previous sections, including the size of measurement reliability, scale invariance and equivariance of weights and reliability coefficients, and the sensitivity of weights. The data and model for the first example are from a PLS-SEM textbook; and the dataset for the second example is from a classical textbook of multivariate statistics that has been used to illustrate various developments in SEM.

Example 5

The path diagram in Fig. 1.3 of Henseler (2021, p. 6) presented a model with 21 reflective indicators and 4 latent constructs. One of the 21 indicators is gender, playing the role of a covariate (ξ_1). The other 20 indicators include eight organizational prestige indicators for a latent construct ξ_2 (organizational prestige), six organizational identification indicators for a latent construct η_1 (organizational identification), four affective commitment indicators for a latent construct η_2 (joy), and two affective commitment indicators for a latent construct η_3 (love). The wording of the indicators can be found in Table 6.1 of Henseler (2021, p. 135). According to the table, this organization-culture dataset has 22 variables from 305 participants, and they were part of a larger survey among South Korean employees conducted and reported by Bergami and Bagozzi (2000). One of the indicators (orgcmt6) in Table 6.1 of Henseler (2021) is not used in his Fig. 1.3. Among the 305 participants, there are 157 male employees and 148 female employees. For easy reference, a path diagram for the model is given in Fig. 4.3 of this chapter, which has 7 path coefficients: γ_{21}, γ_{31}, γ_{12}, γ_{22}, γ_{32}, β_{21}, and β_{31}. Note that the labels for joy and love in Fig. 1.3 of Henseler

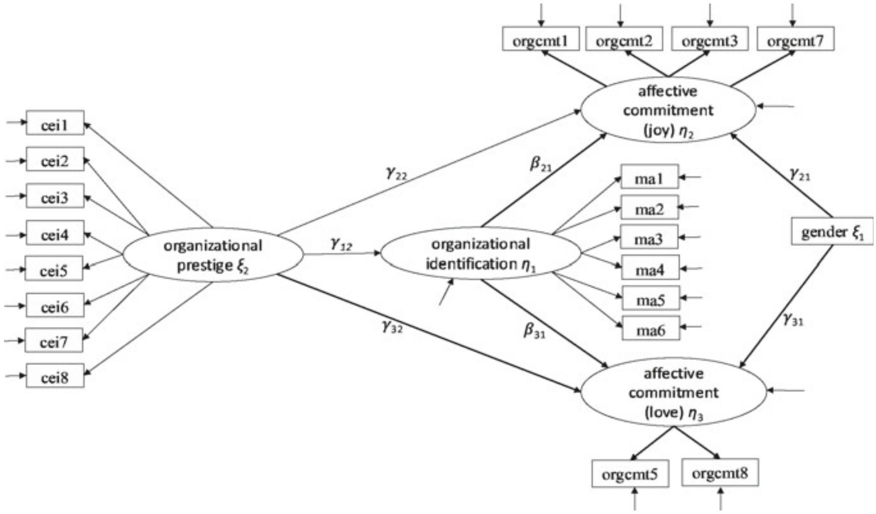

Fig. 4.3 A model with a covariate (gender), four latent variables and twenty indicators (the same model as in Fig. 1.3 on page 6 of Henseler, 2021)

(2021) are switched from his Table 6.1, and the labels in our Fig. 4.3 adopted those in his Table 6.1. Our purpose with this real-data example is to use the textbook model to illustrate the discussed properties of the three modes of the PLS-SEM methodology.

Because both LS regression and the NML method for CB-SEM are strongly influenced by data contamination and/or outlying observations, we first check the distribution properties of this organization-culture dataset. Since gender is unlikely contaminated, it is excluded from the examination. The standardized Mardia's (1970) multivariate kurtosis of the remaining 20 variables is $M_s = 40.481$, which is highly significant when compared against the standard normal distribution. We thus use a robust method to control the heavy tails of the data, and choose a Huber-type M-estimator for the purpose (Huber, 1981). This can be carried out via a robust transformation procedure (Yuan et al., 2000). Note that the mechanism of robustness with Huber-type M-estimator is to give smaller weights to outlying cases in estimating the means and covariances. The purpose is to get more efficient parameter estimates or numerically more stable results in the analysis (Yuan & Gomer, 2021). Let's denote the robust method via Huber-type weights as H(φ) when cases whose Mahalanobis distances (d_M^2) are greater than the $1 - \varphi$ quantile of χ^2_{20} are downweighted. We started with H(0.05), however, the standardized multivariate kurtosis of the transformed sample is still highly significant ($M_s = 9.112$). Following the recommendation in Yuan and Gomer (2021), we continued to increase the value of φ by checking the corresponding standardized multivariate kurtosis until $\varphi = 0.25$, and the corresponding value of the M_s is -0.099. Our analysis and comparison below are to fit the model in Fig. 4.3 to the transformed sample by H(0.25), where gender is not subject to the transformation.

Clearly, the model in Fig. 4.3 can be estimated under both PLS-SEM and CB-SEM. Although our main interest in this chapter is to study psychometric and statistical properties of PLS-SEM, these properties are characterized via the model-implied covariance matrix. Thus, we will first estimate the model under CB-SEM via the NML method to obtain this covariance matrix. Considering that PLS-SEM researchers may not have much interest in results under CB-SEM, these are put in Appendix 3 of this chapter. Instead, we will include the results of path analysis with EWCs, since the method lacks the fundamental properties of a principled method but was favored against PLS-SEM.

For each of the four latent variables (ξ_2, η_1, η_2, η_3), fixing their first factor loading at 1.0 for model identification, the CB-SEM model has 48 free parameters. Fitting the model in Fig. 4.3 to the robustly transformed sample by NML results in $T_{ml} = 613.756$, corresponding to a p-value that is essentially 0 when referred to χ^2_{183}. Fit indices (RMSEA = 0.088, CFI = 0.871) also indicate that the model in Fig. 4.3 fits the data marginally[5] according to the established norms (Hu & Bentler, 1999). This is not unusual when working with real data. The goodness-of-fit can be improved by modifying the model in Fig. 4.3 (e.g., to include correlated errors and/or cross loadings). But our purpose is to use the textbook example with the original model to illustrate the fundamental properties of the PLS methodology, as stated earlier.

The estimates of the factor loadings (λ), factor variances (ϕ), path coefficients (γ, β), measurement error variances (ψ) and prediction-error variances (σ^2_ζ) of the CB-SEM model are reported in Table 4.10 of Appendix 3, where the standard errors (SE) and z-statistics are computed according to the ML (i.e., NML) method in EQS (Bentler, 2006). All the parameter estimates are statistically significant at the level of 0.05.

We next apply PLS-SEM modes A, $\mathrm{B_A}$ and B to estimate the model in Fig. 4.3. When working with the unstandardized variables (modeling the sample covariance matrix $\mathbf{S}$) of the robustly transformed sample the 21 estimated weights by each method are given in the left panel of Table 4.4, and those with the standardized variables (modeling the sample correlation matrix $\mathbf{R}$) are in the middle panel. The right panel of Table 4.4 contains the results of $\mathbf{D}_s\hat{\mathbf{w}}_s$, where $\mathbf{D}_s$ is a diagonal matrix whose diagonal elements are the square root of the diagonal elements of $\mathbf{S}$, and $\hat{\mathbf{w}}_s$ is the vector of weights on the left panel of the table. Clearly, the estimated weights by mode B under modeling $\mathbf{R}$ are identical to those under $\mathbf{D}_s\hat{\mathbf{w}}_s$, verifying the property of scale-inverse equivariance of the mode. In contrast, the estimated weights by mode A do not enjoy such a property. The weights under mode $\mathrm{B_A}$ in Table 4.4 are not strictly scale-inverse equivariant either, due to sampling errors and model misspecification. But the values of $\hat{w}_{b_a}$ under $\mathbf{D}_s\hat{\mathbf{w}}_s$ are rather close to those under modeling $\mathbf{R}$.

Note that the first value of the estimated weights for each block of indicators in Table 4.4 is set as positive. However, five of the eight values of $\hat{w}_b$ for the indicators of ξ_2 are negative. This shows the sensitivity of mode B to model misspecifica-

[5] When the CB-SEM model is fitted to the original (not robustly transformed) data by NML, the results are $T_{ml} = 669.183$, RMSEA = 0.093, and CFI = 0.848. The estimate of γ_{32} corresponds to a z-statistic at -1.840.

Table 4.4 Estimated weights of composites by three methods for the model in Fig. 4.3 ($p = 21$, $N = 305$). The results are obtained with a robustly transformed sample via H(0.25)

Indicator	Modeling $\mathbf{S}$ ($\hat{\mathbf{w}}_s$)			Modeling $\mathbf{R}$ ($\hat{\mathbf{w}}_r$)			$\mathbf{D}_s\hat{\mathbf{w}}_s$		
	$\hat{w}_a$	$\hat{w}_{b_a}$	$\hat{w}_b$	$\hat{w}_a$	$\hat{w}_{b_a}$	$\hat{w}_b$	$\hat{w}_a$	$\hat{w}_{b_a}$	$\hat{w}_b$
$x_{1,1}$	2.001	2.001	2.001	1.000	1.000	1.000	1.000	1.000	1.000
$x_{2,2}$	0.166	0.101	0.140	0.122	0.069	0.094	0.111	0.068	0.094
$x_{3,2}$	0.196	0.131	0.273	0.137	0.091	0.190	0.136	0.091	0.190
$x_{4,2}$	0.251	0.222	−0.589	0.161	0.163	−0.443	0.189	0.167	−0.443
$x_{5,2}$	0.199	0.251	−0.182	0.159	0.155	−0.111	0.121	0.153	−0.111
$x_{6,2}$	0.221	0.230	−0.480	0.160	0.160	−0.324	0.149	0.155	−0.324
$x_{7,2}$	0.262	0.350	−0.467	0.174	0.258	−0.342	0.192	0.256	−0.342
$x_{8,2}$	0.251	0.181	0.003	0.155	0.137	0.003	0.196	0.141	0.003
$x_{9,2}$	0.217	0.294	−0.350	0.165	0.184	−0.222	0.138	0.187	−0.222
$y_{1,1}$	0.257	0.231	0.179	0.211	0.171	0.132	0.190	0.171	0.132
$y_{2,1}$	0.257	0.241	0.289	0.215	0.181	0.212	0.188	0.177	0.212
$y_{3,1}$	0.209	0.154	0.196	0.176	0.113	0.142	0.152	0.112	0.142
$y_{4,1}$	0.350	0.448	0.445	0.257	0.368	0.368	0.289	0.370	0.368
$y_{5,1}$	0.345	0.342	0.369	0.245	0.289	0.315	0.294	0.292	0.315
$y_{6,1}$	0.236	0.194	0.132	0.196	0.142	0.097	0.173	0.142	0.097
$y_{7,2}$	0.428	0.330	0.299	0.305	0.265	0.242	0.347	0.268	0.242
$y_{8,2}$	0.417	0.428	0.415	0.326	0.314	0.309	0.310	0.318	0.309
$y_{9,2}$	0.474	0.597	0.659	0.363	0.453	0.501	0.360	0.453	0.501
$y_{10,2}$	0.363	0.314	0.282	0.292	0.238	0.208	0.267	0.230	0.208
$y_{11,3}$	0.678	0.574	0.601	0.522	0.412	0.441	0.498	0.422	0.441
$y_{12,3}$	0.871	0.956	0.935	0.649	0.743	0.720	0.670	0.735	0.720

Note $\mathbf{S} = (s_{ij})$ and $\mathbf{R} = (r_{ij})$ are respectively the sample covariance and correlation matrices of the robustly transformed sample, and the d_s is the square root of the corresponding diagonal element of $\mathbf{S}$

tion/sampling errors, although the weights are scale-inverse equivariant. In contrast, weights under modes A and $\mathrm{B_A}$ are all positive, conforming with the expectation in formulating composites.

Table 4.5 contains the estimated path coefficients of the structural model in Fig. 4.3, where EWC regression is also included for comparison purpose. Clearly, the results by mode B remains the same whether working with the unstandardized variables (modeling **S**) or the standardized variables (modeling **R**). The results by mode $\mathrm{B_A}$ under modeling **R** are almost identical to those under modeling **S**, whereas those by PLS-SEM mode A clearly depend on the scales of the observed indicators. The results of EWC regression in Table 4.5 are even more affected by the scales of the observed indicators than those of PLS-SEM mode A, indicating that the former is not a principled method. Note that the signs of the estimated values for coefficients γ_{12}, γ_{22}, and γ_{32} by mode B are opposite to those by the other methods, due to five

Table 4.5 Estimated path coefficients and the corresponding R-squares for the model in Fig. 4.3 ($p = 21$, $N = 305$). The results are obtained with a robustly transformed sample via H(0.25)

	Modeling **S**				Modeling **R**			
Parameter	EWC_{reg}	PLS_A	PLS_{B_A}	PLS_B	EWC_{reg}	PLS_A	PLS_{B_A}	PLS_B
γ_{21}	−0.169	−0.145	−0.151	−0.148	−0.110	−0.143	−0.151	−0.148
γ_{31}	0.127	0.114	0.117	0.112	0.084	0.111	0.117	0.112
γ_{12}	0.365	0.327	0.325	−0.337	0.327	0.326	0.325	−0.337
γ_{22}	0.258	0.208	0.200	−0.191	0.236	0.210	0.200	−0.191
γ_{32}	−0.206	−0.178	−0.185	0.191	−0.190	−0.179	−0.185	0.191
β_{21}	0.572	0.540	0.554	0.556	0.576	0.538	0.554	0.556
β_{31}	−0.442	−0.430	−0.431	−0.430	−0.447	−0.423	−0.430	−0.430
$R^2_{\eta 1}$	0.107	0.107	0.106	0.114	0.106	0.107	0.106	0.114
$R^2_{\eta 2}$	0.417	0.425	0.437	0.437	0.415	0.424	0.437	0.437
$R^2_{\eta 3}$	0.264	0.277	0.282	0.287	0.259	0.270	0.281	0.287

Note $\mathbf{S} = (s_{ij})$ and $\mathbf{R} = (r_{ij})$ are respectively the sample covariance and correlation matrices of the robustly transformed sample

of the weights being negative for the eight indicators of ξ_2. This can be addressed by reversing the signs of the eight estimated weights.

Estimated reliabilities of the four composites ($\hat{\xi}_2$, $\hat{\eta}_1$, $\hat{\eta}_2$, $\hat{\eta}_3$) by six different methods are presented in Table 4.6, where each method is applied to both the unstandardized (modeling **S**) and standardized items (modeling **R**). The six methods are respectively (1) EWC; (2) PLS_A with weights estimated by PLS-SEM mode A; (3) PLS_{A_m} with weights being proportional to the factor loadings $\hat{\boldsymbol{\lambda}}$ under CB-SEM presented in Table 4.10, where the m in the subscript is for model-implied weights (Dijkstra, 1983); (4) PLS_B with weights estimated by PLS-SEM modes B; (5) PLS_{B_A} with weights estimated according to Sect. 4.4 of the chapter; and (6) PLS_{B_m} with model-implied weights that are proportional to $\hat{\boldsymbol{\Psi}}^{-1}\hat{\boldsymbol{\lambda}}$ (Dijkstra, 1983; Yuan & Deng, 2021), where $\hat{\boldsymbol{\lambda}}$ and $\hat{\boldsymbol{\Psi}}$ are respectively the NML estimates of factor loadings and error variances under CB-SEM. The reliability of each composite is computed via the model-implied covariance matrix according to the NML estimates reported in Table 4.10. The estimated reliabilities of the individual items are also included in Table 4.6, which are from the default output of EQS (Bentler, 2006).

The results in Table 4.6 show that the reliabilities of composites by PLS_B and PLS_{B_m} are scale invariant while those by PLS_{B_A} are close to scale invariant. The reliabilities of composites by PLS_A and PLS_{A_m} are rather close but neither set is scale invariant. The reliabilities of the EWCs are clearly not scale invariant. Regarding the size of the reliability estimates, those of $\hat{\xi}_2$ by both PLS_A and PLS_B are smaller than that of the EWC under modeling **S**, and that by PLS_B is also smaller than that of the EWC under modeling **R**. For all the other composites, the EWCs have the smallest reliability estimates. Note that, for correctly specified models, mode B supposes to yield composites with the maximum reliabilities. The reason for PLS_B to perform poorly with $\hat{\xi}_2$ is because multiple weights are negative, due to the sensitivity of the

Table 4.6 Reliabilities of individual items (ρ_j) as well as of composites (ξ_2, η_2, η_2, η_3) by six methods for the model in Fig. 4.3 ($p = 21$, $N = 305$). The results are obtained with a robustly transformed sample via H(0.25)

Item	ρ_j	Item	ρ_j	Item	ρ_j	Item	ρ_j
$x_{2,2}$	0.515	$y_{1,1}$	0.482	$y_{7,2}$	0.430	$y_{11,3}$	0.402
$x_{3,2}$	0.595	$y_{2,1}$	0.419	$y_{8,2}$	0.492	$y_{12,3}$	0.512
$x_{4,2}$	0.507	$y_{3,1}$	0.274	$y_{9,2}$	0.613		
$x_{5,2}$	0.665	$y_{4,1}$	0.704	$y_{10,2}$	0.360		
$x_{6,2}$	0.649	$y_{5,1}$	0.653				
$x_{7,2}$	0.688	$y_{6,1}$	0.458				
$x_{8,2}$	0.551						
$x_{9,2}$	0.696						

Method	Modeling **S**				Modeling **R**			
	$\hat{\xi}_2$	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$	$\hat{\xi}_2$	$\hat{\eta}_1$	$\hat{\eta}_2$	$\hat{\eta}_3$
EWC	0.923	0.859	0.781	0.628	0.925	0.854	0.781	0.627
PLS_{A_m}	0.923	0.873	0.787	0.632	0.927	0.867	0.789	0.630
PLS_{A}	0.921	0.872	0.787	0.633	0.927	0.865	0.788	0.632
PLS_{B_m}	0.929	0.877	0.795	0.633	0.929	0.877	0.795	0.633
PLS_{B}	0.803	0.870	0.794	0.631	0.803	0.870	0.794	0.631
PLS_{B_A}	0.924	0.876	0.795	0.630	0.925	0.876	0.794	0.629

Note $\mathbf{S} = (s_{ij})$ and $\mathbf{R} = (r_{ij})$ are respectively the sample covariance and correlation matrices of the robustly transformed sample

weights to model misspecification and/or sampling errors, as presented in Sect. 6 of the chapter. For this example, all the reliability estimates for all the composites are greater than those of the individual items.

The comparison between EWC and PLS-SEM mode A in Table 4.6 is consistent with what was concluded by Henseler et al. (2014).

Example 6

Mardia et al. (1979, Table 1.2.1) contain test scores on 5 subjects from $N = 88$ students. The five subjects are: Mechanics (y_1), Vectors (y_2), Algebra (x_1), Analysis (x_2), and Statistics (x_3). The first two scores were obtained with closed-book exams and the last three were with open-book exams. Tanaka et al. (1991) fitted the dataset by a two-factor model, one factor representing the trait for taking closed-book exams, and the other representing the trait for taking open-book exams. This dataset has been used to illustrate new developments in CB-SEM and PLS-SEM (e.g., Poon & Poon, 2002; Yuan et al., 2020). We will use the dataset to compare the reliabilities of differently formulated composites. The standardized Mardia's multivariate kurtosis for this test-score dataset is $M_s = 0.057$, and our analysis will be conducted on the observed sample without robust transformation.

Table 4.7 Reliabilities of individual items (ρ_j) as well as of composites (ξ, η) by six methods for test-score data ($p = 5$, $N = 88$)

Individual item			Modeling **S**		Modeling **R**	
Item	ρ_j	Method	$\hat{\xi}$	$\hat{\eta}$	$\hat{\xi}$	$\hat{\eta}$
x_1	0.857	EWC	0.823	0.699	0.852	0.715
x_2	0.599	PLS_{A_m}	0.808	0.687	0.865	0.719
x_3	0.526	PLS_A	0.814	0.687	0.870	0.720
y_1	0.491	PLS_{B_m}	0.896	0.724	0.896	0.724
y_2	0.624	PLS_B	0.884	0.724	0.884	0.724
		PLS_{B_A}	0.858	0.724	0.876	0.724

Note $\mathbf{S} = (s_{ij})$ and $\mathbf{R} = (r_{ij})$ are respectively the sample covariance and correlation matrices of the observed sample

Let ξ represent the trait underlying the three open-book test scores, and η represent the trait underlying the two closed-book test scores. The regression model $\eta = \gamma\xi + \zeta$ is then estimated by NML under CB-SEM, EWC regression, BFS regression, PLS-SEM modes A, B_A and B, respectively. The estimated regression coefficient under each method as well as the weights under the PLS methods follow the same patterns as observed with the previous organization-culture example, and we do not display them to save space. Table 4.7 contains the reliabilities of the 5 individual test scores estimated under CB-SEM as well as those of the weighted composites for ξ and η by 6 methods. Note that the reliability of Algebra (x_1) is 0.857. When working with the unstandardized variables (modeling **S**), three of the six composites for ξ are less reliable than the single item x_1. Also, the reliabilities of $\hat{\xi}$ by PLS_A and PLS_{A_m} are smaller than that of the EWC. When the methods are applied to the standardized variables (modeling **R**), the reliability of the EWC $\hat{\xi}$ is still smaller than that of the single item x_1, while those by the other methods are greater than that of x_1.

The results in Table 4.7 also show that the estimated reliabilities under PLS_{B_m} and PLS_B remain the same whether working with the standardized variables or the unstandardized variables. However, the estimated reliabilities of $\hat{\xi}$ and $\hat{\eta}$ by the other methods are not scale invariant. The causes for the reliability estimates by PLS_{B_A} not being scale invariant are sampling errors and/or possible model misspecification, and the reliabilities of EWCs and the composites under PLS_A and PLS_{A_m} are not scale invariant even under idealized conditions (correct model and without sampling error).

4.8 Conclusion and Discussion

In this chapter we examined several properties of PLS-SEM methodology analytically and illustrated them both numerically and via real-data examples. Although mode A with standardized variables was routinely used for models with reflective indicators, the method does not possess solid statistical or psychometric properties. Mode B possesses good psychometric and statistical properties at the level of population but it is rather sensitive to model misspecification and sampling errors. In contrast, mode B_A possesses the advantages of both modes A and B. The resulting composites by mode B_A are asymptotically most reliable, and the other results of this mode are either asymptotically scale-inverse equivariant or scale invariant and are also numerically more stable than those by mode B. We thus recommend its routine use in practice.

The sensitivity of mode B is driven by the need to maximize the relationship between predictors and the corresponding environmental variable. In particular, the weights under mode B are obtained by pulling the strength of all the indicators in each block to predict the environmental variable, which is a linear combination of the indicators of the directly connected constructs. When the model does not fit the data perfectly, mode B will pick up the additional associations not represented by the model in order to account for the relationship among the indicators. The additional associations among indicators can render the regression coefficients (the weights) negative in predicting the environmental variable if the associations are not in the same direction expressed by the parameters over the existing paths. While the weights under mode A also partially maximize the associations among the indicators via the environmental variable (see, e.g., Boardman et al., 1981), each indicator under mode A is solely responsible for its own weight due to being computed by simple regression, and the weight would not change its sign unless the extra association of the focal indicator with the other blocks dominates the relationship.

As with any maximization process, neither mode A nor mode B distinguishes between systematic correlations and spurious correlations due to chance errors. In order to properly utilize the maximization mechanism of PLS-SEM, additional studies are needed to separate systematic correlations from chance errors. Compared to modes A and B, mode B_A is relatively new and few studies examined its behavior with small samples or under model misspecification. Since both the systematic effect due to model misspecification and the chance effect due to sampling errors associated with $\hat{\mathbf{w}}_a$ will be inherited by $\hat{\mathbf{w}}_{b_a}$, we might expect that mode B_A will also be affected by the two types of errors, and additional studies are needed to better understand the strength of mode B_A.

There are also developments for PLS-SEM to yield estimates that are consistent with those under CB-SEM (e.g., Dijkstra & Henseler, 2015a, 2015b; Yuan et al., 2020). As we noted in the introduction of this chapter, the values of the path coefficients under CB-SEM depend on the scales of the latent variables, and those under PLS-SEM depend on the scales of the weighted composites. Consistent estimates between the two classes of methods can be achieved by proper scaling of the latent variables or the weighted composites. Alternative methods that deviate from the standard PLS-SEM procedures can make the resulting regression equations lose the desired properties in yielding predicted values with smallest mean-squared errors (MSE), although the path coefficients are consistent with those under CB-SEM. Also, consistent path coefficients by an alternative method may not be proper if the regression equation is used for the prediction or diagnosis of individuals/participants. Nevertheless, one may also develop corrections to the estimates under PLS-SEM mode B_A so that they are consistent with those defined under CB-SEM. If estimates consistent with those under CB-SEM are of primary concern, then one should start with CB-SEM rather than correcting the estimates following the PLS-SEM methodology. In addition to consistent estimates, CB-SEM also facilitates evaluations of several other features, e.g., the goodness-of-fit of the overall model structure, item reliability, unidimensionality, etc.

As noted in the introduction of this chapter, Wold (1980, 1982) recommended mode B for models with formative indicators, and there is also advice on when and how to use composites with formative indicators (e.g., Jarvis et al., 2003; Petter et al., 2007). Rationales for not studying formative indicators have been given in the introduction section of this chapter. Because formative indicators do not need to share a single underlying common trait, other reasons that we did not study formative indicators include: (1) The property and substantive meaning of the composites may change as the number of indicators increases, due to different compositions. (2) The meaning of a composite will also change when the structural model changes, due to the fact that weights will change when the composition of the environmental variable or the connections among the latent variables change (Treiblmaier et al., 2011). Such a dynamic nature is an integrated part of formative indicators and the corresponding composite model, which directly serves the need to maximize the relationship among different blocks of indicators. However, the data themselves do not know whether they are error-free or the variables share any common construct. The weights by mode B are still scale-inverse equivariant and the composites are scale invariant regardless of the nature of the indicators. Also, mode B may result in negative weights for truly formative indicators. Interested readers are referred to Henseler et al. (2014), Sarstedt et al. (2016), Dijkstra (2017), Hwang et al. (2020), and Cho et al. (2022b, 2023) for detailed studies with composite models.

We have showed statistical and psychometric properties of PLS-SEM analytically and numerically as well as by real-data examples. While PLS-SEM mode B enjoys many theoretical and/or asymptotic advantages, results also showed that the method is rather sensitive to sampling errors. Further analytical or Monte Carlo studies are needed to see the speed for mode B to converge to its asymptotic results or when the method yields similar empirical results as BFS regression.

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Appendix 1: Population and Sample Covariance Matrices

The tables in this appendix contain the population and sample covariance matrices that are used to compute the results in Tables 4.2 and 4.3, respectively. The values for the population covariance matrix (Table 4.8) are exact, and those for the sample covariance matrix are rounded. Note that the sample covariance matrix is unbiased.

Table 4.8 The population covariance matrix $\mathbf{\Sigma}$

	x_1	x_2	x_3	y_1	y_2	y_3	y_4
x_1	1.1900	0.8000	0.9600	0.5600	0.6720	0.4480	0.8400
x_2	0.8000	1.6000	1.2000	0.7000	0.8400	0.5600	1.0500
x_3	0.9600	1.2000	1.8400	0.8400	1.0080	0.6720	1.2600
y_1	0.5600	0.7000	0.8400	1.4700	1.0680	0.7120	1.3350
y_2	0.6720	0.8400	1.0080	1.0680	1.9316	0.8544	1.6020
y_3	0.4480	0.5600	0.6720	0.7120	0.8544	1.1696	1.0680
y_4	0.8400	1.0500	1.2600	1.3350	1.6020	1.0680	2.4025

Table 4.9 The (unbiased) sample covariance matrix **S**

	x_1	x_2	x_3	y_1	y_2	y_3	y_4
x_1	1.5429	1.1706	1.4051	0.4285	0.7840	0.5716	1.1351
x_2	1.1706	1.6088	1.4303	0.4590	0.8221	0.7012	1.1209
x_3	1.4051	1.4303	2.0897	0.5471	1.0944	0.7674	1.3803
y_1	0.4285	0.4590	0.5471	1.4250	0.8699	0.6080	1.1202
y_2	0.7840	0.8221	1.0944	0.8699	1.7641	0.8380	1.4730
y_3	0.5716	0.7012	0.7674	0.6080	0.8380	1.5575	1.0482
y_4	1.1351	1.1209	1.3803	1.1202	1.4730	1.0482	2.3187

Appendix 2: The SAS IML Code That Generates the Sample Covariance Matrix in Table 4.9

```
proc iml;
n=100; *sample size;
p_x=3;
p_y=4;
p=p_x+p_y; *number of variables;
*------------------------;
*population values;
lamb_x0={0.8, 1.0, 1.2}; *loadings;
lamb_y0={1.0, 1.2, 0.8, 1.5};
lamb0=(lamb_x0||j(3,1,0))//(j(4,1,0)||lamb_y0);
phi_11=1.0; *factor variance;
gamma=.7; *regression coefficient;
sig2_zeta=.40; *prediction error variance;

phi_12=gamma;
phi_21=phi_12;
phi_22=gamma*gamma+sig2_zeta;

phi0=
(phi_11||phi_12)//
(phi_21||phi_22);
psi0={.55,.6,.4,.58,.65,.6,.4}; *measurement error variances;
psi_mat0=diag(psi0);

Sig_0=lamb0*Phi0*(lamb0`)+psi_mat0;*population covariance matrix;

call eigen(sval0,svec0,Sig_0); *eigenvalue decomposition;
sig_012=svec0*diag(sqrt(sval0))*svec0`; *Sig_0^{1/2};
*------------------------;
seed=1111111111;
z=normal(j(n,p,seed));
*a 100 by 7 matrix of independent random numbers following N(0,1);
x=z*sig_012; *the observed sample;
*each row of x follows a 7-variate normal distribution N(0,Sig0);
print x;
scov_x=x`*(i(n)-j(n,n,1)/n)*x/(n-1); *the sample covariance matrix;
print scov_x;
```

Appendix 3: Normal-Distribution-Based Maximum Likelihood (NML) Estimates for the Model in Fig. 4.3

The table in this appendix contains the NML estimates by fitting the model in Fig. 4.3 to the robustly transformed sample via H(.25). The dataset was originally analyzed by Bergami and Bagozzi (2000). The data and model used in this chapter are from the book by Henseler (2021). The likelihood ratio statistic and goodness-of-fit indices (RMSEA and CFI) were reported in the chapter and are also included in the Table 4.10.

Table 4.10 Parameter estimates (est), their SEs (se) and z-statistics for the CB-SEM model represented by Fig. 4.3 ($p = 21$, $N = 305$, $T_{ml} = 613.756$, $df = 183$, p-value = 0; RMSEA = 0.088, and CFI = 0.871). The results are obtained using NML with a robustly transformed sample via H(0.25)

θ	est	se	z	θ	est	se	z
$\lambda_{x1,1}$	1.000			ψ_{x1}	0		
$\lambda_{x2,2}$	1.000			ψ_{x2}	0.217	0.019	11.341
$\lambda_{x3,2}$	1.121	0.086	13.105	ψ_{x3}	0.197	0.018	10.960
$\lambda_{x4,2}$	1.119	0.093	12.082	ψ_{x4}	0.281	0.025	11.373
$\lambda_{x5,2}$	1.036	0.075	13.862	ψ_{x5}	0.125	0.012	10.475
$\lambda_{x6,2}$	1.132	0.083	13.689	ψ_{x6}	0.160	0.015	10.605
$\lambda_{x7,2}$	1.266	0.090	14.102	ψ_{x7}	0.168	0.016	10.268
$\lambda_{x8,2}$	1.210	0.096	12.597	ψ_{x8}	0.275	0.025	11.189
$\lambda_{x9,2}$	1.107	0.078	14.186	ψ_{x9}	0.123	0.012	10.187
$\lambda_{y1,1}$	1.000			ψ_{y1}	0.285	0.026	10.940
$\lambda_{y2,1}$	0.922	0.089	10.379	ψ_{y2}	0.313	0.028	11.257
$\lambda_{y3,1}$	0.739	0.087	8.480	ψ_{y3}	0.383	0.033	11.771
$\lambda_{y4,1}$	1.347	0.103	13.112	ψ_{y4}	0.203	0.023	8.756
$\lambda_{y5,1}$	1.340	0.105	12.707	ψ_{y5}	0.254	0.027	9.494
$\lambda_{y6,1}$	0.964	0.089	10.820	ψ_{y6}	0.292	0.026	11.071
$\lambda_{y7,2}$	1.000			ψ_{y7}	0.378	0.036	10.513
$\lambda_{y8,2}$	0.980	0.098	10.029	ψ_{y8}	0.282	0.028	9.975
$\lambda_{y9,2}$	1.118	0.103	10.814	ψ_{y9}	0.225	0.027	8.450
$\lambda_{y10,2}$	0.828	0.094	8.844	ψ_{y10}	0.347	0.032	10.981
$\lambda_{y11,3}$	1.000			ψ_{y11}	0.325	0.036	8.960
$\lambda_{y12,3}$	1.183	0.151	7.811	ψ_{y12}	0.290	0.042	6.908
ϕ_{11}	0.251	0.020	12.329				
ϕ_{22}	0.231	0.033	7.068				
γ_{21}	−0.182	0.052	−3.498	β_{21}	0.713	0.086	8.309
γ_{31}	0.135	0.057	2.365	β_{31}	−0.564	0.084	−6.735
γ_{12}	0.372	0.072	5.206	$\sigma^2_{\zeta_1}$	0.233	0.036	6.567
γ_{22}	0.222	0.063	3.551	$\sigma^2_{\zeta_2}$	0.103	0.021	4.855
γ_{32}	−0.197	0.068	−2.881	$\sigma^2_{\zeta_3}$	0.101	0.026	3.933

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Chapter 5
Software Packages for Partial Least Squares Structural Equation Modeling: An Updated Review

Sergio Venturini, Mehmet Mehmetoglu, and Hengky Latan

Abstract As a result of its ability to deal with situations that are difficult to address using other SEM methods, the partial least squares (PLS) approach to structural equation modeling (SEM) has attracted a lot of attention in recent years from applied researchers and practitioners in various fields. One reason for this growth in interest is represented by the many theoretical contributions emerging from the PLS-SEM research community, which have allowed us to deepen our knowledge of the method and extend its capabilities into new contexts. However, these contributions would have remained confined to academic journals if not for a parallel and similar development in the software packages available to implement these methodological innovations. Indeed, it is a well-known fact in the history of PLS-SEM that the lack of advanced and user-friendly software has been the main reason for the delay in the diffusion of this method in the applied sciences. Fortunately, we find ourselves nowadays in the opposite situation, as many high-quality packages for performing all varieties of PLS-SEM analyses have become available. In this chapter we present an updated review of the most popular commercial and open-source software packages for PLS-SEM. In particular, we discuss and compare **ADANCO**, **SmartPLS**, **WarpPLS**, **XLSTAT-PLSPM**, the **plssem** package for Stata, and the **cSEM** and **SEMinR** packages for R. Using a publicly available data set, we briefly illustrate the

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main features of each of these software packages and examine their corresponding strengths and weaknesses.

5.1 Introduction

Structural equation modeling (SEM) is a popular statistical method for performing multivariate data analysis used in the behavioral and social sciences (Hwang & Takane 2014; Jöreskog et al. 2016; Hair et al. 2022). The main reasons for its popularity are: (1) it enables researchers to analyze both linear and non-linear relationships between unobserved variables involved in the analysis; (2) it is extremely flexible since it encompasses traditional statistical techniques, such as linear regression, path analysis or factor analysis, as well as advanced methods such as confirmatory factor analysis, latent growth curve modeling and multilevel modeling; (3) it allows users to estimate theoretical models that include observed and latent variables; and (4) it enables users to control for random measurement errors when estimating the relationships between latent variables representing the theoretical constructs in the statistical model (see for example Jöreskog et al. 2016; Loehlin and Beaujean 2017; Whittaker & Schumacker, 2022).

In general, SEM is a large family of techniques, consisting among others of covariance-based SEM (CB-SEM; Jöreskog et al., 1969), partial least squares SEM (PLS-SEM; Wold, 1982; 1989) and generalized structured component analysis (GSCA; Hwang & Takane, 2004). This chapter focuses on PLS-SEM, a path modeling approach introduced by Herman Wold. PLS was originally developed to focus on the predictive ability of the model measured in terms of the portion of the variance in endogenous variables that can be accounted for by the model itself (Henseler 2021; Mehmetoglu & Venturini 2021; Hair et al. 2022). Meanwhile, CB-SEM minimizes the discrepancy between the implied model and the sample variance-covariance matrix. Therefore, PLS-SEM has a different basic principle and approach compared with CB-SEM. While CB-SEM uses the maximum likelihood (ML) estimator, PLS works through the least squares (LS) approach. PLS-SEM was created to overcome a number of weaknesses of CB-SEM, such as solving the issue of convergence, minimizing multivariate assumptions and aiming to test causal-predictive relationships between unobserved variables where there is a scarcity of theory and prior knowledge (Wold 1982, 1989). PLS has experienced significant growth and development in the last decade, a period referred to as "the golden age" (Latan 2018), which includes the development of new methods such as the consistent PLS algorithm (PLSc; Dijkstra & Henseler, 2015a; 2015b), the PLSpredict algorithm (Shmueli et al., 2016), ordinal PLS (ordPLS; Cantaluppi & Boari, 2016; Schuberth et al., 2018b), methods for dealing with unobserved heterogeneity (Hahn et al., 2002), confirmatory composite analysis (CCA; Henseler & Schuberth, 2020), necessary condition analysis (NCA; Dul, 2020), and others, all supported by sophisticated software.

However, the increasing popularity of PLS and the various advances in the use of this approach have not escaped controversy and debate in the field. The ongoing debate as to the relative strengths and weaknesses of PLS-SEM (see for example Cadogan and Lee 2023; Evermann & Rönkkö 2023; Henseler and Schuberth, 2023; Rönkkö et al., 2023; Russo and Stol 2022) has led to the emergence of two groups among the proponents of PLS-SEM, each of which seems to have quite different views regarding the role of PLS-SEM. More specifically, one of the groups considers PLS-SEM to be a complementary approach to CB-SEM (see for example Hair et al., 2022). By contrast, the second group of researchers regards PLS-SEM as an alternative estimator for SEM (Schuberth et al., 2023) in its own right. Although it is not our aim to continue to fuel this debate, it is worth mentioning it here because these different approaches to its use have far-reaching consequences for conducting a study using PLS-SEM, for the interpretation of the output provided by different PLS-SEM packages, as well as for their further development (e.g., with respect to the relevance of the overall model fit).

One of the reasons that allowed CB-SEM to quickly gain popularity among researchers was the availability of reliable software packages for its implementation, in particular **LISREL** (Jöreskog & Sörbom, 2022; Jöreskog et al., 2016), which has been available for the last four decades. On the other hand, the lack of readily available software for PLS-SEM during its gestation period (Noonan, 2017) has been the main reason for the delay in its adoption within the social sciences community. The first—and for a long time unique—software available for PLS-SEM was Lohmöller's **LVPLS** (Lohmöller, 1989), a DOS-based program that included two different modules, LVPLSC for the analysis of an observed covariance matrix, and LVPLSX for the analysis of raw data. This program offered blindfolding and jackknifing as resampling methods. It was only many years later that graphical user interfaces (GUIs) were added to LVPLS, such as **PLS-Graph** (Chin, 2001), **PLS-GUI** (Li, 2005), **VisualPLS** (Fu, 2006), or that new pieces of software, such as **SPAD-PLS** (Coheris, 2021), started to be developed. All of these packages were Windows-based and offered different options with regard to weighting schemes and resampling methods. The latter program, **SPAD-PLS**, is actually part of a larger statistical software package, **SPAD**, which focuses on tools for the analysis of multidimensional data. The most significant advancement provided by these programs was the possibility to draw the path model using drawing tools directly in the graphical user interface, an approach which has become standard, at least in the commercial software currently available for PLS-SEM. With the exception of **SPAD**, which is now called **Coheris SPAD**,[1] none of these programs are still maintained, because they are only graphical interfaces for LVPLS, so that opportunities for further development are very limited.

The aim of this chapter is to present a comprehensive and updated review of a new generation of PLS-SEM software that has been developed over the last few years. More specifically, in the sections below we describe the characteristics of **ADANCO**, **SmartPLS**, **WarpPLS**, **XLSTAT-PLSPM**, **plssem**, **cSEM** and **SEMinR**. The first three are stand-alone programs, **XLSTAT-PLSPM** is a Microsoft

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[1] https://www.chapsvision.com/softwares-data/data-mining-machine-learning/.

Excel add-in, **plssem** is a Stata package,[2] while the last two are R packages.[3] As regards the R packages, we highlight that other packages are also available to perform a PLS-SEM analysis, namely **matrixpls** (Rönkkö, 2021), **plspm** (Sanchez et al., 2017) and **semPLS** (Monecke & Leisch, 2012). However, since these are either no longer being developed or are more limited in their scope, we will not discuss them here. As a further remark, we do not include software that implements approaches that are similar to the PLS-SEM philosophy, but with different characteristics, such as **GSCA Pro** (Hwang et al., 2021).

A number of varying reviews of PLS-SEM software have been published so far, such as Temme et al. (2010), and the more recent Memon et al. (2021) and Chuah et al. (2021), with the former comparing only commercial software, while the latter covers only some R packages. With regard to these recent reviews, the present chapter aims to cover a broader range of software, since we also discuss **XLSTAT-PLSPM** and **plssem**. Moreover, this chapter directly compares the features of both commercial and open-source software. In addition, the discussion presented here provides a much deeper comparison of software features, which will allow the reader to better appreciate the characteristics of each program. Finally, this chapter provides an updated review, since we present the most recent versions of all the software packages covered.

The remainder of this chapter is organized as follows: Sect. 5.2 discusses each of the pieces of software mentioned earlier, including basic information, input data, user interface and model specifications, implemented procedures, output and reporting and additional features. This section ends with a summary and a brief comparison of the software covered. In Sect. 5.3 conclusions are made and some suggestions for the further development of PLS-SEM software are given.

5.2 Software for PLS-SEM

Before moving on to the description of the software, we feel it is appropriate to set the stage by providing some classifications and definitions. A first relevant distinction can be made between commercial and open-source software. In the first category we find **ADANCO**, **SmartPLS**, **WarpPLS** and **XLSTAT-PLSPM**, while **plssem**, **cSEM** and **SEMinR** are open-source packages. Apart from the difference in terms of the license that is included with the software, and the fact that commercial software typically requires payment of a fee for unlimited use of the license, this distinction is important because it hides a more substantive difference. This is that all commercial software available for PLS-SEM provides a GUI for specifying the model, while open-source packages require users to specify the model through a list of equations that must follow package-specific rules. Another reason to distinguish between commercial and open-source software, which may be more relevant for less experienced

[2] https://www.stata.com.

[3] https://www.r-project.org.

users, is that commercial software licenses typically include technical support as well as the possibility of benefiting from some form of training. In the open-source category, the level of support depends upon the availability of the developers, which can vary widely. Finally, the learning curve for commercial software is generally steeper compared to that for open-source packages, because the former are usually menu-driven while the latter are syntax-based.

A further distinction to note is between stand-alone software and packages that are part of a larger bundle of software. In the first group we find **ADANCO**, **SmartPLS** and **WarpPLS**, while **XLSTAT-PLSPM**, **plssem**, **cSEM** and **SEMinR** belong to the second category. The reason for this classification is that stand-alone software includes tools and algorithms for performing PLS-SEM, but does not generally allow the use of further procedures that can be applied before or after the main PLS-SEM analysis. On the other hand, packages that run inside a software bundle permit the use of all the tools and procedures that are available in the parent software. This is especially useful for `R` and Stata, since they are full-featured statistical software packages and include a vast set of procedures and methods that can be applied at any step of the PLS-SEM workflow.

In the following sections we describe the variety of software features available. For each of them we illustrate the following characteristics:

- Basic information, such as the version at the time of writing
- Data input, user interface, and model specification
- Procedures implemented
- Output format and reporting of the results
- Additional features

However, we will not discuss features that are common to all relevant software. In particular, we will not address the possibility of fit models that include higher-order constructs, the ability to perform mediation and moderation analyses, or the calculation of indirect and total effects, because these characteristics are available, in one form or another, in all the software presented in this review. We recommend that interested readers refer to the official software documentation for further details.

To illustrate the software capabilities, we use the renowned corporate reputation data set (Eberl, 2010) throughout. The aim of this data was to examine the effects of corporate-level marketing activities on corporate reputation as a mediating construct and its subsequent effects on customer loyalty (indicated as *CUSL* in the path diagrams reported below). Corporate reputation represents a company's overall evaluation by its stakeholders (Helm et al., 2010). Following Schwaiger (2004), corporate reputation is conceptualized as consisting of two dimensions:

- The company's competence (*COMP*), which represents the cognitive evaluations of the company
- Perceptions of the company's likeability (*LIKE*), which captures affective judgments

In addition, the following four antecedent dimensions are hypothesized as drivers of corporate reputation:

- The quality of a company's products and services (*QUAL*)
- The company's economic and managerial performance (*PERF*)
- The company's corporate social responsibility level (*CSOR*)
- The company's attractiveness as an employer (*ATTR*)

Furthermore, customer satisfaction (*CUSA*) is included as a mediating variable for the effect of corporate reputation on customer loyalty. The measurement models are constructed as follows:

- Quality, performance, corporate social responsibility and attractiveness are formed of eight, five, five and three indicators respectively
- Competence, likeability and loyalty are reflected in three indicators
- Satisfaction is a single-item construct

It is not our aim here to show a full analysis of these data. A detailed discussion of the corporate reputation model can be found elsewhere, for example in Hair et al. Hair et al. (2018, 2022). To avoid taking up too much space here, some outputs will be omitted. However, the full material (i.e., code and data files) behind the examples covered here can be retrieved on Github at https://github.com/sergioventurini/PLSSEM-software-review.

5.2.1 ADANCO

5.2.1.1 Basic Information

ADANCO, which stands for ADvanced ANalysis of COmposites, is a stand-alone piece of software for conducting composite-based SEM distributed by Composite Modeling GmbH & Co. KG (Germany).[4] The current version of **ADANCO** is 2.3.1 (Henseler & Dijkstra, 2021), and it is available for both Windows and macOS operating systems. In addition to the supporting material that is accessible on the **ADANCO** website (e.g., user manual, example projects, video tutorials), the main relevant learning resource is the book by Henseler (2021), which provides a step-by-step presentation of its features.

ADANCO is offered in a variety of different editions, starting with the trial edition, which allows for a single construct that can be estimated using the PLSc approach, up to the unlimited professional edition, which is particularly suited for corporate use.

5.2.1.2 Data Input, User Interface, and Model Specification

Data can be imported into **ADANCO** only as a Microsoft Excel file (both `.xls` and `.xlsx` formats are accepted). The first row should contain the indicator names. If no

[4] https://www.composite-modeling.com.

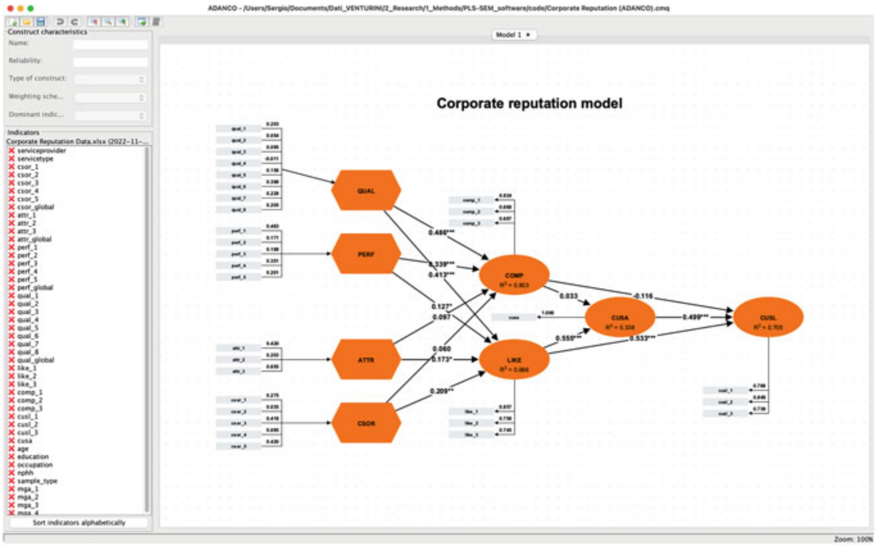

Fig. 5.1 Graphical user interface of **ADANCO**. Path model for corporate reputation data showing the coefficient estimates

indicator names are found, ADANCO will automatically generate indicator names. The source file should contain only values with no formatting (colors, frames, etc.), images or macros. The data import procedure allows the user to specify a separate missing value code for each column in the data set. Once imported, it is also possible to replace the current data with new data by specifying how to match the variables in the old data set with those in the new one.

Specification of the model in **ADANCO** is constructed by drawing it directly in the program GUI (see Fig. 5.1). The user interface is intuitive, so that all options can be accessed through double-clicking on the corresponding item in the model diagram. Following Henseler's approach to PLS-SEM, **ADANCO** distinguishes between two types of constructs, that is *latent* and *emergent* variables (Henseler & Schuberth, 2020; Henseler, 2021). Latent variables with reflective indicators, shown as ovals in the program interface, are modeled as common factors and are typically used as statistical stand-ins for theoretical concepts in behavioral research (e.g., attitudes, emotions, traits). On the other hand, emergent variables with formative/composite indicators, visualized as hexagons, are modeled as composites and provide an operationalization of artifacts created by humans (i.e., phenomena that do not naturally occur), such as instruments or indices (Schamberger et al., 2023; Yu et al., 2021). Different models can be specified within the same project.

5.2.1.3 Implemented Procedures

ADANCO implements the following estimation procedures:

- The classic PLS-SEM algorithm for composite models—this algorithm is used to estimate the composite-formative measurement models (Wold, 1982; Lohmöller, 1989)
- The PLSc approach for common factor models—this algorithm is used to estimate the reflective measurement models, and this is the default option for latent variables
- OLS regression on sum scores

Construct initialization uses sum scores, but no other choices are available. In addition, the following global estimation options can be set:

- The inner weighting scheme, which can either be the factorial or the centroid scheme[5]
- Options for choosing the weights, either mode A or mode B, sum scores for emergent measurement models, as well as mode A (consistent), mode A, and sum scores for reflective measurement models
- The stopping criterion (default to 10^{-6})
- The maximum number of iterations (default to 200)
- As for the treatment of missing values, the user can choose simply to ignore (i.e., discard) the rows containing any missing values (this choice is called casewise deletion) or to impute them before running the estimation algorithm. In the latter case, one can opt for mean or median imputation, rather than substituting the missing data with a constant or with randomly generated values

ADANCO adopts the "dominant indicator" approach to solve sign indeterminacy; that is, the fact that all indicators of a construct may have the opposite sign compared to what was expected a priori. This approach consists of choosing one indicator for each construct whose loading/weight is constrained to be equal to one, which then dictates the orientation of the whole construct. The dominant indicator should be identified as one for which it is sufficiently certain that the correlation with the construct is positive.

ADANCO also permits the definition of additional parameters derived from the existing path coefficients in the model, or other previously defined parameters, by means of standard algebraic operations (e.g., difference between two model parameters). These derived quantities can be useful to answer specific research questions. The defined parameters are then estimated together with the structural coefficients and inference is performed accordingly.

ADANCO includes a long list of global and local model assessment measures. For the overall model fit, the unweighted least squares (d_{ULS}) and geodesic (d_G) discrepancies (Dijkstra & Henseler, 2015a), as well as the standardized root mean squared

[5] The path weighting scheme (Lohmöller, 1989) is not available because it requires a specific direction of causal structure and thus does not support non-recursive models and unanalyzed relationships (Henseler, 2021, p. 91).

residuals (SRMR; Bentler, 2006) are provided. For each of these, a nonparametric bootstrap-based test is also computed. We note that the popular goodness-of-fit (GoF) or relative GoF indices (Tenenhaus et al., 2005; Esposito Vinzi et al., 2010) are not reported because it has been shown that they can be misleading as a measure of model fit (Schuberth et al., 2023). Regarding the local model assessment, **ADANCO** provides all the standard quantities that are popular in the PLS-SEM literature for assessing both the outer and inner models. More specifically, for the outer model:

- Reliability of construct scores: Dijkstra-Henseler's rho (p_A), Jöreskog's rho (p_c) and Cronbach's alpha (α)
- Convergent validity (average variance extracted)
- Discriminant validity using the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations based on arithmetic or geometric means criteria, also called HTMT (Henseler et al., 2015) and HTMT2 (Roemer et al., 2021) respectively
- Indicator multicollinearity using variance inflation factor (VIF) for mode B

For the structural model, the R^2 and adjusted R^2 indices are provided.

The parameter estimates are reported separately for emergent variables (weights), latent variables (loadings) and for the structural model (path coefficients). For the latter, the indirect and total effects, as well as the Cohen's f^2 effect sizes (Cohen, 1988), are also provided. The significance of all estimates, as well as most of the fit measures, is performed by bootstrapping (only the percentile bootstrap confidence intervals are reported; Davison & Hinkley, 1997). Finally, construct scores are provided in both the standardized and unstandardized forms of the path coefficients.

5.2.1.4 Output and Reporting

ADANCO reports the model estimates and corresponding significance values directly in the GUI, with each result shown next to the corresponding indicator or construct (see Fig. 5.1). In this case, we chose PLSc to estimate the model, which is a combination of latent variables (indicated by ovals) and emergent variables (indicated by hexagons). In addition to this visualization, it is also possible to obtain the full set of results as a Microsoft Excel file or as a browsable HTML file which can be opened with any internet browser. Finally, the results corresponding to each bootstrap replication can also be exported as separate Excel files.

5.2.1.5 Additional Features

ADANCO is a complete software package for composite-based SEM and it also includes an implementation of CCA as developed by Schuberth et al. (2018a) and Henseler & Schuberth (2020).[6] CCA represents the counterpart for

[6] For a review of CCA see also Hubona et al. (2021).

composite models of confirmatory factor analysis (CFA), which is used to test auxiliary theory for theoretical concepts represented by latent variables and modeled as common factors. In other words, the aim of CCA is to test whether composites behave as emergent variables (Schamberger et al., 2023).

As a last note, **ADANCO** currently does not implement any method for assessing unobserved heterogeneity in the model such as REBUS-PLS (Esposito Vinzi et al., 2008) or FIMIX-PLS (Hahn et al., 2002; Sarstedt et al., 2011). However, ADANCO supports several extensions, such as testing of indirect effects (Cepeda et al., 2017), testing of moderating or non-linear effects (Fassott et al., 2016), and hierarchical modeling analysis (Schuberth et al., 2020) and provides all the information needed for these advanced analyses.

5.2.2 SmartPLS

5.2.2.1 Basic Information

SmartPLS is a piece of software for conducting PLS-SEM developed by some of the leading experts in the field: Christian M. Ringle, Sven Wende, and Jan-Michael Becker. **SmartPLS** is distributed by SmartPLS GmbH, and the current release is version 4. **SmartPLS** is available for both the Windows and macOS operating systems (Ringle et al., 2022). The resources listed on the **SmartPLS** web page include articles, videos, and a discussion of the different tools available for PLS-SEM . There is no official manual for **SmartPLS**, but a full explanation of how to use its features can be found in books by Hair et al. (2018, 2022).

SmartPLS is offered in two different versions: a free student version, which allows the use of data sets with at most 100 cases and a limited selection of algorithms (only standard algorithms), and is restricted in the saving and exporting of results. The professional version supports all available features, including an extended list of algorithms, and supports the saving and exporting of results in various formats. It supports an unlimited number of cases for data analysis. Additionally, a fully functioning 31-day free trial can be downloaded to try the professional version of the software.

5.2.2.2 Data Input, User Interface, and Model Specification

SmartPLS, when used with the professional license, allows users to import data in `.csv`, `.txt`, `.xls`, `.xlsx` and `.sav` formats. The student license only allows the `.csv` extension. The source data file must include the variable names in the first row. A single missing value marker can be defined for the entire data set and multiple data sets can be loaded simultaneously in a project. In addition, every empty value in the data set will be considered as missing by **SmartPLS**.

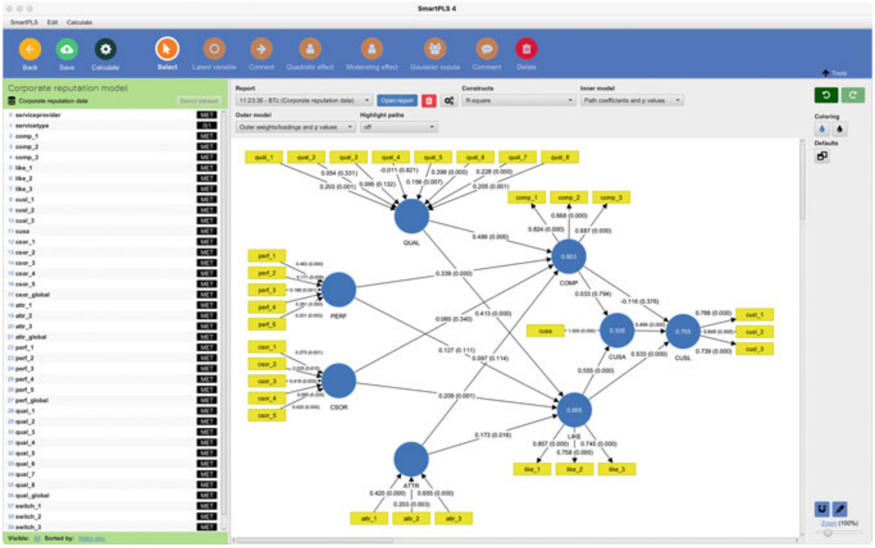

Fig. 5.2 Graphical user interface of **SmartPLS**. Path model for corporate reputation data showing coefficient estimates using the PLSc algorithm

The GUI of **SmartPLS** is intuitive and easy to use (see Fig. 5.2). Previously, there were three options available for drawing a model type in **SmartPLS**: PLS-SEM, path analysis (or PROCESS) and linear regression. The PLS-SEM option is the standard choice for latent variable path modeling. Path analysis is a regression-based technique for estimating models with multiple dependent and independent variables. Unlike PLS-SEM, it is a one-step approach, utilizing equally weighted indicators in case of multiple measurements per construct and operating on unstandardized data. It mimics the results from the PROCCESS macro in SPSS to test the effects of mediation, moderation or conditional process analysis. Finally, linear regression is a model for predicting the value of one dependent variable based on one or more independent variables. Path models must be created directly in the program's interface by dropping in a set of indicators to define a new construct measurement model, and by connecting the constructs with lines that represent their structural relationships. An unlimited number of path models can be created in a single project, especially for the PLS-SEM and PROCESS options, which can use indicators from different data sets. **SmartPLS** adopts the distinction between reflective and formative measurement models, as originally introduced in the literature, and still widely used by many academics and practitioners. However, in the regression option, there is no indicator that can be determined, given that it uses a single indicator (i.e., the subject's scores for all the indicators of a construct). In Fig. 5.2, we used the PLSc algorithm.

5.2.2.3 Implemented Procedures

The following estimation algorithms are available in **SmartPLS**:

- The classic PLS-SEM algorithm (Wold, 1982; Lohmöller, 1989)
- The PLSc approach
- The weighted PLS-SEM algorithm (Becker & Ismail, 2016), which allows for the selection of post-stratification weights to account for sampling units with unequal probabilities
- OLS linear regression analysis with sum scores
- Path analysis with PROCESS

The constructs are initialized using sum scores; that is, by setting all initial outer weights to one. Alternatively, **SmartPLS** allows the user to configure individual initial outer weights for each indicator. This option can be used in PLS-SEM, for example, to implement the dominant indicator approach by setting the initial outer weight of one of the indicators to one, while the other indicators in the same measurement model obtain an initial outer weight equal to zero. Additionally, the following estimation options can be set:

- The weighting scheme, which can be set to either factor or path
- Initial weight, which can be either default or individual
- Missing value algorithms can be chosen to discard data (e.g., by using casewise or pairwise deletion) or impute data, using the mean of the available data (mean replacement)
- Weighting vector, by selecting one of the indicators as the weight vector

As regards the global and local model assessment measures, **SmartPLS** reports the same set of measures as **ADANCO** (see Sect. 5.2.1.3), with the exception of the HTMT2 criterion and with the addition of the chi-square (χ^2; Jöreskog 1969), the normed fit index (NFI; Bentler & Bonett 1980), and the model selection criteria using the Bayesian Information Criterion (BIC). Similarly, inference is performed through bootstrapping, and the user can choose between the percentile, studentized and bias-corrected and accelerated (BCa) methods (see for example Davison and Hinkley, 1997).

5.2.2.4 Output and Reporting

SmartPLS reports the results of PLS-SEM analysis within the GUI as a set of separate tables, as well as graphically in the path model (see Fig. 5.2). Moreover, it also allows users to export the results as a Microsoft Excel file or a browsable HTML file.

5.2.2.5 Additional Features

SmartPLS includes the following additional procedures:

- Confirmatory tetrad analysis (Gudergan et al., 2008) for empirically verifying the measurement model setup (i.e., whether the measures should be specified as reflective or formative)
- Importance-performance map analysis (IPMA; see Ringle & Sarstedt, 2016), a graphical tool that contrasts the structural model's total effects on a specific target construct with the average latent variable scores of this construct's predecessors
- Multi-group analysis (MGA) for testing whether predefined (i.e., observed) data groups have significant differences in their group-specific parameter estimates, also allowing users to compare the groups through permutation tests (Chin & Dibbern, 2010; Hair et al., 2018)
- Latent class segmentation using finite mixture partial least squares (FIMIX-PLS; see Hahn et al. 2002; Sarstedt et al. 2011) for discovering unobserved heterogeneity; the implementation allows users to compare the results corresponding to different solutions by means of a set of information criteria, such as AIC, BIC, CAIC, and others
- Prediction-oriented segmentation (Becker et al., 2013), a distance-based grouping method for PLS-SEM
- PLSpredict (Shmueli et al., 2016, 2019), two cross-validation based approaches to evaluate the predictive power of a PLS path model. For example, the cross-validated predictive ability test (CVPAT; see Liengaard et al.,2020)
- NCA can be used to determine what levels of independent variables are necessary to reach certain levels for the dependent outcome variables (Dul, 2020)
- Gaussian copula approach, used to test for endogeneity bias (Becker et al., 2022)
- Several extensions of the analysis are supported, such as indirect effects, moderating effects, non-linear effects, and hierarchical modeling

Finally, an interesting characteristic of **SmartPLS** is that each dialog window provides a concise description of the meaning and aim of the analysis and of the options the user can select.

5.2.3 WarpPLS

5.2.3.1 Basic Information

WarpPLS is a stand-alone commercial program developed by Ned Kock[7] that performs both composite and factor-based PLS-SEM algorithms thus accounting for

[7] https://scriptwarp.com/warppls/.

measurement error.[8] The current stable release of **WarpPLS** is version 8.0 (Kock, 2022). The first time **WarpPLS** is installed, the setup procedure will also install the MATLAB Compiler Runtime, a set of free-distribution MATLAB[9] libraries whose code is required by the main software. **WarpPLS** is available only for Windows, while Mac users must create a partition on the hard drive or install virtualization software in order to use it. On the **WarpPLS** official website it is possible to find many learning resources (user manual, videos, papers, example projects, etc.).

WarpPLS is offered in a single version. A 3-month fully functional trial can be freely downloaded from the software website.

5.2.3.2 Data Input, User Interface, and Model Specification

The entire analysis procedure in **WarpPLS** is developed by following a guided step-by-step procedure, starting from the creation or loading of a project up to the visualization of results.

Importing data into **WarpPLS** requires a Microsoft Excel file (either `.xls` or `.xlsx`) or a text file with either tab or comma-separated columns. The first row of the data file must contain the variable names, while the rest of the data set must contain only numerical values. Next, a preprocessing step follows, which imputes missing values, standardizes the indicators, and performs some other checks (i.e., for column name duplicates and zero variance variables). The missing values imputation method can be selected from the main window as one of the settings. The options available are: mean imputation, multiple regression imputation, stochastic multiple regression imputation, hierarchical regression imputation and stochastic hierarchical regression imputation (Kock, 2018). Note that missing values must be coded as empty cells in the source data file and are shown as `NaN` in **WarpPLS**.

Similarly to the software packages presented above, the path model is created by defining the constructs and the structural relationships via a selection of menu commands (see Fig. 5.3). The measurement models available for the constructs are reflective and formative. Please note that reflective constructs are marked with (R) and formative constructs with (F) in the graphical user interface of **WarpPLS** (see Fig. 5.3).

5.2.3.3 Implemented Procedures

WarpPLS includes a large number of alternative estimation algorithms for both composite and factor-based models. We do not provide a description for all of them here,

---

[8] Factor-based methods, as implemented in **WarpPLS**, combine elements of PLS-SEM methods and covariance-based SEM and provide estimates of the composites and correlation-preserving factors in a path model. Differently from the PLSc approach, which is a parameter correction technique, factor-based methods estimate prototypical elements, such as factors, which are then used in the production of parameters, thus requiring no corrections. For more details see Kock (2019).

[9] https://www.mathworks.com/products/matlab.html.

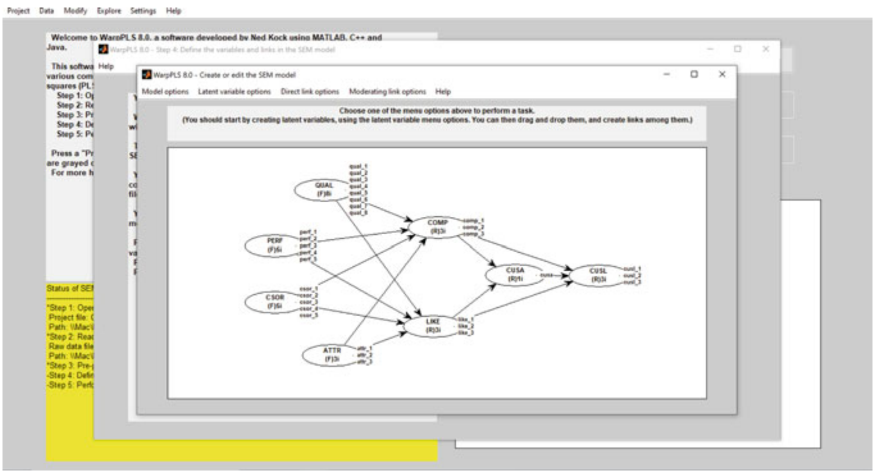

Fig. 5.3 Graphical user interface of **WarpPLS**. Path model for corporate reputation data

but we refer the reader to the software documentation and the references reported therein (Kock, 2022). It also permits the use of non-linear relationships within the inner model. The algorithms available for the estimation of inner model parameters are called Linear, Warp2, Warp2 Basic, Warp3, and Warp3 Basic. The first of these clearly assumes linear relations, while the others assume quadratic or other non-linear relationships. The idea is that non-linear transformations of the predictor construct scores are performed prior to the calculation of path coefficients. Users can view the 3D graph generated by **WarpPLS** to identify whether the relationship between variables follows a U or S shape by looking at the pattern (Kock, 2022).

Initial weights and loading values can be set arbitrarily, while the stopping criterion and number of iterations are defined internally and cannot be modified.

WarpPLS includes the following local and global model assessment measures: Jöreskog's rho and Cronbach's alpha for the basic PLS-SEM algorithms, while Dijkstra-Henseler's rho, true composite reliability, and factor reliability are also reported when factor-based PLS algorithms are used. Other measures, such as average variance extracted (AVE), HTMT and HTMT2, indicators of multicollinearity, R^2 and adjusted R^2 indices, a measure of effect sizes similar to Cohen's f^2 and Stone-Geisser's Q^2 are also available. As regards model fit, the software computes SRMR, the standardized mean absolute residual (SMAR), the chi-square measure, and the goodness-of-fit index introduced by Tenenhaus et al. (2005). In addition, **WarpPLS 8.0** supports a number of other indices, such as Simpson's paradox ratio (SPR), standardized threshold difference count ratio (STDCR), and standardized threshold difference sum ratio (STDSR).

Inference can be performed using the classic normal-based theory or through resampling. The available resampling methods are stable1, stable2, stable3, bootstrapping, jackknifing, blindfolding (only percentile confidence intervals are reported), and parametric (assuming multivariate normality).

Observed heterogeneity in the estimates can be assessed through MGA, but no unobserved heterogeneity method is available.

5.2.3.4 Output and Reporting

WarpPLS provides a graphical output with parameter estimates, but the full set of results is reported through several tables inside the program interface, which can be exported as separate text files. It is also possible to directly copy the tables' contents and paste them into another application for further editing.

5.2.3.5 Additional Features

Currently, **WarpPLS** is the only software for PLS-SEM that provides a tool for power analysis and sample size determination, which are performed using the inverse square root method and the gamma-exponential method introduced by Kock and Hadaya (2018).

Further additional features of **WarpPLS** are:

- The possibility to produce colored three-dimensional surface plots to show the estimates for moderating/interaction effects
- The assessment of measurement model invariance by comparing loadings and weights across different groups
- Full latent growth analysis, this test could be seen as a comprehensive analysis of moderating effects where the moderating variable is "latent" (Kock, 2022)
- Delta segmentation to identify unobserved heterogeneity
- Instrumental variables to test for endogeneity bias and estimate reciprocal relationships
- Supports several extensions of the analysis, such as indirect effects, moderating effects, non-linear effects, and hierarchical modeling.

5.2.4 XLSTAT-PLSPM

5.2.4.1 Basic Information

XLSTAT-PLSPM is the module of the comprehensive **XLSTAT** add-in for Microsoft Excel that is dedicated to component-based structural equation modeling. More specifically, **XLSTAT-PLSPM** is included in the **XLSTAT Premium**, **XLSTAT**

Marketing and **XLSTAT Sensory** product solutions. **XLSTAT** is developed by the French company Addinsoft.[10]

The current release of **XLSTAT** is version 2022.1.2.1259. While **XLSTAT** is available for both Windows and macOS, the **XLSTAT-PLSPM** module can be used only in Excel for Windows.

Various resources are available on the official website for learning how to use **XLSTAT**, such as the full manual (which includes a chapter on the **XLSTAT-PLSPM** module), free webinars, a number of detailed tutorials with examples that can be reproduced by downloading the corresponding data, and short videos showing how to perform some of the analysis.

XLSTAT is offered in different versions, starting with the "Basic" package, which includes only the standard statistical tools, up to the "Premium" version, which includes the basic tools plus all those in the specialized modules (i.e., sensory analysis, life sciences, marketing, forecasting and quality control). A 14-day unlimited free trial is available for download to try out the software.

5.2.4.2 Data Input, User Interface, and Model Specification

Data must be pasted into the first sheet, named `D1`, of the project file. Since the package runs under Microsoft Excel, missing values are identified based on empty cells and no other missing value code is admitted.

Model specification in **XLSTAT-PLSPM** is interactive and is performed in the sheet called `PLSPMGraph` (see Fig. 5.4). When selecting the manifest variables (which is the way indicators are referred to in **XLSTAT-PLSPM**) for each construct, there is also the possibility to select a mixture of quantitative and qualitative variables, where for the latter a set of dummy variables is defined. Interactions (i.e., moderators) can be created at this stage using the constructs already defined. Finally, it is worth noting that in **XLSTAT-PLSPM** higher-order constructs are called "superblocks".

5.2.4.3 Implemented Procedures

XLSTAT-PLSPM allows users to estimate path models using:

- The classic PLS-SEM algorithm (Wold, 1982; Lohmöller, 1989)
- The PLSc approach
- Generalized structured components analysis (GSCA; Hwang & Takane, 2004; 2014)
- Regularized generalized canonical correlation analysis (RGCCA; Tenenhaus and Tenenhaus 2011)

GSCA is a component-based SEM approach that offers a global least squares optimization criterion, which is consistently minimized to obtain the parameter estimates.

[10] https://www.xlstat.com/en/.

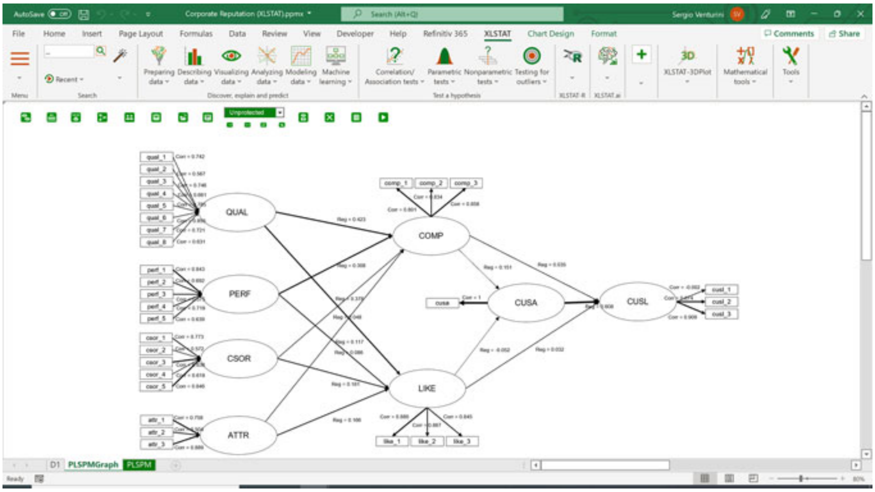

Fig. 5.4 Graphical user interface of **XLSTAT-PLSPM**. Path model for corporate reputation data showing the coefficient estimates

Thus, GSCA is equipped with an overall model fit measure. Similarly, RGCCA allows users to optimize a global criterion using an algorithm very similar to the PLS-SEM algorithm, but which produces only correlations instead of regression coefficients.

Constructs can be modeled using different modes, such as Mode A and Mode B, which correspond to the reflective and formative models respectively, as well as other available options such as Mode C (i.e., the MIMIC model; Tenenhaus et al., 2005).

XLSTAT-PLSPM allows users to set the following global estimation options:

- Different ways to initialize weights and loadings, including the values associated with the first eigenvector for each construct block
- The outer weighting schemes are centroid, factorial and path, but a Horst scheme is also available, which corresponds to sum scores (i.e., all weights are always fixed at a value of one), and a PLS scheme, which instead uses PLS regression[11]
- Path coefficients can be estimated using standard OLS regression or through PLS regression
- Various alternatives are available for the treatment of missing values, including casewise deletion, mean/mode imputation, as well as nearest neighbor, i.e., imputing the missing information of an observation based on that of its most similar observation
- Other tuning options, such as the stopping criterion for convergence and the maximum number of iterations, can also be fixed

[11] We remind that, despite the name similarity, PLS regression must not be confused with PLS-SEM. They share a common origin, but they have different aims.

XLSTAT-PLSPM provides a shorter list of model assessment measures compared to **ADANCO**, **SmartPLS** and **WarpPLS**. Indeed, it provides only the following measures for the outer model:

- Construct reliability (Dillon-Goldstein's rho and Cronbach's alpha)
- Convergent validity (average variance extracted)
- Discriminant validity (Fornell-Larcker criterion only)

For the structural model, the R^2 and adjusted R^2 indices are reported. The blindfolding approach is used to assess model quality. Goodness-of-fit indices (both absolute and relative) are included in the results. In addition, **XLSTAT-PLSPM** also supports fit indices in PLS-SEM, such as SRMR, d_{ULS}, d_G, and χ^2.

Inference is performed by resampling, through either bootstrap (percentile confidence intervals only) or jackknife methods, which are applied to all parameters and model assessment measures. **XLSTAT-PLSPM** only produces standardized path coefficients.

XLSTAT-PLSPM also allows users to perform MGA for assessing observed heterogeneity. The results across different groups can be compared using both parametric (i.e., normal-based theory) and permutation tests. However, the software only allows users to compare the path coefficients. Therefore, MGA can't be used to assess measurement invariance.

5.2.4.4 Output and Reporting

The results are reported in separate worksheets labeled sequentially as `PLSPM1`, `PLSPM2`, `RGCCA`, `GSCA`, depending on the estimation method chosen. The output is neatly formatted in tables that are stacked on top of each other. The user can browse the entire output using the drop-down menu available at top of the sheet. In addition, it is possible to export the whole output, or a portion of it, as a Microsoft Word document or a Microsoft PowerPoint slide presentation. **XLSTAT-PLSPM** also provides a graphical output with estimated parameters.

5.2.4.5 Additional Features

A noticeable feature of **XLSTAT-PLSPM** is that it implements the response-based unit segmentation in the PLS-SEM (REBUS-PLS) algorithm (Esposito Vinzi et al., 2008), one of the first algorithms introduced in the literature for identifying unobserved heterogeneity in estimates. The implementation available here allows users to automatically detect the number of classes/groups, or to set it manually. The output produced includes a dendrogram, obtained through hierarchical clustering. For each observation, the assigned class and the value of the closeness measure are also displayed. For each one of the identified groups, the complete set of results is provided in a separate worksheet. In addition, **XLSTAT-PLSPM** also supports IPMA for each endogenous construct and has an RGCCA (ridge) option to handle multicollinearity. Finally, similar to other PLS software, **XLSTAT-PLSPM** supports several extensions of the analysis, such as indirect effects, moderating effects, non-linear effects, and hierarchical modeling.

5.2.5 plssem

5.2.5.1 Basic Information

plssem is an open-source package for PLS-SEM that runs in Stata (StataCorp, 2021) and has been developed by Venturini and Mehmetoglu 2019. The package is freely available as a GitHub repository at https://github.com/sergioventurini/plssem, where instructions for installing it on your computer are also provided. Currently, **plssem** can be used in Stata 15.1 or later and it is available for both the Windows and macOS operating systems. The main resource for learning how to use the package is the book by Mehmetoglu and Venturini (2021). In addition, the package is provided with detailed documentation that can be accessed directly from within Stata.

5.2.5.2 Data Input, User Interface, and Model Specification

As we remarked above, one of the advantages of using packages that run inside larger statistical software packages is the possibility to use all the tools available in the parent software both before and after the main analysis is performed. Therefore, regarding the importing of data to analyze, users are free to use the different commands available in Stata for this operation. Similarly, users can preprocess the data before using the **plssem** commands.

The specification of the path model in **plssem** is syntax-based and adopts an equation-like style. More specifically, the syntax required by **plssem** is similar, although not identical, to that used for defining covariance-based SEM models with the popular `sem` command in Stata. The outer model must be specified by enclosing each block within a pair of parentheses, while the inner model must be specified as an option by separating the structural relationships using commas. For example, the code below defines and estimates the model for the corporate reputation data we have previously discussed, where the greater-than sign (>) is used to define a reflective construct, while the less-than sign (<) is used for formative constructs (output omitted).

Stata code for the corporate reputation application using the plssem package

```
import excel "Corporate Reputation Data.xlsx", firstrow clear
mvdecode _all, mv(-99)

plssem (LIKE > like_?) (COMP > comp_?) (CUSA > cusa) (CUSL > cusl_?) ///
       (CSOR < csor_?) (ATTR < attr_?) (PERF < perf_?) (QUAL < qual_?), ///
       structural(CUSA COMP LIKE, CUSL COMP LIKE CUSA, ///
                  LIKE QUAL CSOR PERF ATTR, COMP QUAL CSOR PERF ATTR) ///
       wscheme(factorial) digits(4) boot(500) seed(123)

estat htmt
```

5.2.5.3 Implemented Procedures

The estimation algorithms implemented in **plssem** are:

- The classic PLS-SEM algorithm (Wold, 1982; Lohmöller, 1989), which is available through the `plssem` command
- The PLSc approach, which is accessible through the `plssemc` command
- Regression on sum scores, which is available as the `rawsum` option of the `plssem` command

Constructs can be initialized in **plssem** either as the sum of the indicators in the block (default), which amounts to setting the initial weighting values to one for all indicators, or using the scores obtained through a factor analysis with a single factor. As regards global estimation, the following options are available:

- The inner weighting scheme, which can either be centroid, factorial or path
- The stopping criterion (default to 10^{-7})
- Maximum number of iterations (default to 100)
- Convergence criterion to use; choices available are the relative (default) or the square criteria
- Different choices are available for the modes to use for each construct, including the reflective and formative indicators

Missing data can be managed in **plssem** using either casewise deletion, mean imputation or k-nearest neighbors imputation, with k representing the number of closest cases to consider.

The list of model assessment measures returned by **plssem** overlaps with that of **ADANCO** (see Sect. 5.2.1.3), including the HTMT and HTMT2 criteria.

Finally, inference can be performed using the classic normal-based theory or through bootstrap resampling, where for the latter only the percentile confidence intervals are provided.

plssem also allows users to perform MGA to assess heterogeneity that has been observed. The results across different groups can be compared using normal-based theory rather than resampling through permutation or bootstrap-based tests. A graph showing the estimated differences between the groups can also be requested.

5.2.5.4 Output and Reporting

As is standard in Stata, **plssem** provides all output in the results window. In addition, Stata also includes a suite of commands for creating dynamic documents that can be converted into a Microsoft Word or Excel file, or as a PDF or HTML file.[12] A document is said to be dynamic when the results it reports are linked to the code that has been executed to produce them, so that modifying the code and rerunning it will also update the contents of the document. This approach is one of the pillars of reproducible research (Stodden et al., 2014).

5.2.5.5 Additional Features

plssem includes the `estat unobshet` post-estimation command for assessing the presence of unobserved heterogeneity, and it comprises the REBUS-PLS and FIMIX-PLS methods. For REBUS-PLS a permutation test for the global quality index (Esposito Vinzi et al., 2008) of the solution can also be requested, while the FIMIX-PLS implementation allows users to compare the results corresponding to different group numbers by means of a set of information criteria, such as AIC, BIC, CAIC, and others. Finally, similar to other PLS software, **plssem** supports several extensions of the analysis, such as indirect effects, interaction effects, quadratic effects, and hierarchical modeling.

5.2.6 cSEM

5.2.6.1 Basic Information

The **cSEM** package (Rademaker & Schuberth, 2020) is one of the most recent additions to the collection of `R` (R Core Team, 2022) packages for PLS-SEM.[13] Even if it is still in the early development stage, it includes a wide range of modern composite-based methodologies. **cSEM** is developed by Manuel E. Rademaker and Florian Schuberth and is available for both the Windows and macOS operating systems. The most recent stable version of the package can be downloaded from CRAN,[14] while the development version can be installed directly from its Github repository, which is also the package's official webpage.[15] Resources for learning **cSEM** include its website, which includes examples as well as details of the techniques implemented, and the books by Henseler (2021) and Mehmetoglu & Venturini (2021), which describe

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[12] For more information about dynamic documents in Stata, execute the command `help reporting`.

[13] As we already stated in the introduction, there are other `R` packages for PLS-SEM, but they are older and have been superseded by the more modern packages we discuss here.

[14] https://cran.r-project.org/web/packages/cSEM/index.html.

[15] https://m-e-rademaker.github.io/cSEM/.

Table 5.1 Syntax rules from the **lavaan** R package supported by **cSEM** for the specification of a structural equation model.

Syntax	Description	Example
~	Regression onto	Regress `Y` onto `X`: `Y ~ X`
~~	Variance or covariance between two variables	Variance of `Y`: `Y ~~ Y` Covariance between `Y` and `X`: `Y ~~ X`
=~	Defining a common factor	Define `Y` to be a common factor for the indicators `X1` and `X2`: `Y =~ X1 + X2`
<~	Defining a composite	Define `Y` to be a composite of the indicators `X1` and `X2`: `Y <~X1 + X2`
*	Labeling of a parameter	Label the coefficients in the regression of `Y` onto `X`: `Y ~ beta_0*1 + beta_1*X` Label the variance of the variable `Y`: `Y ~~ s2_Y*Y`

most of the **cSEM** functionalities in the appendices of each chapter[16]. We note that the approach adopted in the **cSEM** package and the implementation of the different composite-based algorithms parallel very closely to those included in **ADANCO**.

5.2.6.2 Data Input, User Interface, and Model Specification

Given that **cSEM** runs under R, all the tools available in the latter can be used for importing, screening and manipulating the data. The data set must be fed into the **cSEM** estimation commands as a data frame or a matrix containing the observed values for the manifest variables. One can also provide a list of data frames or matrices, in which case estimation is repeated for each data set in the list.

A model in **cSEM** is specified using the syntax rules defined by the **lavaan** package (Rosseel, 2012), which has become the standard for SEM in R. In particular, **cSEM** currently supports the **lavaan** syntax rules reported in Table 5.1.

As an example, the following code defines the corporate reputation model we described above using the **cSEM** syntax rules.

[16] A further useful resource is the personal webpage of one of the **cSEM** developers, http://florianschuberth.com/csem-2/ where one can find many tutorials regarding specific analyses available in the package.

Code for the corporate reputation model using the cSEM package—Part 1

```
corpmod <- "
  # measurement model
  LIKE =~ like_1 + like_2 + like_3
  COMP =~ comp_1 + comp_2 + comp_3
  CUSA =~ cusa
  CUSL =~ cusl_1 + cusl_2 + cusl_3
  CSOR <~ csor_1 + csor_2 + csor_3 + csor_4 + csor_5
  ATTR <~ attr_1 + attr_2 + attr_3
  PERF <~ perf_1 + perf_2 + perf_3 + perf_4 + perf_5
  QUAL <~ qual_1 + qual_2 + qual_3 + qual_4 + qual_5 + qual_6 + qual_7 + qual_8

  # structural model
  LIKE ~ QUAL + CSOR + PERF + ATTR
  COMP ~ QUAL + CSOR + PERF + ATTR
  CUSA ~ COMP + LIKE
  CUSL ~ COMP + LIKE + CUSA
"
```

Missing values are not accepted in **cSEM**, so they must be removed or imputed beforehand.

5.2.6.3 Implemented Procedures

The **cSEM** is currently the most complete software available for composite-based SEM as regards the estimation algorithms available. In particular, the methods implemented are:

- The classic PLS-SEM algorithm (Wold, 1982; Lohmöller, 1989)
- The PLSc algorithm
- The OrdPLS algorithm, which extends the classic PLS-SEM algorithm to ordinal indicators by computing polychoric correlations in place of Pearson's correlations
- Robust PLS (Schamberger et al., 2020), which improves the breakdown point (i.e., the resistance to outliers and influential observations) of the classic algorithm by replacing the usual covariance with the minimum covariance determinant (MCD), a robust measure of the covariance between variables
- GSCA (Hwang & Takane, 2004, 2014; Hwang et al., 2017) and generalized structured component analysis with uniqueness terms (GSCAm)
- Generalized canonical correlation analysis (GCCA) according to one of the five criteria SUMCORR, MAXVAR, SSQCORR, MINVAR and GENVAR suggested by Kettenring (1971)
- Principal component analysis (PCA)
- Factor score regression using sum score, regression or Bartlett scores (including bias correction using Croon's approach)

The global estimation options available are:

- The inner weighting scheme can be centroid, factorial or path

- The stopping criterion (default to 10^{-5})
- The maximum number of iterations (default to 100)
- The convergence criterion, which can be either the sum of relative, squared or absolute (default) weight differences
- The indicators to use in the dominant indicator approach
- The sign change option to adopt in order to handle sign flipping during resampling
- A list of user-supplied starting values for the weighting algorithm
- Various choices are available for the modes to use for each construct, including mode A and mode B. Even for emergent constructs, mode A (correlation weights) can be chosen, which might be advantageous in case of multicollinearity (see Henseler & Schuberth 2020)

cSEM includes the same global and local model assessment measures that are also computed by **ADANCO** (see Sect. 5.2.1.3), including the heterotrait-monotrait ratio of correlations based on arithmetic means (HTMT), as well as that based on geometric means (HTMT2), for assessing discriminant validity. In addition, **cSEM** also reports a set of further distance and fit measures, such as the comparative fit index (CFI), the goodness-of-fit index (GFI), the incremental fit index (IFI), the normed and non-normed fit indices (NFI and NNFI), the root mean square error of approximation (RMSEA), the root mean square theta (RMS_theta)[17] and the model selection criteria using the Akaike information criterion (AIC), the Bayesian information criterion (BIC) or the Hannan-Quinn criterion (HQ).

Inference is performed by resampling through bootstrap or jackknife for which all flavors of confidence intervals are available, such as the percentile, bias-corrected (BC), bias-corrected and accelerated (BCa) and others (see for example Davison & Hinkley 1997). The code below fits the corporate reputation model using the same estimation options we adopted for the previous software (output omitted).

Code for the corporate reputation model using the cSEM package—Part 2

```
corp.indic <- c(
  "like_1", "like_2", "like_3",
  "comp_1", "comp_2", "comp_3",
  "cusa",
  "cusl_1", "cusl_2", "cusl_3",
  "csor_1", "csor_2", "csor_3", "csor_4", "csor_5",
  "attr_1", "attr_2", "attr_3",
  "perf_1", "perf_2", "perf_3", "perf_4", "perf_5",
  "qual_1", "qual_2", "qual_3", "qual_4", "qual_5", "qual_6", "qual_7", "qual_8")

corprep.est <- csem(
  .data = na.omit(corprep[, corp.indic]),
  .model = corp.mod,
  .PLS_weight_scheme_inner = "factorial",
  .disattenuate = FALSE,
  .tolerance = 1e-07,
```

[17] For the complete list of fit measures returned by **cSEM** and the corresponding definitions, see the package webpage at https://m-e-rademaker.github.io/cSEM/articles/Using-assess.html and the references therein.

```
    .iter_max = 100,
    .PLS_modes =
      list(LIKE = "modeA", COMP = "modeA",
           CUSA = "modeA", CUSL = "modeA",
           CSOR = "modeB", ATTR = "modeB",
           PERF = "modeB", QUAL = "modeB"),
    .resample_method = "bootstrap",
    .R = 500,
    .seed = 123)

summarize(.object = corprep.est, .ci = "CI_percentile", .alpha = 0.05)
assess(corprep.est)
```

---

cSEM also allows users to perform MGA, whose results across subgroups can be compared by means of resampling (i.e., bootstrap or jackknife). For more details about the tests for multi-group comparisons available in **cSEM** see Klesel et al. (2022).

5.2.6.4 Output and Reporting

The output produced by the commands in **cSEM** is reported in the `R` console window and can be saved using the standard tools available in `R`. Moreover, dynamic documents can be produced using `R` markdown (Xie et al., 2019). Finally, the **cSEM** package includes the function `exportToExcel()` to export the results into a Microsoft Excel file.

5.2.6.5 Additional Features

The package includes additional functionalities to perform more specialized analyses. In particular, the package allows users to conduct PLSpredict, IPMA and CCA. Also, it permits users to use parallel calculations. Moreover, **cSEM** allows users to assess the invariance of the measurement model through the measurement invariance of composites across groups (MICOM) approach proposed by Henseler et al. (2016). Finally, the package includes features to support extension analyses as in other software. More specifically, **cSEM** permits users to incorporate non-linear terms (e.g., interactions or polynomials) in the structural model following the approach presented in Dijkstra and SchermellehEngel (2014). The package also offers various graphical representations of a model that contains non-linear terms, including the so-called floodlight analysis introduced by Spiller et al. (2013). In addition, **cSEM** also supports testing of indirect effects, interaction effects, hierarchical modeling and several post-estimation results, such as assessing endogeneity bias with the Hausman test. However, no tool is yet available to check for the presence of unobserved heterogeneity.

5.2.7 SEMinR

5.2.7.1 Basic Information

The last piece of software we will review herein is the **SEMinR** (Ray et al., 2022) package for R, developed by Soumya Ray, Nicholas Danks and André Calero Valdez. The package supports both Windows and macOS and is available for installation from CRAN[18] as well as from its Github repository.[19] As its name suggests, **SEMinR** has been developed as a general tool to work with structural equation models using both the covariance-based and composite-based approaches. Here, we focus on its capabilities in terms of the latter.

The examples included in the package's documentation provide an easy way to get acquainted with its philosophy and commands. A further resource to learn how to use this software is the book by Hair et al. (2021).

5.2.7.2 Data Input, User Interface, and Model Specification

Loading of data in **SEMinR** is similar to **cSEM**, since they both run under the R framework. Indeed, **SEMinR** commands expect the data to be structured as a data frame or as a matrix object.

Model specification in **SEMinR** follows its own set of syntax rules. In particular, the outer model is specified through the `constructs()` function, which must include the list of constructs set out using the convenience function `composite()`. The latter function creates the composite measurement model matrix for a specific construct, specifying the relevant items of the construct and assigning the relationships either correlation weights (Mode A) or regression weights (Mode B). Note that another function, `reflective()`, also allows users to specify reflective common factor constructs, but in this case the constructs are estimated using the PLSc algorithm. In the path diagram, reflective constructs are displayed as ovals and composites as hexagons (see Fig. 5.5). The structural model must be specified using the `relationships()` function within which each structural relationship must be enclosed by calling on the `paths()` function. The following code shows the **SEMinR** full syntax for the corporate reputation model mentioned above.

Code for the corporate reputation model using the SEMinR package—Part 1

```
# Specification of the measurement model
corprep_mm <- constructs(
  composite("PERF", multi_items("perf_", 1:5), weights = mode_B),
  composite("CSOR", multi_items("csor_", 1:5), weights = mode_B),
  composite("ATTR", multi_items("attr_", 1:3), weights = mode_B),
```

[18] https://cran.r-project.org/web/packages/seminr.

[19] https://github.com/sem-in-r/seminr.

```
  composite("QUAL", multi_items("qual_", 1:8), weights = mode_B),
  reflective("COMP", multi_items("comp_", 1:3)),
  reflective("LIKE", multi_items("like_", 1:3)),
  reflective("CUSA", single_item("cusa")),
  reflective("CUSL", multi_items("cusl_", 1:3)))

# Specification of the structural model
corprep_sm <- relationships(
  paths(from = c("PERF", "CSOR", "ATTR", "QUAL"), to = c("COMP", "LIKE")),
  paths(from = c("COMP", "LIKE"), to = c("CUSA", "CUSL")),
  paths(from = c("CUSA"), to = c("CUSL")))
```

Differently from **cSEM**, **SEMinR** is able to deal with missing values because it allows users to specify a single missing value code (e.g., `-99` for the corporate reputation data). Moreover, in addition to the default casewise deletion option, missing data can be filled in by specifying a user-defined imputation procedure (the only one already included in the package is the `mean_replacement()` function to perform mean imputation).

5.2.7.3 Implemented Procedures

The **SEMinR** package includes the classic PLS-SEM estimation algorithm and automatically applies PLSc to common factor constructs specified through the `reflective()` function to get consistent estimates. The global estimation options that can be specified are:

- The inner model weighting scheme can be set to factorial or path (the centroid weighting scheme is not available)
- The maximum number of iterations and the stopping criterion can be set arbitrarily
- It is not possible to choose the construct starting values

The list of model assessment measures presented by **SEMinR** overlaps with that of **ADANCO** (see Sect. 5.2.1.3), with the exception of the Cohen's f^2 effect sizes. Moreover, **SEMinR** does not report any overall fit measure.

Inference is performed by bootstrapping, which can be parallelized using a specified number of cores. Only the bootstrap percentile confidence intervals are returned. The code below relates to the corporate reputation model (output omitted, but see Fig. 5.5 for the corresponding path diagram).

Code for the corporate reputation model using the SEMinR package—Part 2

```
corp_indic <- c(
  "like_1", "like_2", "like_3",
  "comp_1", "comp_2", "comp_3",
  "cusa",
  "cusl_1", "cusl_2", "cusl_3",
```

```
  "csor_1", "csor_2", "csor_3", "csor_4", "csor_5",
  "attr_1", "attr_2", "attr_3",
  "perf_1", "perf_2", "perf_3", "perf_4", "perf_5",
  "qual_1", "qual_2", "qual_3", "qual_4", "qual_5", "qual_6", "qual_7", "qual_8")

casewise_deletion <- function(data) {
  return(data)
}

corprep_est <- estimate_pls(
  data = corp_rep_data[, corp_indic],
  measurement_model = corprep_mm,
  structural_model = corprep_sm,
  missing_value = -99,
  inner_weights = path_factorial,
  missing = casewise_deletion)

plot(corprep_est, title = "Corporate Reputation Model")

corprep_sum <- summary(corprep_est)
corprep_sum
# str(corprep_sum)
plot(corprep_sum$reliability)

nc <- parallel::detectCores()
corprep_boot <- bootstrap_model(corprep_est, nboot = 500, cores = nc, seed = 123)

corprep_boot_sum <- summary(corprep_boot, alpha = 0.05)
corprep_boot_sum
plot(corprep_boot, title = "Corporate Reputation Model (using bootstrap)")
```

Currently, **SEMinR** allows users to perform MGA, although only for two groups at a time. The results across groups are compared through bootstrapping. The group-specific parameter estimates, their differences and the corresponding p-values are reported. However, the software only allows users to compare the path coefficients. Therefore, MGA, as it is implemented in **SEMinR**, cannot be used to assess measurement invariance.

5.2.7.4 Output and Reporting

The reporting in **SEMinR** consists of a `summary` method for the class of objects returned by the `estimate_pls()` function. The content of the summary is a table reporting the path coefficient estimates together with the R^2 indices of the corresponding structural relationships, plus a table containing the construct reliability indices. To obtain more results, the user must look into the elements of the list object returned by the `summary()` function. An additional output reporting the bootstrap standard errors is provided by the `summary` method for objects returned by `bootstrap_model()`. As we discussed for **cSEM**, the standard `R` tools are still available for exporting the results, but no convenience function is provided to automatically save them in any format.

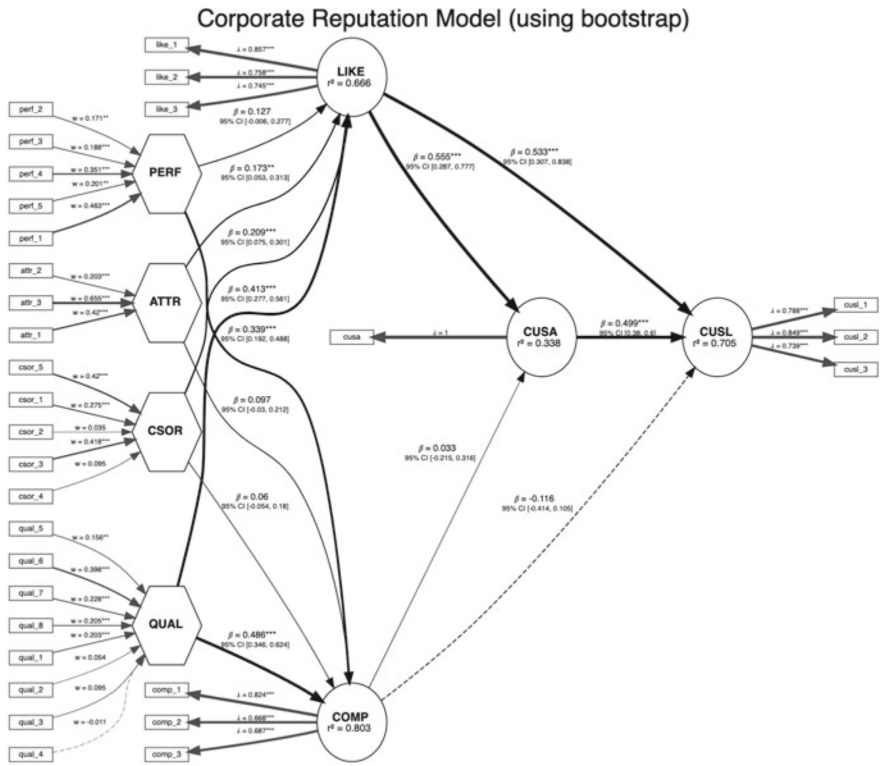

Fig. 5.5 Plot of the model estimates for the corporate reputation data produced by the **SEMinR** R package

A nice feature of **SEMinR** compared to **cSEM** is the option to plot the path model together with the coefficient estimates (see Fig. 5.5 for the plot of the corporate reputation data).

5.2.7.5 Additional Features

At the time of writing, the **SEMinR** package does not include any more advanced features (i.e., detecting unobserved heterogeneity, running PLSpredict, etc.). We can, however, mention the availability of the `csem2seminr()` function for converting the **lavaan**-based syntax used by the **cSEM** package to the **SEMinR** model specification format. However, **SEMinR** does support several extensions of the analysis, such as testing of mediating and moderating effects.

5.2.8 Summary of Software Features

To facilitate comparison, Table 5.2, which spans multiple pages, provides a synthesis of all the characteristics we have presented so far.

5.3 Conclusion

As is always the case, every piece of software has its own strengths and weaknesses. Moreover, each user has different needs and preferences, so that one package may suit some types of users, while another could be the best choice for a different set of users. For these reasons, we do believe that none of the software packages we have presented in this review dominates the others, neither in terms of features and functionalities, nor in terms of flexibility and ease-of-use. Our aim here was to provide a comparative presentation of the different packages available, so that the reader will be able to make a more informed decision about which one to adopt as the appropriate tool for conducting his or her own PLS-SEM analysis.

One difficulty in comparing the software is the fact that they use dissimilar terminologies to refer to components of the model, options or estimation algorithms. Moreover, the technical details of the algorithms are not always fully disclosed or available in the literature. This issue is clearly more common for commercial software than for open-source packages, because for the latter the full code is typically available. For this reason, it is sometimes difficult to replicate the results and compare them across different software. However, using the correct model specification (e.g., the corporate reputation model in our example) the results obtained should be identical when using the same settings across PLS-SEM software. Therefore, a desirable additional feature to include would be a set of commands for importing and exporting models from one software package to the others. This characteristic would allow us to more easily compare the results produced by the different packages.

Speaking of desirable features, given the fact that a consistent PLS approach is already implemented in most of the existing software, and that it does provide a valid alternative to CB-SEM, we recommend that more statistical procedures of the advanced type available in CB-SEM software be developed and added to the current PLS-SEM software as well. One such statistical procedure could for instance be multilevel or mixed model analysis. Another area where all the software available for PLS-SEM is still lacking is missing data imputation (e.g., multiple imputations). Such additions will probably be easier to develop in PLS-SEM packages running within larger software frameworks, such as Stata and R. We believe that these contributions will surely allow for advancing empirical-based science, as well as making PLS-SEM more attractive to quantitatively-orientated academics around the world. The reason for this is that the CB-SEM software often produces convergence issues when complex research models are estimated using advanced statistical techniques (Chen et al., 2001; Deng et al., 2018). The unwelcome implication of this is that the researcher simplifies, modifies or at worst leaves the research model untested. We think it would

Table 5.2 Summary of features of the software presented in this chapter.

Feature	ADANCO	SmartPLS	WarpPLS	XLSTAT-PLSPM	plssem	cSEM	SEMinR
Version	2.3.1	4.0.8.4	8.0	2022.1.2.1259	0.4.0	0.5.0	2.3.2
License	Commercial	Commercial	Commercial	Commercial	Open-source	Open-source	Open-source
Operating systems	Windows, macOS	Windows, macOS	Windows	Windows	Windows, macOS	Windows, macOS	Windows, macOS
Data input	`*.xls`, `*.xlsx`	`*.csv`, `*.txt`, `*.xls`, `*.xlsx`, `*.sav`	`*.xls`, `*.xlsx`	Any	Any	Any	Any
Model specification	Graphical	Graphical	Graphical	Graphical	Syntax-based	Syntax-based (lavaan)	Syntax-based
Estimation procedures	–classic PLS-SEM –PLSc	–Classic PLS-SEM –PLSc –OLS linear regression with sum scores –path analysis with PROCESS	–Classic PLS-SEM –PLSc –factor-based PLS –PLS regression –robust path analysis	–Classic PLS-SEM –PLSc –GSCA –RGCCA	–Classic PLS-SEM –PLSc –OLS on sum scores	–Classic PLS-SEM –PLSc –OrdPLS –Robust PLS –GSCA and GSCAm –GCCA –PCA –OLS on sum scores	–Classic PLS-SEM –PLSc

(continued)

Table 5.2 (continued)

Feature	ADANCO	SmartPLS	WarpPLS	XLSTAT-PLSPM	plssem	cSEM	SEMinR
Evaluation of reflective measurement models	–Dijkstra-Henseler's rho –Jöreskog's rho –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker –HTMT, HTMT2	–Dijkstra-Henseler's rho –Jöreskog's rho –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker –HTMT	–Dijkstra-Henseler's rho –Jöreskog's rho –True composite reliability –Factor reliability –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker –HTMT, HTMT2	–Jöreskog's rho –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker	–Dijkstra-Henseler's rho –Jöreskog's rho –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker –HTMT, HTMT2	–Dijkstra-Henseler's rho –Jöreskog's rho –Cronbach's alpha –Split-half reliability –Weighted tau-equivalent reliability –Factor loadings –AVE –Fornell-Larcker –HTMT, HTMT2	–Dijkstra-Henseler's rho –Jöreskog's rho –Cronbach's alpha –Factor loadings –AVE –Fornell-Larcker –HTMT, HTMT2
Evaluation of formative measurement models	–Indicators weights and VIF values –CCA	–Indicators weights and VIF values	–Indicators weights and VIF values	–Indicators weights and VIF values	–Indicators weights and VIF values	–Indicators weights and VIF values –CCA	–Indicators weights and VIF values
Evaluation of structural model	–R^2 –Adjusted R^2 –Cohen's f^2	–R^2 –Adjusted R^2 –Cohen's f^2	–R^2 –Adjusted R^2 –Effect sizes –Stone-Geisser's Q^2	–R^2 –Adjusted R^2 –Stone-Geisser's Q^2	–R^2 –Adjusted R^2	–R^2 –Adjusted R^2 –Cohen's f^2	–R^2 –Adjusted R^2
Evaluation of model fit	–SRMR –d_{ULS} –d_G	–SRMR –d_{ULS} –d_G –χ^2 –NFI	–SPR –SRMR –SMAR –STDCR –STDSR –χ^2 –GoF (absolute)	–GoF (absolute, relative)	–GoF (absolute, relative) –SRMR –d_{ULS} –d_G –χ^2	–SRMR –RMSEA –RMS_theta –d_{ULS} –d_G –χ^2 –CFI –CN –GFI –IFI –NFI, NNFI	(none)

(continued)

Table 5.2 (continued)

Feature	ADANCO	SmartPLS	WarpPLS	XLSTAT-PLSPM	plssem	cSEM	SEMinR
Types of functional relationships	–Linear –Quadratic –Interactions	–Linear –Quadratic –Interactions	–Linear –Quadratic –Interactions –Non-recursive	–Linear –Quadratic –Interactions	–Linear –Quadratic –Interactions	–Linear –Quadratic –Interactions –Non-recursive	–Linear –Quadratic –Interactions
Bootstrap methods	–Percentile	–Percentile –Studentized –BCa	–Percentile	–Percentile	–Percentile	–Percentile –Studentized –BC –BCa	–Percentile
Missing data methods	–Casewise deletion –Mean imputation	–Casewise deletion –Pairwise deletion –Mean imputation	–Casewise deletion –Mean imputation –(stochastic) regression imputation –(stochastic) hierarchical regression imputation	–Casewise deletion –Mean imputation –Nearest neighbors	–Casewise deletion –Mean imputation –*k*-nearest neighbors	(none)	–Casewise deletion –Mean imputation –User-defined function
Power analysis and sample size determination	(none)	–Post-hoc minimum sample size	–Inverse square root method –Gamma-exponential method	Available on the basic features of XLSTAT	Available on the basic features of Stata	Available on the basic features of R	Available on the basic features of R
Observed heterogeneity	(none)	–Multiple groups –Measurement invariance	–Multiple groups –Measurement invariance	–Multiple groups	–Multiple groups –Measurement invariance	–Multiple groups –Measurement invariance	–Two groups
Unobserved heterogeneity	(none)	–FIMIX-PLS –PLS-POS	–Delta segmentation	–REBUS-PLS	–FIMIX-PLS –REBUS-PLS	(none)	(none)
Additional features	–Extensions analysis is supported	–Confirma-tory tetrad analysis –IPMA –PLSpredict –NCA –Gaussian copula approach –Extensions analysis is supported	–3D plots –Full latent growth analysis –Instrumental variables approach –Extensions analysis is supported	–IPMA –RGCCA (ridge) –Extensions analysis is supported	–Extensions analysis is supported	–IPMA –Floodlight analysis –PLSpredict –Post-estimation supported like Hausman test –Extensions analysis is supported	–Import of **cSEM** models –Extensions analysis is supported

not be controversial to state that both CB-SEM and PLS-SEM software packages are not always homogeneous in terms of algorithms, features, criteria, and so on. For example, the comparison between **ADANCO** versus **SmartPLS** shows some differences in advanced features, as well as goodness-of-fit indices. This shows that every developer has a different point of view regarding the addition of new features to their own PLS-SEM software to show its sophistication. For this reason, it is sometimes difficult to replicate the results and compare them across different software packages. As long as competition in PLS-SEM software development remains healthy, we believe that such a development may also contribute to increasing the credibility of PLS-SEM as a statistical framework. This will, however, require close collaboration and exchange among theorists and software developers to improve the capabilities of each existing piece of software. Despite the differences among and heterogeneous nature of the existing PLS-SEM software, we are nevertheless able to enjoy many useful pieces of software that have come about mainly in the past decade. We can in fact blame or thank—depending on your view—these software for the prodigious amount of relevant scientific papers now being published in international journals.

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Part II
Methodological Issues

Chapter 6
Revisiting and Extending PLS for Ordinal Measurement and Prediction

Tamara Schamberger, Gabriele Cantaluppi, and Florian Schuberth

Abstract Traditionally, partial least squares (PLS) and consistent partial least squares (PLSc) assume the indicators to be continuous. To relax this restrictive assumption, ordinal partial least squares (OrdPLS) and ordinal consistent partial least squares have been developed. They are extensions of PLS and PLSc, respectively, that are able to take into account the nature of ordinal variables—both belonging to exogenous and endogenous constructs. In the PLS context, assessing the out-of-sample predictive power of models has increasingly gained interest. In contrast to PLS and PLSc, performing out-of-sample predictions is not a straightforward process for OrdPLS and OrdPLSc because the two assume that ordinal indicators are the outcome of categorized unobserved continuous variables, i.e., they rely on polychoric and polyserial correlations. In this chapter, we present OrdPLSpredict and OrdPLScpredict to perform out-of-sample predictions with models estimated by OrdPLS and OrdPLSc. A Monte Carlo simulation demonstrates the performance of

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our proposed approach. Finally, we provide concise guidelines using the open source R package cSEM to enable researchers to apply OrdPLSpredict and OrdPLScpredict using an empirical example.

6.1 Introduction

In empirical research, scholars often encounter variables that are measured on an ordinal scale. Such ordinal variables are often the outcomes of surveys that measure constructs such as organizational identification using Likert scales (e.g., 1: strongly disagree to 5: strongly agree; Hwang & Takane, 2004). Similarly, classified variables such educational level, e.g., high school or less, university student, university graduate and postgraduate or more, and grouped age, e.g., below 18 years, between 18 and 35 years and above 35 years, are ordinal variables. In contrast to metric variables, the differences between the outcomes of ordinal variables are not interpretable. Specifically, the outcomes of ordinal variables are discrete and possess a natural order (Vogt, 1993). Therefore, not taking into account the ordinal scale of variables and treating them as metric can lead to distorted results as acknowledged in the partial least squares (PLS) literature. For instance, Lohmöller (1989, p.155) recognizes that "standard procedures cannot be used for the categorical and ordinal-scaled variables". To address this issue, ordinal partial least squares (OrdPLS, Cantaluppi, 2012; Cantaluppi & Boari, 2016) and ordinal consistent partial least squares (OrdPLSc, Schuberth et al., 2018; Schuberth & Cantaluppi, 2017) were developed. They are similar to PLS (Wold, 1974, 1982) and consistent partial least squares (PLSc, Dijkstra & Henseler, 2015a, 2015b) and can deal with models containing exogenous and endogenous constructs associated with ordinal indicators. However, the originally used Pearson correlations in PLS and PLSc are replaced by polychoric and polyserial correlations which assume that an ordinal indicator is the outcome of a categorized unobserved standard normally distributed random variable (Poon & Lee, 1987). Consequently, researchers who want to apply PLS and PLSc and strive for consistent estimates in the case of ordinal indicators are advised to apply OrdPLS and OrdPLSc, respectively.

Over the last years, the causal-predictive nature of PLS was emphasized in which the assessment of a model's out-of-sample predictive performance plays a crucial role (Chin et al., 2020; Sarstedt et al., 2023). Although Cantaluppi and Schuberth (2019) proposed an approach that is based on OrdPLS and OrdPLSc to perform out-of-sample predictions and thus takes into account the nature of ordinal indicators, this approach is limited to situations where all indicators are on an ordinal scale. However, empirical studies applying PLS often deal with both metric and ordinal indicators. For instance, IT integration capability was modeled as a composite composed of ordinal variables each measured on a 5-point Likert scale, while the control variable firm performance was measured by a metric variable, namely the natural logarithm of the number of employees (Braojos et al., 2020). The necessity to make predictions of ordinal variables based on a mix of metric and ordinal variables is also observable in other fields such as credit scoring. In this setting, final predictions need to be formulated on ordinal scales in order to take decisions, e.g., grant or do not grant a credit or assign a rating to a customer.

To address this issue, we propose OrdPLScpredict and OrdPLSpredict which are extensions of the approaches of Cantaluppi and Schuberth (2019) and Shmueli et al. (2016) to perform out-of-sample predictions based on models estimated by OrdPLS and OrdPLSc containing both continuous and ordinal indicators. The remainder of the chapter is organized as follows: Sect. 6.2 presents OrdPLS and OrdPLSc. Section 6.3 gives an overview of performing out-of-sample predictions using PLSpredict and PLScpredict, i.e., the approaches originally proposed to perform out-of-sample prediction based on models estimated by PLS and PLSc, respectively (Shmueli et al,, 2016). In Sect. 6.4, we present OrdPLSpredict and OrdPLScpredict, our two proposed approaches to perform out-of-sample predictions using models estimated by OrdPLS and OrdPLSc, respectively. In Sect. 6.5, we conduct a Monte Carlo simulation to evaluate the performance of our two proposed approaches. Section 6.6 provides guidelines for the two approaches and shows how they can be applied in the open source R package cSEM (Rademaker & Schuberth, 2020) using an illustrative example. Our chapter closes with a discussion given in Sect. 6.7.

6.2 Ordinal (Consistent) Partial Least Squares Path Modeling

Wold (1966) originally developed PLS as an approach for principal component analysis and (generalized) canonical correlation analysis, which at the time were still known as nonlinear iterative least squares and nonlinear iterative partial least squares, respectively (Tenenhaus et al., 2005). A few years later, Wold proposed PLS as a computational efficient estimation method for structural models containing latent variables (Wold, 1974; 1982). In this case, weights are determined by the PLS algorithm to form proxies and subsequently these proxies are used to estimate the relationships between the latent variables. As various researchers emphasized, PLS estimates for this type of model are only consistent at large; i.e., only as both the number of observations and the number of indicators go to infinity, will PLS estimates converge in probability to the respective population parameters (e.g., Hui & Wold, 1982, Dijkstra, 1985). However, recently, various studies have shown that PLS produces consistent estimates for models containing interrelated emergent variables (Dijkstra 2017; Cho & Choi 2020; Henseler 2021; Schuberth 2021).[1] For an elaboration about emergent variables and their potential use, the interested reader is referred to Yu et al. (2021).

[1] In line with recent literature (e.g., Benitez et al., 2020; Yu et al., 2021; Schamberger et al., 2023), we use the term ‘emergent variable’ to emphasize that the variable is not only a composite, i.e., a weighted linear combination of variables, but also a composite that conveys all the information between its indicators and other variables in the model.

In its most modern appearance known as PLSc, it produces consistent parameter estimates for structural models containing latent and emergent variables (Dijkstra & Henseler, 2015b). Similar to PLS, PLSc relies on the PLS algorithm to determine the weights to build proxies for the constructs. In cases that constructs are modeled as latent variables, it applies a correction for attenuation to correlations. In this way, it is ensured that the construct correlation matrix is consistently estimated, and thus, consistent path coefficient estimates can be obtained. Moreover, in contrast to PLS which relies on ordinary least squares (OLS) to estimate the model parameters, PLSc applies two-stage least squares (2SLS) in the case of non-recursive structural models (Dijkstra & Henseler, 2015a). Finally, a recent development allows PLSc to deal with correlated random measurement errors within a block of indicators measuring a latent variable (Rademaker et al., 2019). For an overview on latent variable models that can be estimated by PLSc, we refer to the study of Schuberth et al. (2023b).

PLS including PLSc assumes that the observed variables are measured on a metric scale. However, in empirical research observed variables are often measured on an ordinal scale. For instance, a model about customer satisfaction (Sarstedt et al., 2011), and a model about young consumer's adoption intentions (Miltgen et al., 2016) rely on observed variables that are measured on an ordinal scale. To overcome the limitation of PLS considering the scale of the observed variables, various modifications of PLS have been developed to cope with non-metric variables such as partial maximum-likelihood partial least squares (Jakobowicz & Derquenne, 2007) and non-metric partial least squares (Russolillo, 2012). A further approach that was developed to deal with ordinal indicators in a classic psychometric way is OrdPLS (Cantaluppi, 2012). OrdPLS is similar to PLS, but applies polychoric and polyserial correlations instead of Pearson correlations as input for the PLS algorithm to take the nature of ordinal indicators into account. Consequently, the original PLS algorithm remains untouched. In the same way as PLS was extended by PLSc, OrdPLS was extended by OrdPLSc to consistently estimate structural models containing latent variables and ordinal indicators (Schuberth & Cantaluppi, 2017; Schuberth et al., 2018). Figure 6.1 illustrates the four steps of OrdPLSc: (i) calculating the polychoric/polyserial correlations, (ii) performing the PLS algorithm, (iii) correcting for attenuation if some constructs are modeled as latent variables, and (iv) estimating the path coefficients by OLS and 2SLS, respectively. Obviously, OrdPLSc only differs from traditional PLSc in step (i). The three other steps are the same for PLSc and OrdPLSc. In the following, we elaborate each of the four steps.[2]

6.2.1 Calculating Polychoric/Polyserial Correlations

Following Pearson's idea of a polytomous variable, we assume an ordinal indicator x to be the result of a categorized unobservable standard normally distributed random

[2] Note that the following subsections contain large parts adapted from Schuberth et al. (2018). Which is released under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

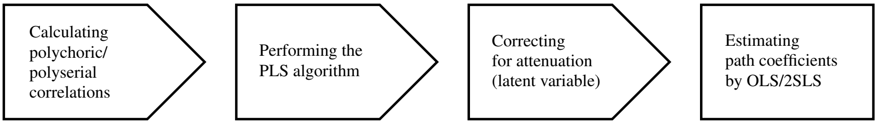

Fig. 6.1 Ordinal consistent partial least squares (adopted from Schuberth et al. (2018) which is released under a Creative Commons Attribution 4.0 International License (CC BY 4.0))

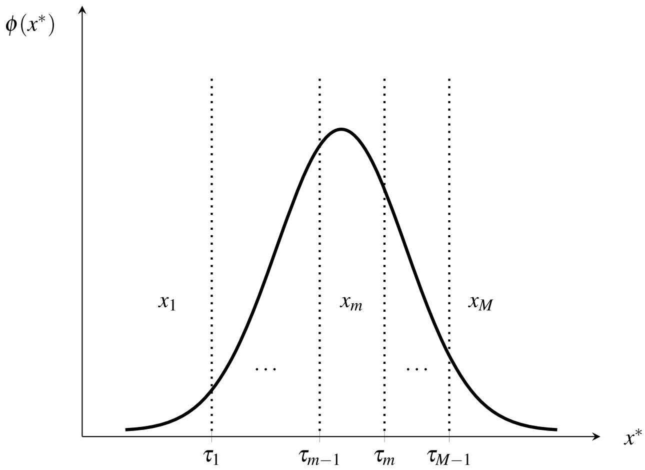

Fig. 6.2 Pearson's idea of an ordinal variable (taken from Schuberth et al. (2018) which is released under a Creative Commons Attribution 4.0 International License (CC BY 4.0))

variable x^* (Pearson, 1900, 1913)

$$x = x_m \quad \text{if} \quad \tau_{m-1} \leq x^* < \tau_m \quad m = 1, \ldots, M \tag{6.1}$$

where the threshold parameters $\tau_0, \ldots, \tau_M$ determine the observed categories. The first and last thresholds are fixed: $\tau_0 = -\infty$ and $\tau_M = \infty$. Moreover, we assume the thresholds to be strictly increasing: $\tau_0 < \tau_1 < \ldots < \tau_M$.[3] Figure 6.2 depicts the idea of an underlying continuous variable, i.e., for indicator x, category x_m is observed if the realization of the underlying continuous variable x^* falls between the thresholds τ_{m-1} and τ_m.

Since we assume an ordinal variable to be determined by an underlying continuous variable, it is more appropriate to consider the correlation between these underlying continuous variables for evaluating the linear relationship of interest. This is achieved by using the polychoric correlation (Drasgow, 1986). In cases where the correlation between an ordinal variable and a continuous variable is calculated the polyserial correlation can be used (Lee & Poon, 1986) which considers the correlation between the

[3] In empirical work two consecutive threshold parameters can be equal, $\tau_{m-1} = \tau_m$, if the corresponding category x_m is not observed.

continuous variable and the ordinal variable's underlying continuous variable. Various estimators have been proposed to obtain these correlation coefficients (Drasgow, 1986). In the following, we apply the two-step estimator which is computationally efficient.

As input for OrdPLS and OrdPLSc, the indicators' sample correlation matrix $\boldsymbol{S}$ is required and thus needs to be calculated. Since OrdPLS and OrdPLSc allow for both ordinal and continuous indicators, the sample correlation matrix $\boldsymbol{S}$ can comprise polychoric, polyserial and Pearson correlation coefficients. In specific, the sample correlation between two ordinal indicators equals their estimated polychoric correlation, the sample correlation between an ordinal and a continuous indicator equals their estimated polyserial correlation and the sample correlation between two continuous indicators equals their estimated Pearson correlation.

6.2.2 Performing the PLS Algorithm

The second step of OrdPLS and OrdPLSc involves applying the PLS algorithm to the sample correlation matrix $\boldsymbol{S}$ calculated in the previous step. The PLS algorithm remains untouched by OrdPLS and OrdPLSc and thus is the same as for their traditional counterparts. For simplicity, the K_j indicators belonging to one construct η_j, i.e., a latent variable or an emergent variable, are grouped to form the block j with $j = 1, \ldots, J$ and where $\sum_{j=1}^{J} K_j = K$, i.e., each indicator belongs exactly to one block.

The PLS algorithm is an iterative algorithm which starts with initial arbitrary weights $\hat{\boldsymbol{w}}_j^{(0)}$ $(K_j \times 1)$. The initial weights are chosen in such a way that they satisfy the following condition: $\hat{\boldsymbol{w}}_j^{(0)\prime} \boldsymbol{S}_{jj} \hat{\boldsymbol{w}}_j^{(0)} = 1$ for each block j where the $(K_j \times K_j)$ matrix $\boldsymbol{S}_{jj}$ contains the sample correlations of the indicators of block j. This condition holds for all weights in each iteration i and can be achieved by using a scaling factor $(\hat{\boldsymbol{w}}_j^{(i)\prime} \boldsymbol{S}_{jj} \hat{\boldsymbol{w}}_j^{(i)})^{-\frac{1}{2}}$ for the weights $\hat{\boldsymbol{w}}_j^{(i)}$.

The PLS algorithm aims to determine weights to build proxies for the J constructs. This can be done in three ways, identified as *Mode A*, *Mode B*, and *Mode C*. In the case of Mode A, the weights, also known as correlation weights, are determined as follows:

$$\hat{\boldsymbol{w}}_j^{(i+1)} \propto \sum_{l=1}^{J} \boldsymbol{S}_{jl} \hat{\boldsymbol{w}}_l^{(i)} e_{jl}^{(i)} \quad \text{with} \quad \hat{\boldsymbol{w}}_j^{(i+1)\prime} \boldsymbol{S}_{jj} \hat{\boldsymbol{w}}_j^{(i+1)} = 1. \tag{6.2}$$

In the case of *Mode B*, the weights, also known as regression weights, are calculated as follows:

$$\hat{\boldsymbol{w}}_j^{(i+1)} \propto \boldsymbol{S}_{jj}^{-1} \sum_{l=1}^{J} \boldsymbol{S}_{jl} \hat{\boldsymbol{w}}_l^{(i)} e_{jl}^{(i)} \quad \text{with} \quad \hat{\boldsymbol{w}}_j^{(i+1)\prime} \boldsymbol{S}_{jj} \hat{\boldsymbol{w}}_j^{(i+1)} = 1. \tag{6.3}$$

Mode C, also known as *MIMIC mode*, is a mixture of mode A and B, which we do not consider here. The inner weights e_{jl} can be obtained in three different ways, following the *centroid* (Wold, 1982), *factorial* (Lohmöller, 1989), and *path* weighting scheme. All inner weighting schemes produce essentially the same results (Noonan & Wold, 1982), hence, we consider the path weighting scheme here.[4] For the path weighting scheme, the inner weight jl is chosen as follows:

$$e_{jl}^{(i)} = \begin{cases} \hat{\boldsymbol{w}}_j^{(i)\prime} \boldsymbol{S}_{jl} \hat{\boldsymbol{w}}_l^{(i)} & \text{if } \eta_l \text{ is a consequence of } \eta_j \\ \hat{\beta}_l & \text{if } \eta_l \text{ is an antecedent of } \eta_j \\ 0 & \text{otherwise} \end{cases} \tag{6.4}$$

As Eq. (6.4) shows, the inner weight e_{jl} equals the covariance between the proxies of the constructs η_j and η_l if construct η_l is a consequence of the construct η_j. In contrast, if the construct η_l is an antecedent of the construct η_j, the inner weight e_{jl} is equal to the regression coefficient $\hat{\beta}_l$ of a multiple regression of the construct η_j on its antecedents. Otherwise, if the two constructs are not connected via the structural model, the inner weight is set to 0.

Since the PLS algorithm has no single criterion to be optimized, the new weights $\hat{\boldsymbol{w}}_j^{(i+1)}$ are checked for significant changes compared with the weights $\hat{\boldsymbol{w}}_j^{(i)}$ in the previous iteration step. When the change in weights exceeds a certain limit, the algorithm starts again. Otherwise, the final weights $\hat{\boldsymbol{w}}_j$ equal the stable weights determined in the last iteration. Finally, the standardized loading estimates, which are in PLS equal to the estimated correlations between a proxy and its indicators, are calculated as:

$$\hat{\boldsymbol{\lambda}}_j = \boldsymbol{S}_{jj} \hat{\boldsymbol{w}}_j \tag{6.5}$$

If we apply OrdPLS, the standardized loading estimates are calculated in the same way. The only difference is that the polychoric/polyserial correlation matrix is taken into account and therefore the calculation considers correlations with the underlying continuous variables that correspond to ordinal indicators of a latent variable. Note, as for PLS, the loading estimates of OrdPLS are not consistent for latent variable models.

6.2.3 *Correcting for Attenuation if Constructs Are Modeled as Latent Variables*

PLS creates composites as proxies for constructs. Consequently, its estimates are not consistent if the constructs are modeled as latent variables. To overcome this issue,

[4] Note that the choice of inner weighting scheme can substantially affect the estimates in the case of models containing second-order constructs (Becker et al., 2012; Schuberth et al., 2020). For more details on the other inner weighting schemes, see Tenenhaus et al. (2005).

Dijkstra and Henseler (2015a, 2015b) proposed PLSc which applies a correction to obtain consistent parameter estimates. OrdPLSc applies the same correction to obtain consistent estimates for models containing latent variables. Consequently, this step is the same for PLSc and OrdPLSc.

The correction exploits the linearity between standardized population factor loadings and the population weights, $\boldsymbol{\lambda}_j = c_j \boldsymbol{w}_j$ and requires that each latent variable be measured by at least two indicators. The estimated correction factor for block j satisfies the following condition

$$\text{plim } \hat{c}_j = \sqrt{\boldsymbol{\lambda}_j' \boldsymbol{\Sigma}_{jj} \boldsymbol{\lambda}_j}, \tag{6.6}$$

where $\boldsymbol{\lambda}_j$ is a column vector of length K_j containing the population loadings of latent variable η_j and $\boldsymbol{\Sigma}_{jj}$ is the $(K_j \times K_j)$ population correlation matrix of the indicators of block j.[5] The correction factor $\hat{c}_j$ can be obtained by

$$\hat{c}_j^2 = \frac{\hat{\boldsymbol{w}}_j'(\boldsymbol{S}_{jj} - \text{diag}(\boldsymbol{S}_{jj}))\hat{\boldsymbol{w}}_j}{\hat{\boldsymbol{w}}_j'(\hat{\boldsymbol{w}}_j\hat{\boldsymbol{w}}_j' - \text{diag}(\hat{\boldsymbol{w}}_j\hat{\boldsymbol{w}}_j'))\hat{\boldsymbol{w}}_j}. \tag{6.7}$$

It is chosen in such a way that the Euclidean distance between

$$\boldsymbol{S}_{jj} - \text{diag}(\boldsymbol{S}_{jj}) \quad \text{and} \quad (c_j\hat{\boldsymbol{w}}_j)(c_j\hat{\boldsymbol{w}}_j)' - \text{diag}((c_j\hat{\boldsymbol{w}}_j)(c_j\hat{\boldsymbol{w}}_j')) \tag{6.8}$$

is minimized (Dijkstra & Henseler, 2015a). For other ways to obtain correction factors, the interested reader is referred to Dijkstra (2013). Finally. the standardized factor loadings of block j can be consistently estimated as

$$\hat{\boldsymbol{\lambda}}_j = \hat{c}_j \hat{\boldsymbol{w}}_j. \tag{6.9}$$

6.2.4 Estimating Path Coefficients by OLS/2SLS

In the last step, we estimate the path coefficients based on the proxies' correlation matrix, i.e., $\hat{\boldsymbol{W}}'\boldsymbol{S}\hat{\boldsymbol{W}}$, where the matrix $\hat{\boldsymbol{W}}$ of dimension $K \times J$ contains all the weight estimates. In PLS and OrdPLS, this matrix is directly applied to estimate the parameters of the structural model by OLS. In contrast, if constructs are modeled as latent variables, PLSc and OrdPLSc apply a correction for attenuation to the proxies' correlation matrix before calculating the path coefficients. The correlation between the two latent variables η_j and η_l where $j \neq l$ can be consistently estimated by:

$$\widehat{\text{cor}}(\eta_j, \eta_l) = \frac{\hat{\boldsymbol{w}}_j'\boldsymbol{S}_{jl}\hat{\boldsymbol{w}}_l}{\hat{c}_j^2\hat{\boldsymbol{w}}_j'\hat{\boldsymbol{w}}_j\hat{c}_l^2\hat{\boldsymbol{w}}_l'\hat{\boldsymbol{w}}_l} \tag{6.10}$$

[5] Here we do not consider the use of *Mode B* for latent variables. For a consistent version of PLS using Mode B, the interested reader is referred to Dijkstra (2011).

Similarly, if construct η_j is modeled as a latent variable and construct η_l as an emergent variable, the consistently estimated correlation is obtained by

$$\widehat{\text{cor}}(\eta_j, \eta_l) = \frac{\hat{\boldsymbol{w}}_j' \boldsymbol{S}_{jl} \hat{\boldsymbol{w}}_l}{\hat{c}_j^2 \hat{\boldsymbol{w}}_j' \hat{\boldsymbol{w}}_j}. \tag{6.11}$$

In the case of both constructs being modeled as emergent variables, no correction of the correlation is required because we assume that the correlation between two emergent variables is not affected by attenuation. Finally, in OrdPLSc the path coefficients are estimated by OLS or 2SLS depending on the structure of the underlying structural model.

6.3 Model-Based Predictions Using PLS and PLSc (PLSpredict and PLScpredict)

In the PLS context, out-of-sample predictions have increasingly gained attention (Evermann & Tate, 2014; Carrión et al., 2016; Shmueli et al., 2016, 2019; Sarstedt & Danks, 2022). To perform such out-of-sample predictions, a procedure called PLSpredict was introduced (Shmueli et al., 2016). In PLSpredict, values of variables are predicted based on a model estimated by PLS. In cases where the model parameters are estimated by PLSc, we label the procedure PLScpredict. In the following exposition we present the steps of PLSpredict and PLScpredict.

We begin by splitting a sample into two datasets, i.e., the train dataset $\boldsymbol{X}_{\text{train}}$ and the test dataset $\boldsymbol{X}_{\text{test}}$. The train dataset contains observations for all indicators and is used to estimate the model parameters by PLS or PLSc, i.e., the weights $\hat{\boldsymbol{w}}_j$, the loadings $\hat{\boldsymbol{\lambda}}_j$, and the path coefficients of the exogenous and endogenous constructs, which are captured in the matrices $\hat{\boldsymbol{\Gamma}}$ and $\hat{\boldsymbol{B}}$, respectively. Subsequently, out-of-sample predictions can be performed based on the estimated model and the observations given in the test dataset. The test dataset comprises N observations for at least all indicators connected to exogenous constructs, i.e., constructs that are not explained by other constructs in the structural model. Importantly, the observations of the test dataset are not used during the model estimation.

In the context of PLSpredict, we can distinguish different types of predictions (Shmueli et al., 2016; Lohmöller, 1989): (i) *valid predictions* in which predictions for scores of exogenous constructs are obtained by observations of their associated indicators, (ii) *structural predictions* in which predictions for scores of endogenous constructs are obtained by exogenous construct scores, (iii) *communal predictions* in which predictions for values of indicators associated with endogenous constructs are obtained by scores of their associated constructs, (iv) *redundant predictions* in which predictions for values of the indicators associated with endogenous constructs are obtained by exogenous construct scores and the estimated structural model, (v) *latent predictions* in which predictions for scores of endogenous constructs are obtained by observations of the indicators associated with exogenous constructs and the estimated structural model, and (vi) *operative predictions* in which predictions for values of indicators associated with endogenous constructs are obtained by observations for the indicators associated with exogenous constructs and the estimated structural model.

Obviously, operative predictions are the most general case in that they involve all the steps of the other types of predictions. Additionally, predictions can only be evaluated if they are performed on item level, i.e., if values of the indicators are predicted. Against this background, we will now focus on operative predictions. Note that other types of predictions can be obtained by starting or stopping the approach we describe below at a later or earlier stage.

To obtain operative predictions, valid predictions have to be performed first. To do this, we standardize the N observations of the test dataset $\boldsymbol{X}_{\text{test}}$ for the indicators associated with the exogenous constructs using the corresponding moments estimated on the basis of the train dataset (Shmueli et al., 2016). Subsequently, for all J_{exo} exogenous constructs, we predict scores as the weighted sum of their associated indicators using the observations from the test dataset. Consequently, the predicted scores of the exogenous constructs are obtained as follows:

$$\hat{\boldsymbol{\eta}}_{j,\text{exo}} = \boldsymbol{X}_{j,\text{test}}\hat{\boldsymbol{w}}_j \qquad j = 1, \ldots, J_{\text{exo}} \tag{6.12}$$

In a next step, we use the predicted scores of the exogenous constructs to predict the scores of the J_{end} endogenous constructs in accordance with the structural model, i.e., we perform structural predictions:

$$\hat{\boldsymbol{\eta}}_{\text{end}} = \hat{\boldsymbol{\eta}}_{\text{exo}}\hat{\boldsymbol{\Gamma}}'(\boldsymbol{I} - \hat{\boldsymbol{B}}')^{-1}, \tag{6.13}$$

where $\hat{\boldsymbol{\eta}}_{\text{end}}$ is a matrix of dimension $N \times J_{\text{end}}$ that contains the predictions for the scores of the endogenous constructs in its columns.

Finally, in the last step, we use the scores of the endogenous constructs to predict values of the indicators connected to endogenous constructs, i.e., we perform communal predictions:

$$\hat{\boldsymbol{X}}_{\text{end}} = \hat{\boldsymbol{\eta}}_{\text{end}}\hat{\boldsymbol{\Lambda}}'_{\text{end}} \tag{6.14}$$

where the matrix $\hat{\boldsymbol{\Lambda}}_{\text{end}}$ contains the estimated loadings of the indicators connected to endogenous constructs in its columns. To obtain the final predictions for continuous indicators, the values in $\hat{\boldsymbol{X}}_{\text{end}}$ are brought back to their original scale using the mean and standard deviation of the train dataset (see Shmueli et al., 2016). In cases where ordinal indicators are associated with endogenous constructs, Cantaluppi and Schuberth (2019) proposed rounding the predicted values to an integer. Thereby, we obtain predictions that are in line with the domain of the ordinal indicators. However, the scale of the ordinal indicators was not taken into account during parameter estimation.

To evaluate the model's predictive power, the test dataset must contain observations for all indicators. In such a case, the observed values of the indicators can be compared to their predicted counterparts (Shmueli, 2010). As predictive performance measures, the mean absolute error (MAE), and the root mean squared error (RMSE) can be used to evaluate the predictive power of the model (Evermann & Tate, 2014). The MAE is the average absolute deviation of the predicted value of an indicator from its observed counterpart, $\frac{1}{N}\sum_{i=1}^{N}|\hat{x}_i - x_i|$, where N is the sample size of the test dataset. Similarly, the RMSE is the square root of the average squared deviation of the predicted value from its observed counterpart, $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}$.

6.4 Model-Based Predictions Using OrdPLS and OrdPLSc

In this section, we present an approach to perform predictions based on a model estimated by OrdPLS and OrdPLSc, which we label OrdPLSpredict and OrdPLScpredict, respectively. These approaches allow for both ordinal and continuous indicators. In fact, our approaches generalize the idea of Cantaluppi and Schuberth (2019) to perform predictions based on a model estimated by OrdPLS or OrdPLSc in cases where all indicators are ordinal.

6.4.1 Relationship Between the Ordinal Indicators and Their Underlying Latent Variables in the Test Dataset

We rely on the idea presented in Sect. 6.2.1 that an ordinal indicator x is the outcome of a polytomized standard normally distributed unobservable random variable x^*, see Eq. (6.1). In cases with more than one ordinal indicator, we assume that the ordinal indicators $\boldsymbol{x}$ are the outcome of categorized underlying multivariate standard normally distributed latent random variables $\boldsymbol{x}^*$. Consequently, the observations of the ordinal indicators $\boldsymbol{x}_j$ belonging to construct j are the outcome of columnwise transformations (as expressed by Eq. (6.1)) of the observations of the underlying multivariate normally distributed random variables that are stacked in the matrix $\boldsymbol{X}_j^*$, expressed as:

$$\boldsymbol{X}_j^* \quad \rightarrow \quad \boldsymbol{X}_j \tag{6.15}$$

As shown in Sect. 6.2, OrdPLS and OrdPLSc can deal with both ordinal and continuous indicators. Note that the transformation is only performed for the observations of the ordinal indicators and not for those of continuous indicators.

As in PLSpredict, the first step is to estimate the model parameters. In the context of OrdPLSpredict and OrdPLScpredict this is done by OrdPLS and OrdPLSc, respectively, based on the train dataset which contains observations for at least one ordinal indicator. Otherwise, if the train dataset contains no ordinal indicator, there is no need to apply OrdPLS or OrdPLSc.

Next, the estimated model and the observations of the test dataset are used to perform out-of-sample predictions. For this purpose, the test dataset must at least contain observations for the indicators associated with the exogenous constructs which are stored in the matrix $\boldsymbol{X}_{\text{test, exo}}$.[6] We assume the observations of ordinal indicators of the test dataset to be the columnwise transformations of a multivariate *truncated* normally distributed dataset, as stated by Eq. (6.1):

$$\boldsymbol{X}^{\text{Trunc},*}_{\text{test, exo}} \quad \rightarrow \quad \boldsymbol{X}_{\text{test, exo}} \tag{6.16}$$

The observations from the multivariate truncated normal distribution $\boldsymbol{X}^{\text{Trunc},*}_{\text{test, exo}}$ are standardized and have the same correlation matrix as the polychoric correlation between the indicators connected to the train data's exogenous constructs. For each subject in the test dataset, given the expressed categories, the domain of $\boldsymbol{X}^{\text{Trunc},*}_{\text{test, exo}}$ is defined by the corresponding pairs of thresholds in the set of thresholds $(\boldsymbol{\tau}_{j-1}, \boldsymbol{\tau}_j)$. These are obtained from the polychoric correlation matrix used for model parameter estimation, i.e., the one based on the train dataset $\boldsymbol{X}_{\text{train}}$. If the test dataset contains additional observations for the indicators associated with endogenous constructs, the model's predictive performance can be evaluated by comparing the indicators' observed values to their predicted counterparts.

6.4.2 *OrdPLSpredict and OrdPLScpredict*

In the following explication, we present the steps OrdPLSpredict and OrdPLScpredict take to perform out-of-sample predictions. Similar to PLSpredict and PLScpredict, the only difference between OrdPLSpredict and OrdPLScpredict is that the former uses OrdPLS estimates, while the latter employs OrdPLSc estimates.

1. Standardize the test dataset $\boldsymbol{X}_{\text{test, exo}}$ using the means and standard deviations of the train dataset. Note that only the continuous indicators are standardized, i.e., the ordinal indicators comprised in the test dataset remain untouched.
2. Predict the scores of the exogenous constructs, i.e., valid predictions. In PLSpredict, scores of construct j are obtained as linear combinations of the observed indicators $\boldsymbol{x}_j$ and the corresponding weight estimates, regardless of the indicators' measurement scale. In contrast, in OrdPLSpredict and OrdPLScpredict the nature of ordinal indicators is explicitly taken into account. Since the number of ordinal indicators associated with exogenous constructs can differ, three cases have to be distinguished, namely ones in which (i) all indicators are continuous, (ii) all indicators are ordinal, and (iii) there is a mixture of continuous and ordinal indicators.

   Considering cases in which all indicators associated with exogenous constructs

[6] In cases where only values of a subset of the indicators associated with endogenous constructs are predicted, a subset of the indicators associated with the exogenous constructs might be sufficient.

are continuous, construct scores are obtained as in PLSpredict:

$$\hat{\boldsymbol{\eta}}_{j,\text{exo}} = \boldsymbol{X}_{j,\text{test,exo}} \hat{\boldsymbol{w}}_j, \qquad j = 1, \ldots, J_{\text{exo}} \tag{6.17}$$

where $\hat{\boldsymbol{w}}_j$ are the weight estimates obtained by OrdPLS/OrdPLSc based on the train data.

Considering cases in which all indicators associated with exogenous constructs are ordinal, the unknown values of the unobservable variables underlying these indicators (see Eq. (6.1)) need to be aggregated (Cantaluppi and Schuberth, 2019). Specifically, the exogenous constructs' scores can be calculated as linear combinations of multivariate truncated normally distributed random variables $\boldsymbol{x}^{\text{Trunc},*}_{j,\text{test,exo}}$ which are continuous. They also have the domain $(\boldsymbol{\tau}_{j-1}, \boldsymbol{\tau}_j)$ defined by the threshold parameters of the polychoric correlations based on the train dataset $\boldsymbol{X}_{\text{train}}$, conditional on categories that characterize the test dataset regarding ordinal indicators. Consequently, we obtain the construct scores as follows:

$$\hat{\boldsymbol{\eta}}_{j,\text{exo}} = \boldsymbol{X}^{\text{Trunc},*}_{j,\text{test,exo}} \hat{\boldsymbol{w}}_j \qquad j = 1, \ldots, J_{\text{exo}} \tag{6.18}$$

As Eq. (6.18) shows, the distribution of the construct scores is a linear combination of multivariate truncated normally distributed random variables with OrdPLS/OrdPLSc weight estimates based on the train data. The distribution of the construct scores has no simple form but can be approximated by simulation. To simulate this distribution for each subject, we generate $n_{\text{pred}} = 100$ drawings from a multivariate truncated normal distribution with a variance-covariance matrix that equals the polychoric correlation matrix of the train dataset and truncation limits that equal the threshold parameter estimates of this polychoric correlation matrix. As a consequence, we obtain n_{pred} draws in total for the unobservable variables underlying the ordinal indicators associated with exogenous constructs $\boldsymbol{X}^{\text{Trunc},*,p}_{j,\text{test,exo}}$ for $p = 1, \ldots, n_{\text{pred}}$, and thus, n_{pred} sets of predicted scores for each exogenous construct:

$$\hat{\boldsymbol{\eta}}^{p}_{j,\text{exo}} = \boldsymbol{X}^{\text{Trunc},*,p}_{j,\text{test,exo}} \hat{\boldsymbol{w}}_j \qquad j = 1, \ldots, J_{\text{exo}}, \quad p = 1, \ldots, n_{\text{pred}} \tag{6.19}$$

Considering a case in which there is a mixture of continuous and ordinal indicators associated with exogenous constructs, we generate n_{pred} drawings from a multivariate truncated normal distribution for both the ordinal and the continuous indicators to obtain construct scores. The variance-covariance matrix of the multivariate truncated normal distribution equals the estimated correlation matrix of the indicators based on the train dataset, which can contain polychoric, polyserial and Pearson correlations. We take the continuous indicators into account during the simulation to preserve the correlation structure. However, their generated values in $\boldsymbol{X}^{\text{Trunc},*,p}_{j,\text{test,exo}}$ are replaced by the corresponding observations from the test data. For the ordinal indicators, the truncation limits are appropriately chosen, conditional on categories that characterize the test data set by using the threshold estimates obtained by the polychoric/polyserial correlations based on the train data. In contrast, for the continuous indicators we use arbitrary lower and upper truncation limits, e.g., -10 and 10. Consequently, we obtain n_{pred} datasets for the indicators connected to exogenous constructs where the observations of the continuous indicators equal the observations from the test data, while for the ordinal indicators we use the generated dataset of the multivariate truncated normal distribution. Based on the resulting samples, we calculate the n_{pred} scores for each exogenous construct as follows:

$$\hat{\boldsymbol{\eta}}^{p}_{j,\text{exo}} = \boldsymbol{X}^{\text{Trunc},*,p}_{j,\text{test},\text{exo}} \hat{\boldsymbol{w}}_j \qquad j = 1, \ldots, J_{\text{exo}}, \quad p = 1, \ldots, n_{\text{pred}} \tag{6.20}$$

3. Predict the endogenous constructs' scores using the exogenous constructs' scores in accordance with the structural model, i.e., structural predictions. Using the n_{pred} predicted scores of the exogenous constructs, n_{pred} scores for the endogenous constructs can be predicted via the structural model:

$$\hat{\boldsymbol{\eta}}^{p}_{\text{end}} = \hat{\boldsymbol{\eta}}^{p}_{\text{exo}} \hat{\boldsymbol{\Gamma}}' (\boldsymbol{I} - \hat{\boldsymbol{B}}')^{-1} \qquad p = 1, \ldots, n_{\text{pred}} \tag{6.21}$$

For the case in which only continuous indicators are connected to exogenous constructs, the matrix with the predicted construct scores $\hat{\boldsymbol{\eta}}^{p}_{\text{exo}}$ is replaced by $\hat{\boldsymbol{\eta}}_{\text{exo}}$ from Eq. (6.17). Consequently, we do not obtain n_{pred} matrices containing predicted scores for the endogenous constructs, but only one matrix $\hat{\boldsymbol{\eta}}_{\text{end}}$.
4. Predict the values of the indicators belonging to the endogenous constructs, i.e., communal predictions. Here, two cases need to be distinguished, namely, ones in which (i) an indicator belonging to an endogenous construct is continuous, and (ii) an indicator belonging to an endogenous construct is ordinal.
If the indicator $\boldsymbol{x}_k$ belonging to the j-th endogenous construct is continuous, first n_{pred} predictions are obtained by multiplying the construct scores with the estimated loading from the train dataset:

$$\hat{\boldsymbol{x}}^{p}_{k,\text{end}} = \hat{\boldsymbol{\eta}}^{p}_{j,\text{end}} \hat{\lambda}_{j,k,\text{end}} \qquad j = 1, \ldots, J_{\text{end}} \quad k = 1, \ldots, K_j \quad p = 1, \ldots, n_{\text{pred}} \tag{6.22}$$

In contrast, if the indicator associated with an endogenous construct is ordinal, predictions for the continuous unobservable variables underlying the ordinal indicator have to be obtained first. As we have predicted n_{pred} scores for an endogenous construct, we also obtain n_{pred} predictions for the unobservable variable underlying the ordinal indicator. This we do by multiplying the endogenous construct's scores with the estimated loading corresponding to the k-th indicator $\boldsymbol{x}_k$ of the j-th endogenous construct η_j:

$$\hat{\boldsymbol{x}}^{*,p}_{k,\text{end}} = \hat{\boldsymbol{\eta}}^{p}_{j,\text{end}} \hat{\lambda}_{j,k,\text{end}} \qquad j = 1, \ldots, J_{\text{end}} \quad k = 1, \ldots, K_j \quad p = 1, \ldots, n_{\text{pred}} \tag{6.23}$$

Obviously, the only difference between the procedure for continuous and ordinal variables is that for the latter the values of the unobservable variable underlying the ordinal variable are predicted.

Finally, to obtain one prediction for each observation of the test dataset, the location of the distribution of the n_{pred} predictions for the indicators of the endogenous constructs need to be obtained. For this purpose, Cantaluppi and Boari (2016) proposed the *mean*, the *median*, and the *mode* approach. In the case of the mean approach, the i-th value of a continuous indicator is predicted as the mean of the n_{pred} draws, expressed as:

$$\hat{x}^*_{k,i,\text{end}} = \frac{1}{n_{\text{pred}}} \sum_{p=1}^{n_{\text{pred}}} \hat{x}^{*,p}_{k,i,\text{end}} \qquad i = 1, \ldots, N \tag{6.24}$$

The median approach works similar to the mean approach; however, instead of using the mean to determine the location of the distribution of the n_{pred} predictions, the median is used. While for continuous indicators the final predictions equal these location values, for ordinal variables, the location values are transformed into ordinal values according to Eq. (6.1) using the estimated thresholds based on the train data.

As a third approach to summarizing the n_{pred} predictions, we can use the mode approach. It uses the maximum of the predicted unobservable variable's empirical density on the intervals defined by the thresholds. Consequently, this approach cannot be used for continuous indicators.

Finally, the continuous indicators' predicted values are brought back to their original scale using the mean and standard deviation of the train data.

6.4.3 Evaluating the Predictive Performance of OrdPLSpredict and OrdPLScpredict

To evaluate the predictive performance of OrdPLSpredict and OrdPLScpredict, the RMSE or MAE as proposed for PLSpredict can be used. However, in the context of OrdPLSpredict and OrdPLScpredict, for ordinal indicators they are interpreted as penalties of 0 in the presence of exact predictions, as penalties of 1 if a category $h-1$ or $h+1$ is predicted for the observed category h, and as penalties of 2 (MAE) or 4 (RMSE) if a category $h-2$ or $h+2$ is predicted for category h, and so on. Moreover, the misclassification error rate (MER) can be computed as the fraction of incorrect classifications (James et al., 2021).

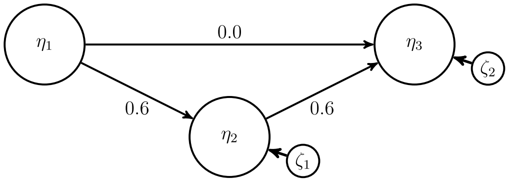

Fig. 6.3 Structural model

6.5 Monte Carlo Simulation

To assess the performance of OrdPLSpredict and OrdPLScpredict, we conducted a Monte Carlo simulation. Specifically, we compared the accuracy of predictions for continuous and ordinal indicators obtained by OrdPLScpredict, OrdPLSpredict, PLScpredict, and PLSpredict. For OrdPLSpredict and OrdPLScpredict, we used the *mean* and the *median* approach to obtain the final predictions of the indicators. To ensure a fair comparison of the different methods in terms of their ability to predict ordinal indicators, we rounded the original continuous predictions of PLSpredict and PLScpredict to integer values to obtain predicted categories.

6.5.1 Simulation Design

To compare the various approaches' performance, we considered a population model consisting of one exogenous latent variable η_1 and two endogenous latent variables η_2 and η_3. We assumed all latent variables to be standardized and related via a structural model, as follows:

$$\eta_2 = 0.6 \cdot \eta_1 + \zeta_1 \tag{6.25}$$

$$\eta_3 = 0.0 \cdot \eta_1 + 0.6 \cdot \eta_2 + \zeta_2 \tag{6.26}$$

Note, the exogenous latent variable η_1 is assumed to be uncorrelated with the structural disturbance terms ζ_1 and ζ_2. The structural model is displayed in Fig. 6.3.

Additionally, we measured each of the three latent variables by three indicators; therefore, x_{11}, x_{12}, and x_{13} loaded on η_1 with factor loadings of 0.8, 0.7, and 0.6, respectively; x_{21}, x_{22}, and x_{23} loaded on η_2 each with a factor loading of 0.7; and x_{31}, x_{32}, and x_{33} loaded on η_3 with factor loadings of 0.5, 0.7, and 0.9, respectively. Similar to the latent variables, the indicators were assumed to be standardized. Moreover, all structural disturbance terms and random measurement errors were assumed to be uncorrelated. Similarly, the latent variables were assumed to be uncorrelated with the random measurement errors. Consequently, we could give the population correlation matrix of the indicators as follows:

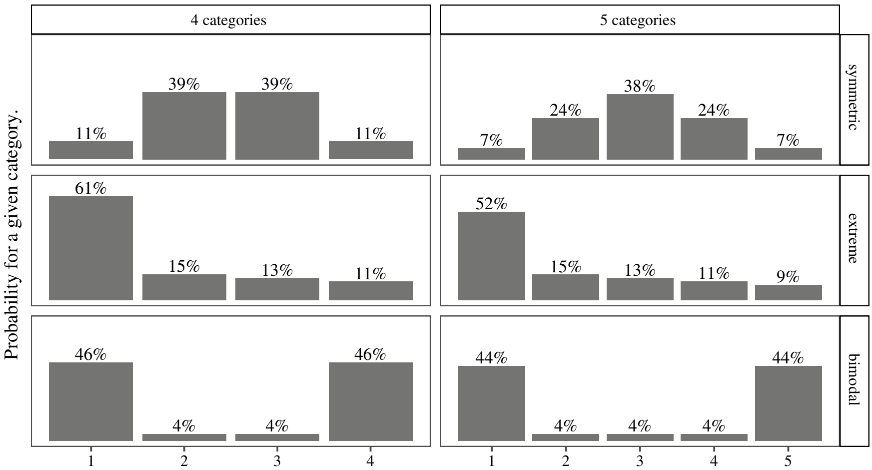

Fig. 6.4 Probability distribution of the ordinal indicators

$$\boldsymbol{\Sigma} = \begin{array}{c} \begin{array}{ccccccccc} \underline{x_{11}} & \underline{x_{12}} & \underline{x_{13}} & \underline{x_{21}} & \underline{x_{22}} & \underline{x_{23}} & \underline{x_{31}} & \underline{x_{32}} & \underline{x_{33}} \end{array} \\ \begin{pmatrix} 1.000 & & & & & & & & \\ 0.560 & 1.000 & & & & & & & \\ 0.480 & 0.420 & 1.000 & & & & & & \\ 0.336 & 0.294 & 0.252 & 1.000 & & & & & \\ 0.336 & 0.294 & 0.252 & 0.490 & 1.000 & & & & \\ 0.336 & 0.294 & 0.252 & 0.490 & 0.490 & 1.000 & & & \\ 0.144 & 0.126 & 0.108 & 0.210 & 0.210 & 0.210 & 1.000 & & \\ 0.202 & 0.176 & 0.151 & 0.294 & 0.294 & 0.294 & 0.350 & 1.000 & \\ 0.259 & 0.227 & 0.194 & 0.378 & 0.378 & 0.378 & 0.450 & 0.630 & 1.000 \end{pmatrix} \end{array} \tag{27}$$

To examine the approaches' performance in predicting ordinal indicators' values, the values of indicators x_{11}, x_{13}, x_{21}, x_{23}, and x_{33} were transformed as described in Sect. 6.2. In doing so, we varied the number of categories between four and five, and we considered three sets of threshold parameters. In the case of symmetrically distributed threshold parameters, all five indicators were categorized using the following threshold parameters: $-\infty$, -1.25, 0, 1.25, ∞ and $-\infty$, -1.5, -0.5, 0.5, 1.5, ∞, respectively. Similarly, for the extreme asymmetric threshold parameter distribution, we set the thresholds to $-\infty$, 0.28, 0.71, 1.23, ∞ in the case of four categories, and to $-\infty$, 0.05, 0.44, 0.84, 1.34, ∞ in the case of five categories. Moreover, we considered a bimodal distribution of the ordinal variables. In this case, the thresholds were set to $-\infty$, -0.1, 0, 0.1, ∞ for four categories and to -∞, -0.15, -0.05, 0.05, 0.15, ∞ for five categories. Figure 6.4 shows the corresponding probability distributions for the categories of the ordinal indicators.

The complete Monte Carlo simulation was carried out in the statistical programming environment R (R Core Team, 2021). To assess the influence of the train dataset's sample size on the approaches' predictive performance, we varied the sample sizes of the train dataset from 200, 500, and 1,000 observations. Hence, in total, we had 36 conditions: three different sample sizes of the train dataset (200, 500, and 1,000 observations) × two different numbers of categories for the ordinal indicators (four and five categories) × three sets of threshold parameters (symmetric, extreme asymmetric and bimodal) × two ways to obtain the final predictions for OrdPLScpredict and OrdPLSpredict (mean and median approach). To assess the approaches' predictive performance, we considered test datasets containing $N = 100$ observations. Additionally, we focused on the following three predictive performance measures: (i) MAE, (ii) RMSE, and (iii) MER. Small values of these measures indicate accurate predictions. For each condition, we conducted 500 simulation runs. In each run, we drew a dataset from the multivariate standard normal distribution with a mean vector of $\mathbf{0}$ and the correlation matrix shown in Eq. (27) using the `mvrnorm()` function of the MASS package (Venables & Ripley, 2002). The number of draws equaled the train dataset's sample size from the corresponding condition plus the 100 observations of the test dataset. Subsequently, we categorized the observations for the variables x_{11}, x_{13}, x_{21}, x_{23}, and x_{33} to obtain ordinal variables using threshold parameters from the corresponding condition. To estimate the model by PLS, PLSc, OrdPLS, and OrdPLSc, we used the `csem()` function of the R package cSEM (Rademaker & Schuberth, 2020). In doing so, the path weighting scheme was used for inner weighting and Mode A was used to calculate the weights to form the proxies for the latent variables. Additionally, we replaced inadmissible estimations, i.e., each condition was based on 500 valid estimations. An inadmissible estimation suffers from at least one of the following problems: (i) the PLS algorithm has not converged, (ii) at least one reliability estimate is larger than 1, (iii) at least one absolute factor loading estimate is larger than 1, (iv) the model-implied construct correlation matrix is not positive semi-definite, and/or (v) the model-implied indicator correlation matrix is not positive semi-definite. Next, to apply OrdPLScpredict, OrdPLSpredict, PLScpredict, and PLSpredict, we used the `predict()` function of the R package cSEM to obtain the predictions for the indicators associated with endogenous constructs.

6.5.2 Simulation Results

In this section, we present the results of our Monte Carlo simulation. Since the results for the ordinal indicators and the continuous indicators, respectively, are very similar, we only present the results for the ordinal indicator x_{23} and for the continuous indicator x_{31}. Further, the results for four and five categories are very similar. Therefore, we only report the results for four categories. Furthermore, the results are only slightly affected by the train dataset's sample size. Hence, we only report the results for 500 observations. Finally, the results for the mean and median approaches used to obtain the predictions with OrdPLScpredict and OrdPLSpredict hardly differ. Therefore,

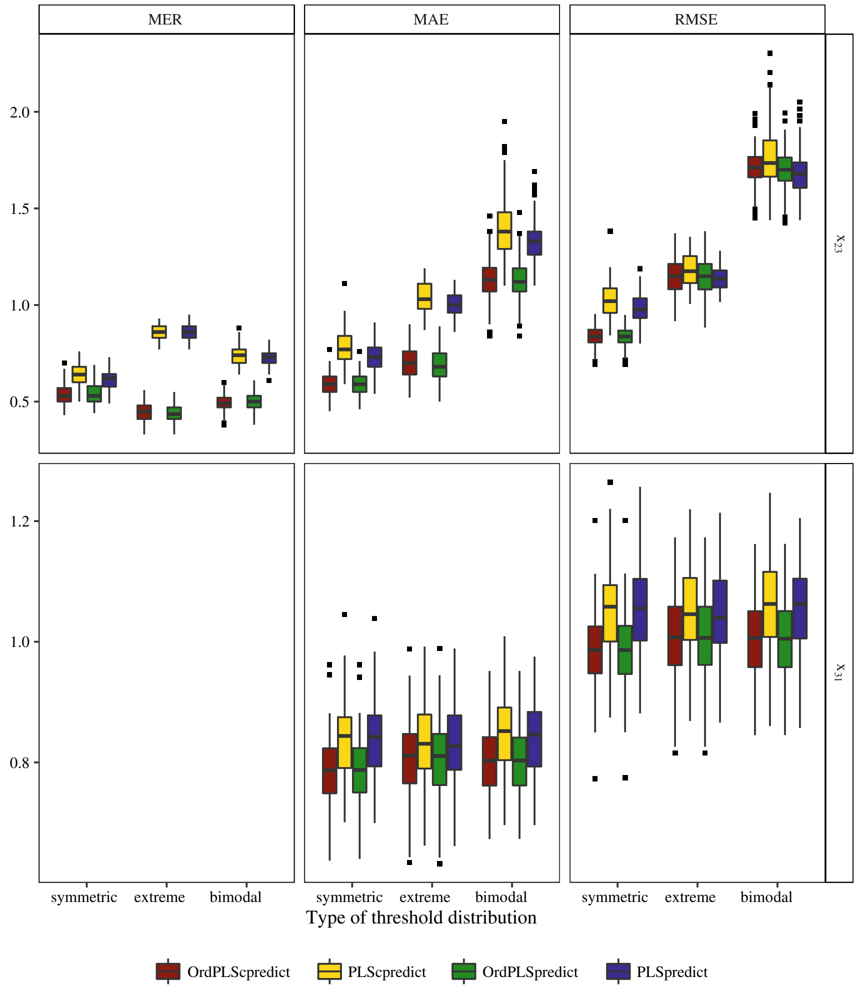

Fig. 6.5 Box plots of the performance measures

we report only the results for the mean approach. The complete results are given in the Supplementary Material.

Figure 6.5 shows the boxplots for the three performance measures, namely, the MER, the MAE, and the RMSE over the 500 simulation runs. In specific, the line in the boxes illustrate the median of the respective performance measure over all simulation runs. While the expanse of the boxes and the length of the whiskers illustrate the variation of the performance measures over all simulation runs, the dots depict outliers. Since the MER is not consistent with the nature of continuous variables for which exact matches are not expected, we only consider the MER for the ordinal indicator x_{23}.

Considering the ordinal indicator x_{23}, OrdPLScpredict and OrdPLSpredict produce very similar results. The same is observed for PLScpredict and PLSpredict. Also, the four approaches produce very similar results in terms of medians of the RMSE for an extremely asymmetric threshold distribution and a bimodal distribution of the ordinal variables. However, there are also differences between the approaches. Considering the median of the MAE and the MER, OrdPLScpredict and OrdPLSpredict outperform PLScpredict and PLSpredict. This is particularly obvious in the case of the extreme asymmetric threshold parameter distribution and a bimodal distribution of the ordinal variables. Considering the variation of predictions per condition, the approaches perform similar for all the performance measures. Considering the continuous indicator x_{31}, OrdPLSpredict and OrdPLScpredict outperform their traditional counterparts considering the median performance measures.

6.5.3 Simulation Insights

The results of our Monte Carlo simulation show that correcting for attenuation in case of latent variables does not increase the prediction accuracy. Moreover, they show that OrdPLSpredict and OrdPLScpredict outperform PLSpredict and PLScpredict for most of the simulation conditions in terms of performance measures' median. This is particularly the case for ordinal indicators with an extremely asymmetric or bimodal distribution of the categories. Finally, the approach to determine the location of the distribution of the predictions of the latent variables underlying the ordinal variables, i.e., mean and median, does not influence the predictive performance. However, the results are less clear for the RMSE in combination with extremely skewed threshold distribution or bimodally distributed ordinal variables.

6.6 Guidelines on Performing Predictions Using the R Package cSEM

To illustrate how researchers can apply OrdPLScpredict, OrdPLSpredict, PLScpredict, and PLSpredict, we provide guidelines for the open source R package cSEM. In doing so, we focus on a model that Hwang and Takane (2004) studied. We display their model in Fig. 6.6. To preserve clarity, we have omitted the random measurement error terms and the structural error terms. For a motivation of the model, the interested reader is referred to the article of Hwang and Takane (2004). As Fig. 6.6 shows, the model consists of the following four latent variables: organizational prestige (OrgPres), organizational identification (OrgIden), affective commitment (Love) (Afflove), and affective commitment (Joy) (AffJoy). Bergami and Bagozzi (2000) give an elaboration of the constructs. The considered dataset is part of the survey data used in Bergami and Bagozzi's (2000) study. It consists of 305 observations for the 21 indicators. Each indicator is measured on a 5-point scale ranging from 1

(=strongly disagree) to 5 (=strongly agree), i.e., all indicators are ordinal. A detailed description of the indicators can be found in Henseler (2021, Table 6.1).

As a first step, we need to estimate the model parameters. For this purpose, we can use the `csem()` function of the cSEM R package. In general, the `csem()` function requires a dataset and a model as input.

To specify models in cSEM, lavaan syntax (Rosseel, 2012) is used. Specifically, the '=~' operator is used to specify the relationship between indicators and latent variables, the '<~' operator is used to specify indicators forming an emergent variable, and the '~' operator is used to specify the structural model. The specification for the model illustrated in Fig. 6.6 is given as follows:

```
.model <-"
#Measurement models
OrgPres =~ cei1 + cei2 + cei3 + cei4 + cei5 + cei6 + cei7 + cei8
OrgIden =~ ma1 + ma2 + ma3 + ma4 + ma5 + ma6
AffJoy  =~ orgcmt1 + orgcmt2 + orgcmt3 + orgcmt7
AffLove =~ orgcmt5 + orgcmt 6 + orgcmt8

# Structural model
OrgIden ~ OrgPres
AffLove ~ OrgIden
AffJoy  ~ OrgIden
"
```

The dataset we use here is publicly available and also provided in the cSEM R package. However, as it is provided in the cSEM package all indicators are labeled as *numeric*. In this case, the `csem()` function uses the Pearson correlations to estimate

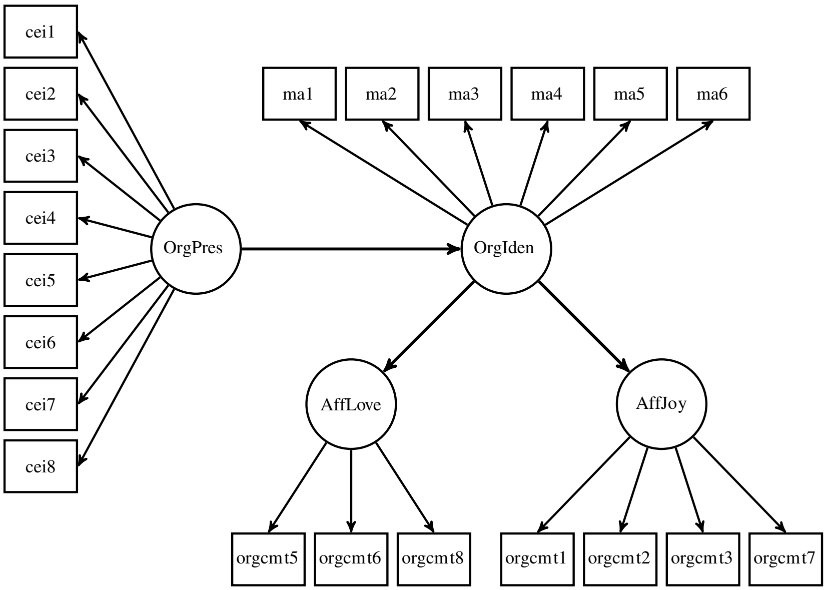

Fig. 6.6 Model from Hwang and Takane (2004)

the model parameters, i.e., PLS or PLSc is employed. To use the polychoric/polyserial correlations, and thus to apply OrdPLS or OrdPLSc, the ordinal indicators need to be labeled as *ordered factors*, as shown in the following:

```
library(cSEM)

# Load the data from the cSEM package
data(BergamiBagozzi2000)

# Transform the numerical indicators into factors
data_new <- as.data.frame(lapply(BergamiBagozzi2000, as.ordered))
```

Finally, to estimate the model parameters, the dataset and the specified model are provided as input to the `csem()` function as the following shows:

```
res <- csem(.model = .model, .data = data_new[1:250,], .resample_method = "bootstrap")
```

To evaluate our model's predictive performance, we use only the first 250 observations of the dataset for the estimation. Note that cSEM applies a correction for attenuation by default if latent variables are included in the model, i.e., PLSc or OrdPLSc is used. Further, by default, cSEM uses the path weighting scheme to calculate the inner weights. In our case, the specified model was estimated by OrdPLSc since at least one indicator is labeled as factor and the model comprises at least one latent variable. If the user aims for statistical inference about the parameter estimates, the argument '.resample_method' has to be set to either 'bootstrap' or 'jackknife', otherwise no standard errors will be estimated. In our case, we used bootstrap for statistical inference. By default, 499 bootstrap runs are conducted. A summary of the estimated model can be obtained via the `summarize()` function.

To assess the estimated model's predictive performance, the `predict()` function is used. Evaluating the predictive performance of a model requires benchmark predictions. For that purpose, the '.benchmark' argument of the `predict()` function can be used to determine how benchmark predictions are obtained. In cases where the original model was estimated by OrdPLSc or OrdPLS, the benchmark predictions are rounded for the ordinal indicators if PLS or PLSc were used to estimate the benchmark model. If predictions based on OrdPLSpredict were to be used as benchmark, the '.benchmark' argument must be set to 'PLS-PM', the argument '.treat_as_continuous' must be set to 'FALSE', and the argument '.disattenuate' has to be set to 'FALSE' to prevent a correction for attenuation. In the case of OrdPLScpredict and OrdPLSpredict, by default $n_{\text{pred}} = 100$ draws are performed from the multivariate truncated normally distributed unobservable variables underlying the ordinal indicators associated with exogenous constructs. To determine the location of the distribution of the n_{pred} predictions for the indicators of the endogenous constructs, the 'mean', 'median', or 'mode' approach can be used. The approach can be chosen separately for the target predictions and the benchmark predictions using the arguments '.approach_score_target' and '.approach_score_benchmark', respectively.

The `predict()` function allows the user to provide a test dataset via the '.test_data' argument. If no test dataset is provided, k fold cross-validation is applied, i.e., the dataset from the original estimation is randomly split into k (approximately) equal parts. Subsequently, the values of each part are predicted based on a model estimated on the basis of the remaining parts. To adjust the number of cross-validation folds the '.cv_folds' argument is used. By default this argument is set to 10. To minimize the effect of random splitting in k fold cross-validation, the k fold cross-validation is repeated several times (Shmueli et al., 2019). In the `predict()` function, the number of repetitions is adjusted via the argument '.r'. If a test dataset is provided, no k fold cross-validation is conducted and predictions are performed based on the observations of the test dataset.

For the considered empirical example, we used PLScpredict as benchmark, and provided the last 55 observations of the original dataset as test dataset, i.e., only the observations of the test dataset were predicted. Additionally, we used the 'median' approach to obtain predictions in OrdPLScpredict. The results of the `predict()` function are as follows.

```
pred <- predict (.object = res, .benchmark = "PLS-PM" , .test_data = data_new[( 251) : 305,],
                 .treat_as_continuous = TRUE, .approach_score_target = "median" )

pred
```

The output contains some general information in the top. Moreover, the user can choose the performance measures to assess the accuracy of the predictions for the indicators associated with the endogenous constructs. For our example, we report the MAE and the MER:

```
print(pred, .metrics = c("MAE", "MER"))
```

```
## ---------------------------------------------------------------------------------
## ----------------------------------- Overview -----------------------------------
##
##  Number of obs. training          = 250
##  Number of obs. test              = 55
##  Number of cv folds               = NA
##  Number of repetitions            = 1
##  Handle inadmissibles             = stop
##  Estimator target                 = 'OrdPLS'
##  Estimator benchmark              = 'PLS-PM'
##  Disattenuation target            = 'TRUE'
##  Disattenuation benchmark         = 'TRUE'
##  Approach to predict              = 'earliest'
##
## ------------------------------ Prediction metrics ------------------------------
##
##
##   Name        MAE target  MAE benchmark   MER target  MER benchmark
##   ma1             0.5091         1.3455       0.4727         0.8909
##   ma2             0.4545         1.3818       0.4364         0.9455
##   ma3             0.5636         1.0000       0.5091         0.7273
##   ma4             0.6000         1.6909       0.5273         0.9455
##   ma5             0.6909         1.6545       0.5636         0.9273
##   ma6             0.5636         1.2182       0.5091         0.8364
##   orgcmt5         0.4000         0.9818       0.3636         0.8182
##   orgcmt6         0.4727         0.6545       0.4545         0.5636
##   orgcmt8         0.7455         0.9091       0.6182         0.6909
##   orgcmt1         0.6727         1.1818       0.6000         0.8182
##   orgcmt2         0.5818         1.1273       0.5455         0.8182
##   orgcmt3         0.5455         1.1273       0.5091         0.8000
##   orgcmt7         0.5636         0.8364       0.5091         0.7091
## ---------------------------------------------------------------------------------
```

Considering our example's MAE, the results show that OrdPLScpredict outperforms PLScpredict. Moreover, it shows that the MER is smaller for all indicators in the case of OrdPLScpredict, which indicates more accurate predictions than those obtained by PLScpredict. These results are also in line with the findings of our Monte Carlo simulation.

In general, the cSEM R package provides users with a lot of flexibility. For more details about the package, we refer the interested reader to the manual. Also, additional tutorials using the cSEM package can be found in Henseler (2021).

6.7 Discussion

The past decade has seen increased scholarly attention to evaluating the predictive power of models estimated by PLS (e.g., Shmueli et al., 2016; Carrión et al., 2016; Shmueli et al., 2019). This is mainly due to the *causal-predictive* nature of PLS (Chin et al,, 2020). However, as Schuberth et al. (2023a) has emphasized, if PLS is applied in the context of explanatory modeling, i.e., in theory testing, researchers should not rely solely on predictive metrics for model evaluation, but should also consider all possible means known from explanatory modeling for model assessment, including overall model fit assessment.

In this chapter, we have focused on the predictive power of models estimated by OrdPLS and OrdPLSc. Specifically, we presented OrdPLScpredict and OrdPLSpredict. The two approaches are similar to those known from PLS and PLSc to perform predictions, namely PLSpredict and PLScpredict. In contrast to PLSpredict and PLScpredict, our two proposed approaches take the nature of ordinal indicators into account. Additionally, our approaches resemble those Cantaluppi and Schuberth (2019) proposed. However, our two proposed approaches are not limited to models containing only ordinal indicators.

The results of our Monte Carlo simulation to evaluate OrdPLScpredict's performance provides several interesting insights. First, OrdPLScpredict and OrdPLSpredict outperform PLScpredict and PLSpredict in cases where values of continuous indicators are predicted. Second, considering the MER and the MAE evaluation metric, OrdPLScpredict and OrdPLSpredict outperform the other approaches in cases where values of ordinal indicators are predicted. Third, the approach to determine the location of the distribution of the predictions of the latent variables underlying the ordinal indicators, i.e., mean or median approach, does not influence the predictive performance of OrdPLSpredict and OrdPLScpredict. Finally, comparing the performance of OrdPLScpredict and OrdPLSpredict to the performance of PLScpredict and PLSpredict, the results show that not correcting for attenuation, even if the parameter estimates are not consistent, does not lead to a worse predictive performance.

A crucial point in predictive research is the principle that estimation should be based solely on the train dataset, while evaluating predictions should be based solely on the test dataset (James et al., 2021). In OrdPLSpredict and OrdPLScpredict, we simulate values for the indicators connected to exogenous constructs from a multivariate truncated normal distribution if ordinal variables are present. Specifically, we use a variance-covariance matrix that equals the estimated correlation matrix and truncation limits that equal the estimated thresholds of the train dataset. Although using estimated threshold parameters based on the train dataset is the only feasible solution in various situations, e.g., in cases of small test datasets, future research should evaluate ways of rendering the current prediction method more robust to situations in which the test data set's correlation structure slightly differs from the one observed on the train data set. For instance, research could consider the effect on a model's predictive performance if the test dataset's correlation matrix instead the train dataset's is used for simulating the scores of exogenous constructs. Moreover, the polychoric and polyserial correlation used in OrdPLS/OrdPLSc show some limitations. For instance, they assume that the continuous variables underlying the ordinal indicators are multivariate normally distributed and require a sufficient sample size to avoid empty cells, i.e., a combination of categories is not present in the dataset. To address a violation of the normality assumption, a robust version of the polychoric correlation has recently been proposed (Lyhagen & Ornstein, 2023). Future research should investigate how this robust version can be used in OrdPLSpredict and OrdPLScpredict. To obtain the final predictions of OrdPLSpredict and OrdPLScpredict, we use the mean, median and mode approach. However, the linear combination of truncated multivariate normally distributed variables does not need to be unimodally distributed, which might negatively impact the performance of the mean, median and mode approach. Consequently, future research should study the distribution of the sets of the predicted exogenous construct scores in more detail. Furthermore, although our results were hardly affected by the performance measure used, i.e., the RMSE, the MAE and the MER, future research should consider further metrics to evaluate the predictive performance in case of ordinal indicators and provide guidelines on which measure to use in which situation. Finally, simulation studies are limited regarding their design. Consequently, future research should evaluate the effect of our chosen simulation parameters, e.g., test data sample size and model complexity, and compare the performance of OrdPLScpredict to predictions based on other estimation methods such as non-metric partial least squares (Russolillo, 2012), generalized structured component analysis (Hwang & Takane, 2004), approaches to generalized canonical correlation analysis (Kettenring, 1971) or maximum-likelihood estimator (Jöreskog, 1970; Schuberth, 2023).

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Chapter 7
Multicollinearity: An Overview and Introduction of Ridge PLS-SEM Estimation

Sandra Streukens and Sara Leroi-Werelds

Abstract Multicollinearity, or the existence of excessive correlations among (combinations of) predictor variables, is a commonly encountered phenomenon that affects (PLS-SEM) parameter estimates. This chapter provides an extensive overview of multicollinearity, its consequences, detection, and possible solutions. Critical to this overview is the explicit distinction among three types of multicollinearity: canonical structural multicollinearity, numerical multicollinearity, and common-factor multicollinearity. In addition, ridge PLS-SEM—an approach that combines the principles of ridge regression and PLS-SEM modeling—is introduced as an effective approach to mitigate the effects of canonical structural multicollinearity on estimation results.

7.1 Introduction

Multicollinearity refers to the existence of excessive correlations among (combinations of) predictor variables and is a common issue in empirical research (Grewal et al., 2004; Iacobucci et al., 2016). In a nutshell, multicollinearity affects parameter estimates and is associated with increased rates of type I and type II errors, meaning that researchers may derive the wrong conclusions from their data. On a more general level, multicollinearity thus may hamper theory development (see also Farley et al., 1998). In summary, it is safe to state that an in-depth understanding of multicollinearity is essential for all researchers, but especially those who work with quantitative data.

However, the literature on (the consequences of) multicollinearity, how to detect or potentially avoid it, and ultimately how to account for it in model estimation is

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often too technical, fragmented, and sometimes even misleading. To illustrate this latter point, consider the deletion of the variable(s) that cause(s) multicollinearity as perhaps the most commonly suggested solution to the multicollinearity problem. Although this may be correct from a strictly technical point of view, it is problematic as it leads to specification errors and thus again to false conclusions.[1]

Against this backdrop, the aim of this chapter is twofold: (1) to provide an extensive overview of key issues related to multicollinearity, and (2) to propose an approach that enables researchers to deal with multicollinearity in a PLS-SEM context. Regarding the first objective, Sect. 7.2 of this chapter focuses on defining multicollinearity, understanding the consequences of multicollinearity, detecting multicollinearity, and providing possible solutions to multicollinearity. Section 7.3 of this chapter focuses on the second objective and proposes an approach that incorporates the idea of Hoerl and Kennard's (1970) ridge estimators in the PLS-SEM estimation method (i.e., ridge PLS-SEM).

Overall, this chapter aims to make the following contributions. First, given the adverse effects of multicollinearity on empirical results and the potential erroneous substantive conclusions drawn from these empirical results, having a good understanding of this phenomenon cannot be underemphasized. The extensive literature overview provided in this chapter aims to offer and expand this knowledge in an accessible way to applied researchers regardless of their domain. A critical consideration is the distinction between different sources of multicollinearity. Although the different types of multicollinearity are all addressed in this chapter, special attention is devoted to canonical structural multicollinearity as ridge PLS-SEM only applies to this type of multicollinearity. Second, deciding whether ridge PLS-SEM is indeed a feasible modeling strategy requires being able to detect the presence of (different sources of) multicollinearity. Therefore, building on recent advances in the field of multicollinearity detection, we propose a comprehensive strategy to assess and evaluate the presence of different types of multicollinearity. Again, canonical structural multicollinearity receives most attention. Third, ridge PLS-SEM offers a generally applicable approach that allows researchers to more optimally realize the benefits of PLS-SEM in situations where canonical structural multicollinearity is present. Although some technicalities are unavoidable in developing this approach, we again aim to make it as accessible as possible for applied researchers. Moreover, while the details to practically implement ridge PLS-SEM are outlined in this chapter, the focus is predominantly on the conceptual and/or theoretical underpinnings of this approach.

[1] Note that the consequences of variable elimination in order to reduce the effects of multicollinearity depend on the type of multicollinearity (see Sect. 7.2).

7.2 Multicollinearity: An Overview

For reasons of clarity but without loss of generalizability, this section focuses on observable variables in the context of a single equation rather than on composites measured by multi-items in a nomological network of relationships. See also Appendix for an overview of the model used in this section.

7.2.1 Multicollinearity Can Stem from Different Sources

Without exception, introductory econometrics textbooks as well as textbooks on business research methods define multicollinearity as a state of high correlation among predictor variables (see, for instance, Ramanathan, 1998; Hair et al., 1998; Malhotra & Birks, 2003). Although this definition is correct, it foregoes that multicollinearity can stem from different sources. Understanding the source of multicollinearity is nontrivial, as it impacts the method that is appropriate to detect multicollinearity as well as the avoidance/remediation of the effects of multicollinearity on estimation results (Kalnins, 2018, 2022; Spanos & McGuirk, 2002).

To understand the sources of multicollinearity, the data generating process (DGP) needs to be considered (Kalnins, 2018). The canonical DGP fully complies with the Gauss-Markov assumptions, and a regression-based model yields the best linear unbiased estimates (i.e., BLUE). Assuming a canonical DGP, Spanos and McGuirk (2002) make a distinction between structural multicollinearity and numerical multicollinearity. In the remainder of this chapter, structural multicollinearity under a canonical DGP will be referred to as canonical structural multicollinearity. Under the common-factor DGP, the outcome variable is acted upon by a factor common to (a pair of) independent variables in the model. This common-factor may represent a common source of measurement error or a meaningful but unobservable causal variable. Note that multicollinearity in case of a common DPG is also structural in nature. As a result, this type of multicollinearity will be referred to as common-factor structural multicollinearity.

Sections 7.2.2, 7.2.3 and 7.2.4 describe each of these three types of multicollinearity (i.e., canonical structural multicollinearity, numerical multicollinearity, and common-factor structural multicollinearity). For each type of multicollinearity, we describe consequences in terms of estimation results, guidelines on its detection, and potential solutions to deal with multicollinearity. As mentioned before, canonical structural multicollinearity is particularly relevant in the context of this chapter, as the suggested ridge PLS-SEM represents an approach that can be used to deal with this type of multicollinearity. Conversely, ridge PLS-SEM does not offer a solution to combat the effects of numerical and common-factor structural multicollinearity.

7.2.2 Canonical Structural Multicollinearity

7.2.2.1 Description

Canonical structural multicollinearity is inherent to the model and the accompanying data (Spanos & McGuirk, 2002). Even with a solid research design it cannot be avoided, and the best strategy is to adopt an estimation approach that effectively deals with (the consequences of) this type of multicollinearity.

7.2.2.2 Consequences

Spanos and McGuirk (2002) formally demonstrate that canonical structural multicollinearity affects the regression coefficients, their variance, and the accompanying *t*-values (see Appendix for a detailed more technical explanation). It is important to stress that the impact of multicollinearity on the various model parameter estimates is complex and nonmonotonic (see also the simulation results presented in Spanos & McGuirk, 2002). First, the magnitudes of the estimated regression coefficients (i.e., $\widehat{\beta}_p$ and $\widehat{\beta}_q$) can be affected by canonical structural multicollinearity, but the Gauss-Markov theorem is not invalidated and the estimators remain BLUE. In terms of predictions based on the regression coefficients, it should be noted that "in general, if the data points at which prediction of the response is made are within the region where the model was fitted and where the same pattern of multicollinearity holds, then prediction if fairly precise" (Ofir & Khuri, 1986, p. 184). Second, canonical structural multicollinearity increases the variance estimates of the parameters (i.e., $var(\widehat{\beta}_p)$ and $(var(\widehat{\beta}_q))$ thereby yielding to the erroneous conclusion that the parameters are statistically insignificant. As the *t*-value accompanying the regression coefficient is the ratio of this coefficient over its (inflated) variance estimated, the t-value will consequently decrease. Put differently, canonical structural multicollinearity rather leads to an underestimate of statistical significance rather than an overestimate. As the idea of *t*-values is inconsistent with the distribution-free nature of PLS-SEM, researchers ideally should use PLS-SEM in combination with (bias-corrected and accelerated) percentile bootstrap confidence intervals (Streukens & Leroi-Werelds, 2016) to draw conclusions about parameter significance. Although the variance estimates do not directly play a role in the construction of these confidence intervals, the width of the bootstrap confidence intervals does increase as a consequence of canonical structural multicollinearity (see Beasley, 2014 for simulation results). These wider confidence intervals (which are due to canonical structural multicollinearity) are not surprising as—theoretically—bootstrap distributions are expected to follow the properties of a statistic if random samples are repeatedly drawn from the same underlying population (Zieffler et al., 2011). Third, highly collinear variables lead to parameter estimates that are highly related, thereby making it very difficult to interpret individual coefficients. This is clear when one considers how the correlation coefficient between two estimated model coefficients $\widehat{\beta}_p$ and $\widehat{\beta}_q$ (i.e., $cor(\widehat{\beta}_p, \widehat{\beta}_q)$) depends on the degree of multicollinearity ρ between the associated variables X_p and X_q.

$$cor\left(\widehat{\beta}_p, \widehat{\beta}_q\right) = \frac{-\sigma^2\rho}{(1-\rho^2)}$$

As can be concluded from this equation, the absolute value of the correlation between the estimated model coefficients substantially increases with higher levels of canonical structural multicollinearity. When coefficient estimates are correlated, each coefficient is capturing part of the effect of the other variable, thereby making it difficult to obtain the separate effects of X_p and X_q on the dependent variable$Y$. Or, as Ramanathan (1998) puts it: one cannot hold X_p constant and increase X_q alone, because due their intercorrelatedness a change in X_q per definition implies a change inX_p.

Despite the consequences of canonical structural multicollinearity outlined above, two remarks are in place to see these consequences in the right perspective. First, if j variables are highly correlated, then canonical structural multicollinearity only affects the standard errors of parameter estimates associated with these variables. Or as Lindner et al. (2020) put it: there is no evidence for "smearing" of the variance inflation to other independent variables. Second, canonical structural multicollinearity is often cited (see also Iacobucci et al. (2016)) as a problem in models containing interaction effects (moderated regression analysis). However, Disatnik and Sivan (2016) and McClelland et al. (2017) show that this is a methodological illusion and that all kinds of procedures such as mean-centering and Lance's (1988) residual centering approach are unnecessary and even may do more harm than good.

7.2.2.3 Detection

Three detection methods are often mentioned in empirical studies, but have some significant drawbacks in the context of canonical structural multicollinearity, include the inspection of pairwise correlations, the combination of a high coefficient of determination with insignificant model coefficients, and the condition number. The first detection method advises researchers to take a look at the pairwise correlations between variables or constructs to detect potential sources of multicollinearity. Although this is technically correct as (canonical) structural multicollinearity is de facto defined as a high degree of correlation between variables, this approach is less helpful than one might initially think. The reason for this is that canonical structural multicollinearity can also occur at a multivariable (i.e., more than 2 variables) level (see for instance Kmenta, 1986) which remains undetected by solely inspecting pairwise correlation coefficients. At the very best, inspection of the correlation matrix should only be used as a very preliminary step in detecting multicollinearity (see also Ofir and Kuhri, 1986). Second, another often-mentioned indicator of multicollinearity mentioned in econometric textbooks is the combination of a highly significant coefficient of determination with very few significant coefficients. Although this indeed can be a sign of (canonical) structural multicollinearity, Spanos and McGuirk

(2002) demonstrate that this is not necessarily the case, thereby compromising the reliability of this detection approach. A third approach is the condition number of the moment matrix of the regressors (i.e., $X^T X$). However, the condition number is a measure of numerical multicollinearity not canonical structural multicollinearity. Put differently, canonical structural multicollinearity cannot be detected by means of the moment matrix' condition number. Therefore, the condition index is discussed in detail in Sect. 7.2.3 that focuses on numerical multicollinearity.

In contrast to the three approaches mentioned above, the variance inflation factor (VIF) seems to be the most feasible approach as it is associated with detecting canonical structural multicollinearity and takes a multivariable perspective (cf. O'Brien, 2007). The VIF is the ratio of the variances of the least squares coefficients relative to a situation in which the independent variables are orthogonal (i.e., correlations among independent variables are equal to zero). Following Marquardt (1970) the VIF can be expressed as

$$\mathrm{VIF}_j = \frac{\mathrm{var}\left(\hat{\beta}_j\right)}{\mathrm{var}\left(\hat{\beta}_{jo}\right)} = \left(1 - R_j^2\right)^{-1}, \quad j - 1, 2, \ldots p$$

where $\widehat{\beta}_j$ is an estimator ofβ_j, $\widehat{\beta}_{j0}$ is the corresponding estimator under a model with the j th regressor orthogonal to the other explanatory variables and R_j^2 is the coefficient of determination resulting from regressing each j th variable on the remaining explanatory variables. For a set of p predictor variables, p VIF values are computed.

Often, the obtained VIFs are compared to a cut-off value in order to decide whether canonical structural multicollinearity poses a threat or not. Commonly used cut-off values include 10 or 4 to indicate the presence of serious canonical structural multicollinearity, whereas SmartPLS (Ringle et al., 2022) flags VIF values that are equal or larger than 5 (in red) and between 3 and 5 (black). As tempting as it may be to (blindly) rely on such cut-off values, modeling reality is more complex. For instance, O'Brien (2007) shows that even a VIF that exceeds the value of 40 may not be problematic. In contrast, Vatcheva et al. (2016) summarize studies illustrating that a relatively low VIF value does not necessarily mean that canonical structural multicollinearity does not have an effect. Apparently there does not seem to be a fixed guideline on how to interpret VIF values and given that multiple other factors may influence the variance of the regression coefficients (see also O'Brien, 2007), it is also very unlikely that such a complex phenomenon can be captured in a single number. So, an important issue that arises is: what should a researcher do when interpreting the obtained VIF values? O'Brien (2007) stresses that VIF values should be seen in light of model characteristics such as the coefficient of determination, effect sizes and sample size. In a field like business research, which is often characterized by relatively small samples and relatively low coefficients of determination and effect sizes (see also Grewal et al., 2004; Peterson et al., 1985), the use of more conservative cut-off VIF values is recommended. With regard to this latter point, the work of Freund and Wilson (1998) is helpful in determining whether a VIF should be seen as indicative of serious canonical structural multicollinearity or not. According to Freund and Wilson (1998), the VIF should be interpreted in light of the model's own coefficient of determination (i.e., R_Y^2). More specifically, they state that a VIF can be considered as high when it meets the following equation.

$$\text{VIF} > 1\big/\left(1 - R_Y^2\right)$$

If this equation holds, it indicates that the correlation between the predictors is stronger than the regression relationship and multicollinearity can affect the estimates (cf. Freund & Wilson, 1998).

It should be noted that the VIF assumes that the correlated predictor variables contain only redundant information about the outcome variable. Although this assumption often holds, exceptions are possible. Curto and Pinto (2011) show, following the work of Hamilton (1987), that if explanatory variables are not redundant, their importance increases due to the inclusion of another explanatory variable in the model which consequently leads to an overestimation of the actual variance inflation. For this particular situation, Curto and Pinto (2011) proposed a corrected VIF (CVIF).

$$CVIF_j = VIF_j \times \frac{1 - R_Y^2}{1 - R_0^2} = \frac{1}{1 - R_j^2} \times \frac{1 - R_Y^2}{1 - R_0^2}$$

In the so-called correction term $\frac{1-R^2}{1-R_0^2}$, R_0^2 is the coefficient of determination of the orthogonal model which can be obtained from the sum of all squared correlation coefficients of the dependent variable and each of the independent variables (i.e., $R_0^2 = R_{yx_1}^2 + R_{yx_2}^2 + \ldots .R_{yx_p}^2$) and R_Y^2 is the coefficient of the regression model without any restrictions in terms of orthogonality.

To determine whether the predictors contain (non) redundant information the regular coefficient of determination (R_Y^2) needs to be compared to the coefficient of determination belonging to the orthogonal model (R_0^2). For models that only contain redundant predictors $R_Y^2 < R_0^2$ is evidenced. In contrast, $R_Y^2 > R_0^2$ indicates the presence of non-redundant correlation among the predictors. In the redundant case, the VIF is appropriate, whereas the CVIF is a better measure for the inflated variance when there is non-redundant correlation present. The procedure to determine whether the CVIF value is indicative of multicollinearity parallels the one for the regular VIF (cf. Curto & Pinto, 2011), meaning the interpretation guidelines outlined above for the VIF also apply to the CVIF.

7.2.2.4 Solution

One often-used strategy to reduce multicollinearity is to remove variables from the model that are highly correlated with other variables (Lindner et al., 2020). While this technically reduces canonical structural multicollinearity, this strategy is far from desirable as it increases the risk of omitted variable bias. More specifically, Lindner et al. (2020) indicate that omitting a relevant but collinear variable leads to deflated standard errors and thereby may lead to spuriously significant and/or biased findings. In terms of theory testing, dropping predictors results in a model that no longer reflects the underlying theory (O'Brien, 2007). However, while generally agreeing that model respecification by eliminating one of more independent variables is indeed often problematic, O'Brien (2007, p. 683) rightfully states "At times, however, it may be reasonable to eliminate or combine highly correlated independent variables, but doing this should be theoretically motivated".

If model respecification is not feasible, estimation techniques that allow researchers to mitigate the effect of multicollinearity on the estimation results are extremely useful. In a PLS-SEM context, the work by Esposito Vinzi and Russolillo (2013), and Jung and Park (2018) is especially noteworthy. Esposito Vinzi and Russolillo (2013) suggest the use of PLS regression (PLS-R) in combination with PLS-SEM to deal with canonical structural multicollinearity. PLS-R combines features of principal component analysis and multiple regression. Statistically the approach is valid, but in the analysis process this approach does not allow to keep the a-priori model specifications (both measurement and structural model) that were chosen based on existing theory. As such, the Esposito Vinzi and Russolillo (2013) approach is more suitable for data exploration. In contrast, the suggested ridge PLS-SEM approach (as well as the approach of Jung and Park (2018) discussed below) takes a more confirmatory stance and requires an explicit and theoretically solid definition of the measurement and structural model prior to conducting the analysis. Regularization techniques such as ridge regression are also well capable of controlling for the effects of canonical structural multicollinearity on the estimation results. Jung and Park (2018) proposed a method referred to as regularized PLSc which combines the idea of a ridge-type regularization parameter and consistent PLS (PLSc). Jung and Park's (2018) regularized PLSc approach, or RegPLSc, closely resembles the ridge PLS-SEM approach suggested in this chapter. The main difference between ridge PLS-SEM and RegPLSc is that the latter approach is restricted to models containing constructs that follow the principles of classical measurement theory (see also Henseler, 2021) For Ridge PLS-SEM this restriction does not apply, thereby offering a more versatile and general approach. It should be noted that Jung and Park's (2018) simulation study revealed that regularized PLSc outperforms standard PLSc in case of canonical structural multicollinearity, and as such provides a promising background for the ridge PLS-SEM approach to be introduced in Sect. 7.3. Please note that the papers of Esposito Vinzi and Russolillo (2013), Jung and Park (2018) provide excellent overviews of, respectively, the PLS-R and RegPLSc approach.

7.2.3 Numerical Multicollinearity

7.2.3.1 Description

Numerical multicollinearity is data-specific and is the result of an ill-conditioned data matrix. An ill-conditioned data matrix means that the resulting regression coefficients are very sensitive to small changes in the data matrix (Spanos & McGuirk, 2002). Numerical multicollinearity makes it hard to find a correct solution for the regression model and results in a solution that is prone to large numerical errors.

7.2.3.2 Consequences

As demonstrated by Spanos and McGuirk (2002) the impact of numerical multicollinearity on the regression output is volatile and cannot be systematically captured.

7.2.3.3 Detection

In assessing numerical multicollinearity, inspection of the condition number of the moment matrix of the regressors (i.e., $X^T X$) plays a central role. The condition number equals the ratio of the largest to the smallest eigenvalue value of the moment matrix and measures the sensitivity of the parameter estimates to small changes in the data matrix (Belsley, 1982). A high condition number means that small changes if the regressors are associated with large changes in the dependent variable (i.e., ill-conditioned matrix).

Traditionally, the following guidelines (cf. Belsley, 1982) are used in evaluating the presence of multicollinearity: condition numbers in the 10–30 range are indicative of moderately strong multicollinearity, and condition numbers larger than 30 indicate strong multicollinearity. However, to assess numerical multicollinearity, these guidelines in isolation are inadequate, as the condition number also conveys information about the presence of canonical structural multicollinearity (Salmerón et al., 2018). As such, Salmerón et al. (2018) suggest to evaluate the presence of numerical multicollinearity by assessing the difference between the condition number and the (corrected) VIF value. Two remarks are vital in this respect. First, it should be noted that the (corrected) VIF typically only captures canonical structural multicollinearity (Salmerón et al., 2018). Second, as outlined in Sect. 7.2.3.4, numerical multicollinearity can and should be avoided as much as possible. Hence, the procedure outlined in this paragraph only is feasible when the conditions to avoid numerical multicollinearity are met.

7.2.3.4 Solution

A special estimation approach to reduce the impact of numerical multicollinearity on estimation results does not exist and is also not feasible given the unpredictable consequences of numerical multicollinearity. Perhaps most important in the discussion of numerical multicollinearity is that it can be avoided to a large extent through the design of the empirical study. Below, several guidelines are summarized that can help researchers avoid numerical multicollinearity as much as possible. The first factor that needs to be considered is the composite reliability of constructs developed in line with paradigm of classic measurement theory. Both Grewal et al. (2004) and Mason and Perreault (1991) demonstrate that low reliability amplifies the effects of multicollinearity on the estimation results. This implies that even before data collection, numerical multicollinearity can be reduced by devoting attention to the development of multi-item measurement instruments of which the indicators are highly consistent (cf. classic measurement theory). Second, sample size has an impact on the extent to which multicollinearity impacts estimation results. This relationship, which is empirically demonstrated by Grewal et al. (2004), underscores the need for conducting formal a-priori power analyses to determine the sample size. Additionally, this is a warning against relying on the still widespread idea that in PLS-SEM the required sample size can simply be determined based on the number of variables in the model. Third, Mason and Perreault (1991) show that increasing the amount of variance explained in the outcome variable also mitigates the effects of multicollinearity. At first glance, this implies that researchers should pay attention to the inclusion of all important predictors in a model, either as regular predictors or as control variables. However, this should be viewed in light of model parsimony and the risk of overfitting. As such, consistent with Grewal et al. (2004), increasing the amount of variance explained may not always be a feasible option to avoid numerical multicollinearity. Nevertheless, researchers should avoid a too narrow specification of the model and include a set of key constructs that together lead to a substantial amount of explained variance in the outcome. Put differently, even though PLS-SEM is often positioned as the ideal tool in early stages of theory development, a solid conceptual basis is needed to warrant sound estimation results.

Although measurement reliability, predictive power, and sample size are discussed separately, it is important to stress that these factors reinforce each other. Thus, researchers should strive for optimal performance on all factors simultaneously.

7.2.4 Common-Factor Structural Multicollinearity

7.2.4.1 Description

Following Pearson's (1920) seminal work on correlations, Kalnins (2018) refers to common-factor structural multicollinearity as the amount of correlation among variables via an unobserved common-factor. Such an unobserved common-factor may include a substantive variable (see Kalnins 2018, for examples) or measurement error common to a set of variables.

7.2.4.2 Consequences

Kalnins (2018, 2022) convincingly demonstrated the effects of common-factor structural multicollinearity on the estimation results. First, it increases (in absolute sense) the magnitude of regression coefficients. Second, inflated *t*-values may lead to the inappropriate conclusion that there is a significant effect (i.e., false positive). Common-factor structural multicollinearity is thus associated with type I errors. Third, per pair of correlated independent variables, the signs of the coefficients are opposite and one of the signs does not align with its hypothesized direction.

7.2.4.3 Detection

It should be noted that frequently used measures to detect multicollinearity, such as variance inflation factors and condition numbers, are not suitable for the detection of common-factor structural multicollinearity. For example, as indicated by Kalnins (2018), common-factor multicollinearity may still be present even when VIFs are substantially below the cut-off values put forward in the literature. In order to assess the presence of possible common-factor structural multicollinearity, Kalnins (2018, 2022) proposes to carefully inspect empirical results using the following guidelines. First, is it likely that a substantive or structural common-factor structure impacts the data? Second, is the correlation between two variables positive (negative) while the variables' regression coefficients have opposite (same) signs? Third, is the correlation coefficient between the two variables 0.30 or more in absolute magnitude? If the answer to all three questions is affirmative, common-factor multicollinearity is evidenced. Alternatively, Kalnins (2018) recommends researchers to present the results of separate regressions (i.e., a regression per collinear variable as well as a regression in which all variables are included) and check whether the signs are consistent and magnitudes are roughly consistent in all specifications. If this is the case, it is unlikely that common-factor structural multicollinearity is distorting the results.

7.2.4.4 Solution

Before turning to a possible solution to common-factor structural multicollinearity, it is important to stress that the often-made suggestion to increase the sample size (i.e., the collection of additional data) in order to battle the adverse effects of multicollinearity actually worsens the consequences of common-factor structural multicollinearity (see also Kalnins, 2022). Furthermore, approaches such as ridge regression are not suitable in case of common-factor multicollinearity (Kalnins, 2018).

Furthermore, the elimination of variables as a strategy to battle multicollinearity has different implications in case of common-factor structural multicollinearity. Whereas the omission of variables under a canonical DGP is problematic (i.e., omitted variable bias), under a common-factor DGP the bias and the risk of type I error are problematic when the collinear variables are all included (see also Kalnins, 2018).

To mitigate the impact of common-factor structural multicollinearity, Kalnins (2018, 2022) suggests the use of variable combination strategies such a summation and division. From a technical point of view, combining variables eliminates distortion of the coefficients toward the infinite, if the combined variable is not highly correlated with other variables in the model. Furthermore, the variable combination strategy is only feasible when the combination of variables is based on an explicit theoretical rationale (Kalnins, 2018).

7.3 Ridge PLS-SEM

In line with the second objective of this chapter, this section proposes ridge PLS-SEM—which implies the integration of the ridge estimator in the context of PLS-SEM—as a method to mitigate the effects of canonical structural multicollinearity. This section is structured as follows. After a brief review of the PLS-SEM estimation approach as well as the principles of ridge regression, we provide a detailed outline of the practical implementation of ridge PLS-SEM using a combination of SmartPLS and SAS. For illustrative purposes, the model presented in Fig. 7.1 is used throughout this section. Please note that, although all materials to conduct ridge PLS-SEM are provided (see Table 7.1), the explanation in this chapter predominantly focuses on the more conceptual aspects.

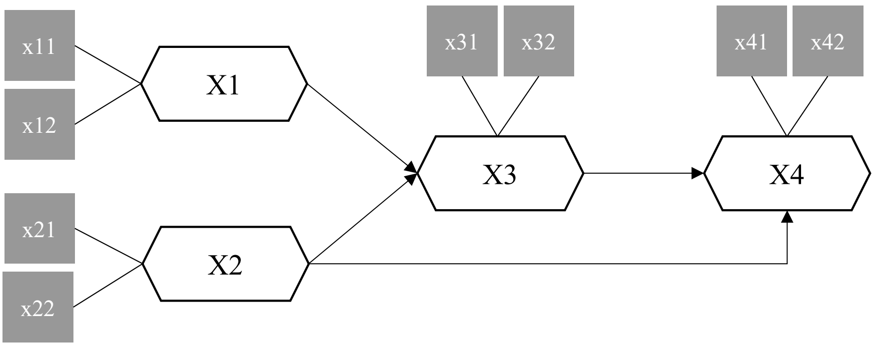

Fig. 7.1 Example model

Table 7.1 Overview of the needed SAS syntaxes

	SAS syntax	Additional information to the syntax
Step 2: Creation of J bootstrap samples	`proc surveyselect data= example Out= exampleboot` `seed= 30459584` `method= urs` `samprate= 1` `outhits rep= J;` `run;`	Example is the data matrix created in step 1 Exampleboot is the name for the dataset to be created containing all bootstrap samples. A seed is set to enable exact replication. URS is random sampling with replacement. Samprate = 1 leads to a sample size that is equal to the original sample size. Finally, rep denotes the number of bootstrap samples to be created.
Step 3: Ridge trace (original sample)	`proc reg data= example` `outest= name ridge= 0 to 1 by 0.1;` `model X3 = X1 X2;` `plot / ridgeplot nomodel nostat;` `run;`	Here the minimum and maximum value for the ridge constant k are set to 0 and 1, but this can be altered. The same holds for the size of the increments of k (here 0.1).
Step 3: Ridge estimation (original sample)	`proc reg data= example outest= originalRR;` `model X3 = X1 X2 /ridge= k;` `run;`	To obtain ridge estimators for the original sample use the data matrix created in step 1. The output data matrix is called *originalRR* here to denote the original sample estimates.
Step 3: Ridge estimation for J bootstrap samples	`proc reg data = exampleboot` `outest= name;` `by replicate;` `model X3 = X1 X2 X3` `/ridge= k;` `run;`	Run this syntax for each equation of the model that suffers from multicollinearity. The input dataset remains the same for each equation, but make sure that you give the output file a different name each time you run the syntax for an equation to avoid overwriting. The k-value can be different for each equation
Step 3: OLS estimation original sample	`proc reg data= example outest= originalOLS;` `model x31 = X3;` `run;`	To obtain OLS estimators for the original sample use the data matrix created in step 1. The output data matrix is called *originalOLS* here to denote the original sample estimates.
Step 3: OLS estimation for J bootstrap samples	`proc reg data = exampleboot` `outest= name;` `by replicate;` `model x31 = X3;` `run;`	Run this syntax for each equation of the model that does not suffer from multicollinearity. The input dataset remains the same for each equation, but make sure that you give the output file a different name each time you run the syntax for an equation to avoid overwriting.

7.3.1 The Building Blocks of Ridge PLS-SEM

7.3.1.1 The PLS-SEM Algorithm

To understand how the idea of ridge regression can be implemented in a PLS-SEM context, it is imperative to have insight in the PLS-SEM estimation algorithm. The PLS-SEM algorithm (see also Sarstedt et al. 2022; Lohmöller 1989) contains the (iterative) stages summarized in Fig. 7.2. For a detailed, non-technical discussion of the PLS-SEM algorithm the reader is referred to Hair et al. (2011).

In the context of this chapter, it is important to realize in which stages of the PLS-SEM algorithm canonical structural multicollinearity can play a role. In general terms, these are the stages in which multiple regression is used to estimate coefficients. Depending on the exact specification of the model, multicollinearity may influence the estimation results at three particular moments in the estimation process. First, in the determination of the outer weights for using mode B estimation (stage 1.4). Second, in the determination of the inner weights when using the path weighting

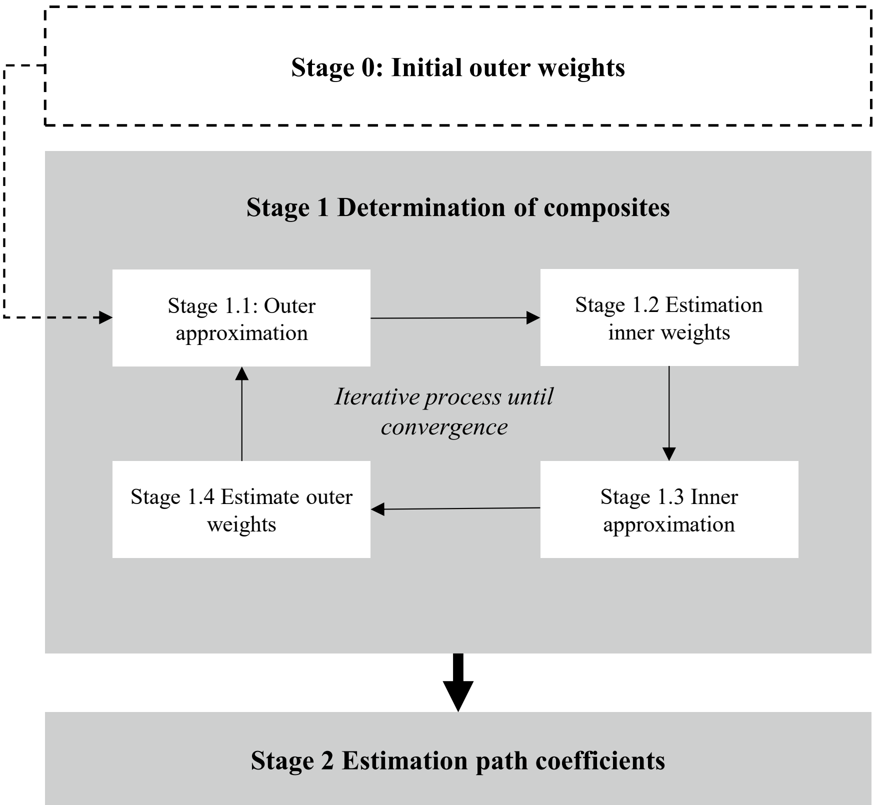

Fig. 7.2 The PLS-SEM algorithm

scheme to estimate the inner weights connecting a predecessor construct to one of its outcome constructs (stage 1.3). Third, in estimating the structural model coefficients (stage 2). Following Ofir and Khuri (1986)—who state that the data points at which prediction of the response is made are within the region where the model was fitted and where the same pattern of multicollinearity is observed are precise—we assume that the composite scores determined in Stage 1 are accurate. This assumption is tenable as it reflects the typical modeling reality in PLS-SEM applications.

7.3.1.2 The Idea of Ridge Regression

Ridge regression, developed by Hoerl and Kennard (1970), is an effective estimation technique that mitigates the impact of multicollinearity on the estimation results. Overall, ridge regression has been shown to perform well (see also Wilcox, 2019), and is commonly used in empirical studies (e.g., Dost et al., 2019; Moosmayer et al., 2012). As "conceptually and practically, PLS-SEM is similar to using multiple regression analysis" (Hair et al., 2011, p. 140), the idea of the ridge estimator can be integrated in the PLS-SEM estimation procedure.[2]

Assuming a canonical DGP, consider the following linear model to illustrate the notion of ridge regression.

$$Y = X\beta + \varepsilon$$

where Y is an $(n \times 1)$ vector containing n observations on a response variable y; X is an $(n \times p)$ matrix consisting of n observations on p predictor variables; β is a $(p \times 1)$ parameter vector containing p unknown coefficients; and ε is an $(n \times 1)$ vector of normal random errors with $\varepsilon \sim N(0, \sigma^2 I)$.

The OLS estimates are determined as follows

$$\widehat{\beta}_{OLS} = (X^T X)^{-1} X^T Y$$

To obtain a unique estimate of vector β, two conditions must be met: X must be of rank p and $n > p$. If columns of matrix X are perfectly linear dependent, the rank condition is violated and a unique solution for β cannot be derived. More common is a situation where matrix X exhibits non-perfect linear dependency. In this case, estimation of the coefficients is possible, but the estimates are impacted by canonical structural multicollinearity (see also Sect. 7.2.3). To account for this, ridge regression introduces a non-negative bias k (i.e., ridge constant) to the diagonal of the moment

[2] In a similar vein, Hwang (2009) incorporated the idea of a ridge estimator in a generalized structured component analysis (GSCA). GSCA is an alternative component-based SEM approach and in terms of performance closely resembles PLS-SEM (see also Cho et al., 2022). Note that PLS-SEM can be considered as special case of GSCA. Jung and Park (2018) introduced a related method called regularized consistent PLS-SEM (RegPLSc; see also Sect. 7.2.2).

matrix $X^T X$ in exchange for lower variances (i.e., bias-variance tradeoff). The vector of ridge parameters as a function of k (i.e., $\widehat{\beta}_R(k)$) then equals

$$\widehat{\beta}_R(k) = \left(X^T X + kI\right)^{-1} X^T Y$$

If the ridge constant k equals 0, then the ridge estimation results and the OLS estimation results are identical (i.e., $\widehat{\beta}_R(0) = \widehat{\beta}_{OLS}$).

7.3.2 *Ridge PLS-SEM*

The combination of ridge regression and PLS-SEM is not yet available in popular PLS-SEM software packages such as SmartPLS (Ringle et al., 2022). In order to integrate the ridge estimator in a PLS-SEM context, we build on the properties outlined in the previous two paragraphs and propose a generally applicable approach that relies on a mixture of several popular and widely used software packages (i.e., SmartPLS, SAS, and Excel). The general structure of our approach, which will be detailed below using the model presented in Fig. 7.1, is outlined in Fig. 7.3.

Step 0: Assessing potential multicollinearity. Although not part of the procedure outlined in the remainder of this paragraph, the starting point (i.e., step 0) involves assessing whether only canonical structural multicollinearity is present (i.e., there

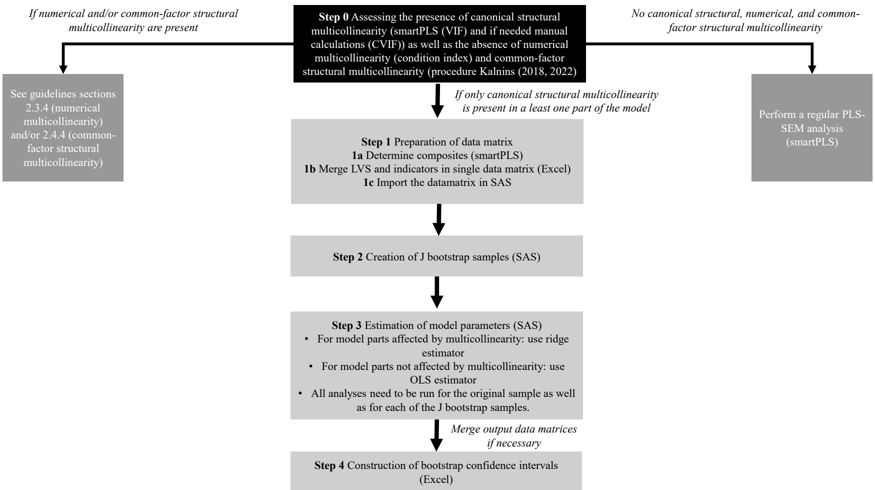

Fig. 7.3 The PLS-SEM ridge estimation procedure

is no numerical or common-factor structural multicollinearity), following the guidelines presented in this chapter (see also Sects. 7.2.2, 7.2.3 and 7.2.4).[3] For the outline of the proposed procedure, it is assumed that there is canonical structural multicollinearity in both structural model equations (i.e., $\boldsymbol{X3} = \boldsymbol{f}(\boldsymbol{X1}, \boldsymbol{X2})$ and $\boldsymbol{X4} = \boldsymbol{f}(\boldsymbol{X2}, \boldsymbol{X3})$) as well as in the composites pertaining to constructs $\boldsymbol{X1}$ and $\boldsymbol{X2}$ (i.e., $\boldsymbol{X1} = \boldsymbol{f}(\boldsymbol{x11}, \boldsymbol{x12})$ and $\boldsymbol{X2} = \boldsymbol{f}(\boldsymbol{x21}, \boldsymbol{x22})$). Note that if none of the model parts is affected by canonical structural multicollinearity, one should continue using the standard PLS-SEM procedures.

Step 1: Preparing data matrix. Having concluded that only canonical structural multicollinearity is present and that the use of a ridge estimator is thus desirable, the data matrix needs to be prepared. Preparation of this data matrix consists of three substeps. First, the composite scores of the model constructs (i.e., $\boldsymbol{X1}$, $\boldsymbol{X2}$, $\boldsymbol{X3}$, $\boldsymbol{X4}$) need to be determined. Second, a data matrix needs to be created in which per row the composite scores and the accompanying indicator variables are listed. For the current example, this would result in a data matrix with $\boldsymbol{N}$ rows ($\boldsymbol{N}$ is the number of respondents) and 12 columns (i.e., composite scores for $\boldsymbol{X1}$, $\boldsymbol{X2}$, $\boldsymbol{X3}$, $\boldsymbol{X4}$**,** and the accompanying indicators $\boldsymbol{x11}$ up to and including $\boldsymbol{x42}$). This data matrix can be made in Excel using the indicator and composite scores obtained from the regular SmartPLS output. The third and final substep is to import this newly created data matrix into SAS. In the remainder of the explanation and in the syntaxes summarized in Table 7.1, this matrix is referred to as “example.”

Step 2: Creating J bootstrap samples. Using the data matrix constructed in step 1, another data matrix needs to be constructed containing the data for J bootstrap samples. This is done using PROC SURVEYSELECT in SAS. Following the guidelines suggested by Streukens and Leroi-Werelds (2016), J is advised to be large (e.g., $J = 10,000$) and all bootstrap sample sizes need to be equal to the original sample size N. Thus, the resulting matrix will contain $J \times N$ rows.

Critical for the remainder of the analysis is the first column of this bootstrap samples data matrix. In SAS, this first column contains an automatically created variable named “replicate.” This particular variable denotes the number of each of the J bootstrap samples and allows us to run the proposed ridge estimator for each of the J bootstrap samples. The accompanying SAS syntax is presented in Table 7.1. In this syntax, the name “exampleboot” is used to denote the data matrix of containing the data for all J bootstrap samples.

Step 3: Estimating model coefficients. For each of the J bootstrap samples, the model coefficients need to be estimated. For the model parts affected by canonical

[3] In practice, the sequence for detecting the presence of multicollinearity is as follows. First, test for the presence of common-factor structural multicollinearity (guidelines Kalnins 2018, 2022). Second, and if the presence of common-factor structural multicollinearity is unlikely, calculate the (corrected) VIFs to evaluate the impact of canonical structural multicollinearity. Third, upon the condition that the study/data is in line with the criteria that need to be met to avoid numerical multicollinearity as much as possible, calculate the condition index. The difference between the (corrected) VIFs and the condition index is an indicator of numerical multicollinearity.

structural multicollinearity this involves running the ridge estimator procedure. For the model parts that are free of multicollinearity this boils down to a regular OLS estimation approach. Thus, for the example model at hand, the ridge estimation is needed for the structural model equations explaining $X3$ and $X4$ as well as the composites of $X1$ and $X2$. For the composites pertaining to $X3$ and $X4$ bivariate OLS regression applies (i.e., mode A). Here, the ridge and/or regular OLS estimation are performed using SAS.

Ridge estimation. The ridge estimation procedure involves two interdependent steps. First, the value of the ridge constant k needs to be determined. Second, the ridge estimation procedure is performed using the chosen k value.

Although there is no simple linear relationship, it should be noted that if k increases, the bias in the parameter increases, and the variance of the parameter decreases. The most commonly used approach to determine the value of k is by means of a so-called ridge trace. The ridge trace is a two-dimensional plot in which values of k (x-axis) are plotted against the (biased) estimates of the model parameters associated with a particular value of k (y-axis). Visual analysis of the ridge trace involves identifying the smallest reasonable value of k at which the parameter estimates show a somewhat stable behavior. As the ridge trace is based on a single regression equation, it is possible to select a different k value for each separate equation in the PLS-SEM model. To determine the value of k by means of a ridge trace, use the SAS syntax presented in Table 7.1. For the example at hand, this syntax needs to be run four times (i.e.,$X3 = f(X1, X2)$; $X4 = f(X2, X3)$; $X1 = f(x11, x12)$ and $X2 = f(x21, x22)$). That is, the syntax is run for all parts that are affected by canonical structural multicollinearity.

Having determined the k values, the next step involves running the ridge estimator for each part of the model that is affected by canonical structural multicollinearity. This analysis needs to be conducted for the original sample as well as for each of the bootstrap samples. The syntax needed for the ridge regression using the original sample data is presented in Table 7.1. To perform the ridge regression for each of the J bootstrap samples in a single run, SAS' PROC SURVEYSELECT is combined with the SAS command for ridge regression. The necessary syntax is again presented in Table 7.1. Note that for each part of the model to which the ridge estimator is applied, a separate datafile containing the estimation results is created. In terms of the example, four new data files are thus produced.

OLS estimation. For all model parts in which multicollinearity does not play a role, a regular OLS estimation is performed for the original sample and all J bootstrap samples. In terms of the example, this implies running OLS regressions to estimate measurement model parameters for constructs $X1$ and $X2$. The syntaxes for these procedures are outlined in Table 7.1. Again, for each analysis a separate datafile containing the estimation results is created.

Step 4: Constructing bootstrap confidence intervals. Now, all parameter estimates are available for the original sample as well as for each of the $\boldsymbol{J}$ bootstrap samples. If the researcher is only interested in the bootstrap confidence interval for each separate coefficient, calculations can be applied to the different data matrices separately. To compute bootstrap confidence intervals for combinations of coefficients (e.g., coefficient of determination, total effects) the separate data matrices need to be merged into a single data matrix.[4] For the formulae needed to construct bootstrap confidence intervals, see Streukens and Leroi-Werelds (2016).

7.4 Concluding Remarks

7.4.1 Conclusion and Contributions

Multicollinearity is a phenomenon frequently encountered in empirical studies. Given that multicollinearity may have a detrimental effect on estimation results, a better understanding of multicollinearity, its consequences and potential solutions is valuable to all researchers. In the subsequent paragraphs several contributions to PLS-SEM theory and practice are outlined.

First, it is important to distinguish between (1) canonical structural, (2) numerical, and (3) common-factor structural multicollinearity. The first type of multicollinearity stems from the model structure and cannot be avoided. However, researchers can use ridge PLS-SEM to deal with canonical structural multicollinearity. Numerical multicollinearity is a data issue and can to a large extent be avoided through a proper research design (e.g., reliable measures, sufficient sample size). Ridge PLS-SEM is not an option for this type of multicollinearity. Common-factor structural multicollinearity—to our best knowledge for the first time described in a PLS-SEM context—arises from a common-factor that impacts the correlations among the variables (i.e., a common-factor DGP applies). Especially noteworthy, is the fact that common-factor structural multicollinearity impacts the estimation results in a different way than canonical structural multicollinearity (i.e., type I errors) and requires a specific approach to detect. Furthermore, remedies such as increasing sample size have an adverse effect for this type of multicollinearity. As outlined in this chapter, possible solutions exist for situations plagued by common-factor structural multicollinearity. However, ridge PLS-SEM is not an effective tool in this case.

Second, it is essential to be able to detect the different types of multicollinearity. The appropriateness of the condition number for detecting numerical multicollinearity is outlined in this chapter. For assessing common-factor structural

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[4] If a ridge regression is used, the dataset resulting from the previous step contains per replication two lines with statistics. One line named PARMS and one line named RIDGE. Delete all lines named PARMS. Also, not all columns in the newly created datasets are relevant. You can delete these. Also make sure that all columns have a unique name that clearly indicates the meaning of the different coefficients. Adjust names manually if needed. Subsequently, merge the datafiles created under step 6 into a single file containing all estimates. To do this, merge the files using the "replicate" variable denoting the J bootstrap samples.

multicollinearity, the procedure suggested by Kalnins (2018, 2022) is required. To identify the presence of canonical structural multicollinearity a more elaborate procedure concerning the VIF is provided. The first step involves determining whether the correlations among the predictor variables are (non) redundant. The VIF is appropriate in situations of redundancy, whereas the corrected VIF (CVIF) should be used when there is non-redundant correlation among the predictor variables. The second step requires an evaluation of the values of the VIF or CVIF compared to the model's own coefficient of determination (R^2) to determine whether canonical structural multicollinearity indeed affects the estimation results. This also implies that researchers should not blindly follow heuristics related to the interpretation of VIFs. Both the VIF an CVIF should be viewed in the study context (i.e., coefficient of determination, sample size, and effect sizes).

Third, in line with the notion that ridge regression is an effective approach to deal with canonical structural multicollinearity, a generally applicable approach to integrate the idea of the ridge estimator with PLS-SEM (i.e., ridge PLS-SEM) is outlined. This approach enables researchers to reap the benefits of PLS-SEM in situations in which canonical structural multicollinearity is present. In addition, in terms of fundamental research (i.e., theory building) as well as applied research having access to an estimation approach that effectively deals with canonical structural multicollinearity, this approach increases confidence in the research results. It should be noted that ridge PLS-SEM is part of a larger set of methods capable of dealing with canonical structural multicollinearity in a PLS-SEM context (see also the work of Esposito Vinzi and Russolillo, 2013 as well as Jung & Park, 2018).

7.4.2 Limitations and Suggestions for Further Research

Every study has limitations that merit further attention in future research endeavors. For this chapter, the following key limitations are particularly relevant. First, at the time of writing, we did not have access to a real-life data set to illustrate the ridge PLS-SEM approach. Hence, practical applications using ridge PLS-SEM are very welcome. This should be possible, as all relevant information about the practical application are provided in this chapter. Second, while we sincerely believe that the ridge PLS-SEM approach is sound and valuable to many researchers, its practical implementation currently requires a lot of work as it involves using multiple software packages and the creation of multiple separate datasets. Hence, we applaud all initiatives and collaboration opportunities that aim to integrate the ideas put forward in this chapter into a single, easy to use code or to include it in existing software packages such as SmartPLS. Third, and related to the previous point, we encourage studies that test the ridge PLS-SEM approach and compare/contrast it with comparable methods under different circumstances. Fourth, as became obvious from our treatment of the VIF and its interpretation, hardly any practical guidelines exist that are rooted in solid and thorough scientific scrutiny. Given that variance inflation depends on more than just canonical structural multicollinearity, empirical studies directed at uncovering the individual effects of several key aspects as well as their interplay on variance inflation are useful in developing better procedures for canonical structural multi-collinearity detection. Finally, the determination of the ridge constant k was based on visual inspection of the ridge trace. Although this is the commonly used approach to determine the appropriate value ofk, it remains subjective. Other more technically advanced procedures to determine k exist. For example, Hwang (2009) suggests a K-fold cross-validation procedure to determine all k values simultaneously using the minimization of prediction error as an objective function. Although a review of the different methods to determine k is beyond the scope of this chapter, future research is needed to determine the most optimal method.

Appendix

In the paragraph "what are the consequences of multicollinearity" we explain how the level of multicollinearity ρ impacts the estimation results in terms of coefficients, the accompanying variance estimates, as well as the resulting t-values. For the interested reader, this appendix provides more detail regarding these consequences by providing the relevant derivations.

Model

Consider the following model based on mean-centered data (i.e., $y = Y - \overline{Y}$; $x_p = X_p - \overline{X}_p$; $x_q = X_q - \overline{X}_q$). Furthermore, subscripts denoting the respondent are ignored in the derivations below.

$$y = \beta_p x_p + \beta_q x_{q2} + \varepsilon$$

Regression Coefficients

The following two normal equations apply to the estimation of the model coefficients β_p and β_q.

$$\sum y x_p = \widehat{\beta}_p \sum x_p^2 + \widehat{\beta}_q \sum x_p x_q$$

$$\sum y x_q = \widehat{\beta}_q \sum x_p x_q + \widehat{\beta}_q \sum x_q^2$$

Using a simplifying notation this can be written as

$$S_{yx_p} = \widehat{\beta}_p S_{x_p x_p} + \widehat{\beta}_q S_{x_p x_q}$$

$$S_{yx_q} = \widehat{\beta}_2 S_{x_p x_q} + \widehat{\beta}_q S_{x_q x_q}$$

Which leads to

$$\widehat{\beta}_p = \frac{\left[S_{yx_p} S_{x_q x_q}\right] - \left[S_{yx_q} S_{x_p x_q}\right]}{\left[S_{x_p x_p} S_{x_q x_q}\right] - S^2_{x_p x_q}}$$

$$\widehat{\beta}_q = \frac{\left[S_{yx_q} S_{x_p x_p}\right] - \left[S_{yx_p} S_{x_p x_q}\right]}{\left[S_{x_p x_p} S_{x_q x_q}\right] - S^2_{x_p x_q}}$$

Standardizing the data ($S_{x_p x_p} = S_{x_q x_q} = 1$) then yields

$$\widehat{\beta}_p = \frac{\left[S_{yx_p}\right] - \left[S_{yx_q} S_{x_p x_q}\right]}{1 - S^2_{x_p x_q}}$$

$$\widehat{\beta}_q = \frac{\left[S_{yx_q}\right] - \left[S_{yx_p} S_{x_p x_q}\right]}{1 - S^2_{x_p x_q}}$$

The term $S^2_{x_p x_q}$ represents the collinearity among the two independent variables in the model. In order to highlight this term, we substitute $S_{x_p x_q} = \rho$. Hence,

$$\widehat{\beta}_p = \frac{\left[S_{yx_p}\right] - \left[S_{yx_q} \rho\right]}{1 - \rho^2}$$

$$\widehat{\beta}_q = \frac{\left[S_{yx_q}\right] - \left[S_{yx_p} \rho\right]}{1 - \rho^2}$$

Variance Regression Coefficients

Again, consider the following model based on mean-centered data (i.e., $y = Y - \overline{Y}$; $x_p = X_p - \overline{X}_p$; $x_q = X_q - \overline{X}_q$). Subscripts denoting the respondent are ignored in the derivations below.

$$y = \beta_p x_p + \beta_q x_{q2} + \varepsilon$$

The variance of the regression coefficients $\widehat{\beta}_p$ and $\widehat{\beta}_q$ can be computed as follows:

$$var(\widehat{\beta}_p) = \frac{\sigma^2 S^2_{x_q x_q}}{S_{x_p x_p} S_{x_q x_q} - S^2_{x_p x_q}}$$

$$var(\widehat{\beta}_q) = \frac{\sigma^2 S^2_{x_p x_p}}{S_{x_p x_p} S_{x_q x_q} - S^2_{x_p x_q}}$$

Standardizing the data ($S_{x_p x_p} = S_{x_q x_q} = 1$), substituting of $S_{x_1 x_2} = \rho$, and rearranging terms the variance for each regression coefficient becomes

$$var(\widehat{\beta}_p) = \frac{\sigma^2}{1 - \rho^2}$$

$$var(\widehat{\beta}_q) = \frac{\sigma^2}{1 - \rho^2}$$

In the equations above, the term σ^2 denotes the error sum of squares (i.e., $\sum u^2 = \sum (Y - \widehat{Y})^2$) and assuming standardized data and using the results derived above it can be computed as follows.

$$\sigma^2 = 1 - \frac{S^2_{yx_p} - 2\rho S_{yx_p} S_{yx_q} + S^2_{yx_q}}{1 - \rho^2}.$$

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Chapter 8
Demystifying Prediction in Mediation Research and the Use of Specific Indirect Effects and Indirect Effect Sizes

James Gaskin, Samuel Ogbeibu, and Paul Benjamin Lowry

Abstract The maturing state of partial least squares structural equation modeling (PLS-SEM) research has seen exceptional knowledge advances over the past decade. However, advances in practice among lay researchers have advanced at a slower pace. We conclude that this gap between PLS-SEM research and practice may be attributed to the sophisticated and arcane approach to detailing new methodological advances. Moreover, prediction has been a peripheral topic in PLS-SEM mediation literature to date. This chapter sits at the intersection of these two gaps. We first seek to advance understanding of the intertwining roles of prediction and mediation. We then provide practical demonstrations of two particularly occluded topics in mediation research: specific indirect effects and indirect effect sizes.

8.1 Introduction

Myriad articles abound on the topic and application of *mediation* analysis in partial least squares (PLS) structural equation modeling (SEM), or PLS-SEM (e.g., Kock, 2011, 2014; Moqbel et al., 2020). However, until recently, these articles have often overlooked the role of prediction in mediation analysis. The conceptual role of a mediator echoes the need for prediction to explain transformative, radical, or gradual changes when estimating causal-predictive models. While seeking to advance mediation methodology, these articles tend to be highly technical and arcane, obscuring the practical gems of application behind expansive reviews and criticisms of past

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research and often difficult-to-understand formulae (e.g., Lachowicz et al., 2018). Although the detailed and complex clarifications in such articles contribute to knowledge, ironically, many authors of such articles lament that methodology practice holds doggedly to old methods and ignores recent advances; however, by writing in an arcane manner, they make such articles difficult for most researchers to process (cf. Sarstedt et al., 2020; Zhao et al., 2010).

In this chapter, we aim to advance the research practice of prediction in mediation by explaining an emerging nuance of prediction that emphasizes the role of temporal order and identifies types of prediction in mediation analysis. We then provide practical demonstrations for a couple of critical aspects of mediation testing when prediction is the goal. Namely, we simplify extant PLS methodological research by providing tutorials and clarifications for (1) the testing of specific indirect effects when multiple mediators are present and (2) the estimation and reporting of indirect effect sizes. As a foundation to understand the types of prediction in mediation research, the first part of this chapter is largely conceptual, rather than mechanical, and therefore does not include tutorial components. Whereas the following two topics and their application will primarily focus on tutorials with screenshots and companion video demonstrations that can be easily followed. Understanding that the history of mediation literature—particularly in the context of PLS-SEM—is explained thoroughly by the other chapters of this book, we forego a full literature review for the sake of avoiding redundancy and instead we move directly to the topics at hand that are unique to this chapter. Nevertheless, we embed relevant literature into our focused topics to better position our intended contributions among those of previous articles.

An article focusing on mediation and prediction in PLS-SEM is needed because extant regression techniques (such as PROCESS) collapse the latent factor structure (hiding information), and covariance-based techniques do not accommodate non-reflective measurement, thus risking misspecification. Thus, prediction and mediation in PLS can be unique when compared to extant established methods. The remainder of the chapter is organized as follows: Sect. 8.2 discusses the issue of prediction in mediation while reviewing relevant literature. Section 8.3 explains the nuances of specific indirect effects, including a tutorial on how to estimate them in SmartPLS. Section 8.4 discusses the issues around effect sizes, particularly with regard to indirect effects, including a tutorial for how to estimate them in SmartPLS. Section 8.5 concludes with a look toward future research. This chapter makes a few clear contributions: (1) using plain but precise language to articulate the issues of prediction in mediation when PLS-SEM is the approach of choice, (2) clarifying the issues around *specific* indirect effects and how to assess them, and (3) demonstrating a new method for estimating specific indirect effect sizes in PLS-SEM.

8.2 Prediction in Mediation

First, we focus on prediction, a concept in mediation that has hitherto been limited in exploration. To clearly forecast the possible occurrence of a particular future outcome, behavioral scientists must engage in the science of prediction (Hofman et al., 2017). The science of prediction is a useful and timely tool that can improve practitioners' and policymakers' accuracy and rigor needed for making more effective decisions (Liengaard et al., 2020). Prediction can also aid organizations in preparing for uncertain future events that could impact their business operations (Athey, 2017). A quick example that reinforces the need to predict and engage in the continued improvement of the science of prediction is the global negative influence of the COVID-19 pandemic on business activities and human behavior (Hall et al., 2020; Keni et al., 2020). Although scientists have long warned of the potential disruptive influence of the next pandemic, innumerable organizations have overlooked the possible effects a pandemic could have on their respective business practices (Smil, 2008; Webster, 2018). This oversight, resulting in many catastrophic business failures, may have been more easily foreseen via the science of prediction (Douglas, 2009; Gossling et al., 2021).

While the science of prediction continues to rapidly emerge, debates in the mediation and prediction literature are yet to sufficiently inform on the distinction between causal and predictive relationships in a mediation model (Danks, 2021; Sarstedt et al., 2020). Thus, conflicting findings of extant research may have also been a consequence of little or no understanding of the distinction between causal and predictive relationships when estimating a theoretically driven mediation model via PLS-SEM (Yarkoni & Westfall, 2017). In a mediation model, causal relationships typify distinct constructs that are theoretically derived from causal reasoning, and propositions that are also usually implied as confirmatory rather than predictive statements of relationships between empirically testable constructs (Sarstedt & Danks, 2021; Sarstedt et al., 2020). Consequently, for causal relationships, the focus is on the direction, significance, and sizes of coefficients that exemplify prior postulated relationships (Douglas, 2009; Hofman et al., 2017). Causal relationships in mediation models describe the estimation of propositions that exemplify why, when, and how a defined empirical phenomenon may occur (Danks & Ray, 2018; Sarstedt & Danks, 2021). Conversely, predictive relationships are chiefly grounded on generating prescriptive propositions that inform what will be, rather than why (Hair et al., 2021; Yarkoni & Westfall, 2017). When prediction is the aim in a mediation model, predictive relationships become concerned with informing on the possible outcome of one or more endogenous constructs without providing explanations that underly causal relationships (Hofman et al., 2017; Sarstedt & Danks, 2021). This is such that the conventional expectations undergirding the technique through which predictions are created are regarded as unnecessary as the focus is on the model's ability to predict outcomes or target constructs, rather than on a model's coefficients' size, significance, and direction (Danks, 2021; Danks & Ray, 2018). Therefore, depending on the overarching question, an investigation aims to pursue, and the underlying theory guiding such investigation, a focus would be on clearly identifying and deciding whether the predictive assessment or the causal estimation of a defined proposition is what's best suited for addressing the key problem identified (Yarkoni & Westfall, 2017).

Historically, mediators have been used to provide more precise explanations of cause-and-effect relationships, specifically in the context of predicting plausible outcomes (Hair & Sarstedt, 2021; Sarstedt & Danks, 2021). Recent research has advocated for and demonstrated distinct approaches to conducting improved prediction in mediation research (Danks, 2021; Sarstedt & Danks, 2021; Shmueli et al., 2019). However, research supporting the science of prediction via mediation modeling is emerging, as it is beginning to gain widespread attention as new guidelines and theories are regularly introduced (Guleria et al., 2022; Yarkoni & Westfall, 2017). To further bolster the science of prediction, recent research has proposed newer prediction metrics, benchmarks, and concepts (Danks, 2021; Hair & Sarstedt, 2021; Sarstedt et al., 2020). Despite these advances, the science of prediction, particularly through mediation, remains limited (Schuberth, 2021). Thus, we advocate a viable solution to using prediction for estimating mediation in PLS modeling or any complex form of SEM.

8.2.1 Conceptual Time Ordering and Types of Prediction in Mediation Analysis

Prior research has emphasized the need for mediation investigations to consider the underlying temporal component of cause-and-effect relationships facilitated by an intervening (mediating) variable (Aguinis et al., 2016). In mediation models, there is an inherent implication of the passage of time (Kline, 2015), such that the influence of X on Y is not always instantaneous (although cognitive or transactional conditions may produce almost instantaneous results) and it may take weeks, months, or even years for X to eventually exert an influence on Y through M (Lapointe-Shaw et al., 2018). The passage of time is further apparent in serial mediation (multiple sequential mediation) models (Aguinis et al., 2016; Bernerth & Aguinis, 2016). Therefore, it is necessary to account for the time differences in prediction-oriented mediation model estimations. Although several studies have proposed distinct approaches to better conceptualize, analyze, and report mediation, the plausible types of prediction that can help guide and position prediction mediation models have yet to be given adequate attention (Douglas, 2009; Hofman et al., 2017; Kline, 2015).

By deploying the appropriate type of prediction via a causal-predictive analysis, one can closely capture distinct possible realities; better explain gradual, transformative, or radical changes represented by intervention conditions; and consequently, provide more valuable and reliable policy implications (Danks & Ray, 2018). Whereas recent debates have proposed novel approaches to further validate causal-predictive analyses, much remains unknown regarding the types of prediction that ought to guide research and cases where each prediction type is useful (Danks, 2021).

Based on extant works (Douglas, 2009; Hofman et al., 2017; Kline, 2015), we review three major types of prediction: cross-sectional, prospective, and longitudinal. Each type affords a unique purpose. An understanding of the types of predictions and conditions when they are useful is necessary for methodologically sound prediction research (Sarstedt & Danks, 2021; Sarstedt et al., 2020).

8.2.1.1 Cross-Sectional Prediction

Cross-sectional prediction is closely related to traditional cross-sectional research associated with survey-based data collection initiatives (Spector, 2019). Cross-sectional prediction is most suited for investigations that aim to capture immediate trends that occur mainly within a short and fixed period (Wang & Cheng, 2020). It also seeks to address questions for which solutions can be provided from a one-time observation or single point in time estimations of a defined phenomenon (Spector, 2019). Cross-sectional prediction is useful as an initial point for accessing and determining a few conditions that require the basic development of simple models because of information scarcity surrounding a given phenomenon.

Under such conditions, cross-sectional mediation models may be designed to uncover new information within the phenomenon of interest (Spector, 2019; Tate, 2015). Over time, however, the law of diminishing marginal returns weighs heavily on repeated cross-sectional studies of the same phenomenon (Agler & De Boeck, 2017). Moreover, in behavioral and business research, because much of the phenomena are cognitive, perceptual, or transactional, one is likely to also see much quicker results in seconds and microseconds, rather than weeks and months like in the case of longitudinal prediction (Spector, 2019). Therefore, it is important that other forms of prediction, such as the prospective and longitudinal types, be considered.

8.2.1.2 Prospective Prediction

Prospective prediction embraces the segmentation approach to mediation analysis (MacKinnon et al., 2007). To foster the reliability of findings when prospective prediction is the chosen technique, it is important that a prior theory and sufficient relative information about a defined phenomenon already exist. Such available information is useful to account for other plausible intervention conditions that may likely influence the path between X and M_1 to M_n and, subsequently, alter the path between M_n and Y—as in cases of multiple mediators and the presence of moderators (Aguinis et al., 2016; MacKinnon, 2011). Prospective prediction allows for the application of rigor via time separations to access and observe the respective impacts of exogeneous variables on their key target constructs via single or multiple mediators (Kline, 2015).

In the case of prospective prediction, data can be obtained for all exogeneous constructs at a single point in time, whereas data for the endogenous or key target constructs should be obtained at different points in time (Stone-Romero & Rosopa, 2008). In models with two or more mediators, researchers need to consider integrating more temporal separations that correspond with the number of mediators estimated. Leveraging prospective prediction to guide data collection and subsequent estimation of causal-predictive mediation models helps to further enhance the reliability of findings (Tate, 2015). Prospective prediction is also relevant for pursuing theoretical advancements that closely parallel reality and therefore provide more meaningful evidence for making effective policy and managerial decisions (Agler & De Boeck, 2017).

8.2.1.3 Longitudinal Prediction

Longitudinal prediction involves an assessment and estimation of a specified model for which data were collected multiple times over a given window (MacKinnon, 2011; Stone-Romero & Rosopa, 2008). Longitudinal prediction becomes a more useful approach when the correlations of constructs captured in a specified model have already been established in prior research. As with cross-sectional and prospective prediction, an established theory is required to support longitudinal prediction (Tate, 2015; Yarkoni & Westfall, 2017). Longitudinal prediction provides the researcher with the advantage of being able to predict and control for single or multiple intervention conditions whose probable effects may have been observed during the defined periods of investigation (Agler & De Boeck, 2017). Consequently, longitudinal prediction would be a more suitable method of predicting discrepancies in the degree of effect that possible waves of intervention conditions might have on key outcome constructs (Douglas, 2009; Yarkoni & Westfall, 2017). Moreover, when a high level of information regarding a defined phenomenon becomes available, models underpinned using longitudinal or prospective prediction ought to be further supported by control variables as an important means of ruling out alternative explanations (Bernerth & Aguinis, 2016).

8.2.2 Types of Prediction and the PLS-SEM Technique

Given the limitations of cross-sectional prediction, which is quite relevant in cases where a target population sample is scarce, challenging to reach, or in the face of data sparseness associated with the emergence of a new phenomenon, the anticipated sample size might be quite small, and analysis of data obtained in this condition may suffer from low levels of statistical power (Hair & Alamer, 2022; Kock & Hadaya, 2018). Consequently, the application of the PLS-SEM technique is advocated to be more suitable under conditions necessitating cross-sectional prediction in as much as such designs might result in smaller sample sizes (Hair et al., 2014). However, as this chapter is largely about mediation, we must also caution scholars against the use of cross-sectional data when estimating indirect effects. Longitudinal data is always preferred when assessing mediation. Because there is no temporal separation in cross-sectional designs, the implied causal effects of mediation are simply theoretical (Aguinis et al., 2017). This issue is further highlighted by Mathieu and Taylor (2006) who argue that strong theoretical justification must be applied to imply causation in mediation analysis.

Likewise, when dealing with a composite construct in a mediation model, the use of prospective or longitudinal prediction can be of key relevance as they provide increased accuracy in model specification and during data collection and analysis (Aguinis et al., 2016; Kline, 2015; MacKinnon, 2011). For example, as the PLS-SEM technique has received widespread validation for easily estimating composite constructs, applying the features of prospective or longitudinal prediction can also help to provide an opportunity for a better understanding of what outcome may occur when a exogenously specified construct is postulated to predict a target endogenous construct (Cheah et al., 2018). The conventional practice of simultaneously estimating the composite constructs without methodological rigor (e.g., time lags), can confound findings that mirror reality (Sarstedt et al., 2019). By carefully accounting for the time specified lower-order variables may take to influence their set higher-order construct (rather than relying on subjective assumptions of existing relationships between higher and lower-order constructs), valid and deeper insights exemplifying a more accurate outcome that is closer to reality can be obtained (Hair & Alamer, 2022; Rigdon et al., 2017).

Moreover, due to the complexity of models estimated across distinct time periods in longitudinal prediction, and often intricate methodological rigor associated with serial mediation models in a specified prediction-oriented investigation, longitudinal prediction thus presents a robust approach of dealing with complex models via the application of PLS-SEM (Hair et al., 2021; Rigdon et al., 2017). This is such that executing a longitudinal prediction type of investigation with the aim of applying the PLS-SEM technique can help to better simplify model complexity across distinct time periods, as PLS-SEM rarely encounters convergence concerns (Sarstedt et al., 2019). Employing the features of the different types of prediction can help to further strengthen the reliability of findings obtained via the estimation of the out-of-sample-prediction analysis which is mainly executed via PLS (Hair & Sarstedt, 2021).

8.3 Hypothesizing and Testing Specific Indirect Effects

In this section, we examine the crucial topic of specific indirect effects. We will also use Fig. 8.1a and b for reference.

Given that mediation, at its most basic form (see Fig. 8.1a), is the multiplication of two paths—*a* (X → M) and *b* (M → Y), comprising the indirect path (a * b) from X to Y—interpretation of analysis results can be confusing when there are multiple indirect paths from X to Y (see Fig. 8.1b). When there are multiple indirect paths through multiple mediators, analysis software has historically estimated "net" indirect effects by summing all indirect paths. In Fig. 8.1b, this would equate to (a_1 * b_1) + (a_2 * b_2). This scenario introduces one critical problem, however, Theory and analysis must match to derive valid conclusions, but mediation hypotheses rarely account for net mediation effects. For example, it is rare to see a hypothesis proposing that

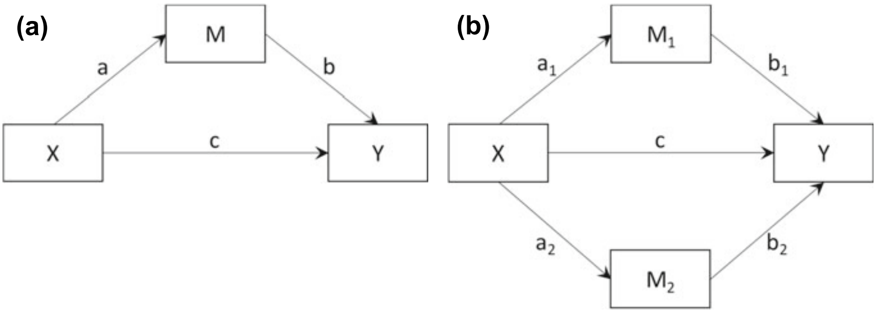

Fig. 8.1 **a** Standard mediation mode. **b** Parallel mediation model

the positive effect of autonomy on job satisfaction is mediated by value recognition, participation, and feedback. Instead, for concision, hypotheses often specify a single mediator but then assess it with net effects. In the example of Fig. 8.1b, that would be like theorizing M_1 as a mediator, but not M_2, and then still including M_2 in the model estimation. Any indirect estimate would therefore be conflated with variance passing through M_2. Or, even worse, scholars may exclude mediators from the model if not associated with a mediation hypothesis while testing that hypothesis. In the example of Fig. 8.1b, that would be like removing M_2 from the model while testing the mediation of M_1. Either of these flawed approaches increases the likelihood of false positives.

In the past, researchers who were aware of these issues could simply theorize net indirect effects—a somewhat opaque reasoning approach—or still test specific indirect effects if they were using syntax-based software that could run PLS-SEM. R and Stata have packages for such purposes; however, doing so in these packages requires added statistical programming expertise to resolve. By contrast, in the social sciences and business disciplines, most uses of PLS-SEM occur through drag-and-drop interfaces rather than syntax-based applications. Thus, until recently, validly theorizing and testing specific indirect effects, when part of a parallel mediation model, was out of the reach of most such scholars.

With the release of SmartPLS 3.2.7 in 2017, specific indirect effects can now be estimated by default. For those who have not taken advantage of this feature, or who would like a refresher, we provide further details in the next section, along with screenshots (see Figs. 8.2, 8.3 and 8.4), the following screenshots, and follow-along video[1] to show how to access and process this information in[2] SmartPLS.

[1] The following link will take the reader to a follow-along video that demonstrates estimating and interpreting specific indirect effects using SmartPLS: https://youtu.be/y9hNHOVeFVk.

[2] We recognize there are many options when it comes to estimating PLS-SEM: SmartPLS, WarpPLS, STATA, R, SAS/STAT, etc. We use SmartPLS in this tutorial since it is the current market leader for PLS-SEM in behavioral research fields.

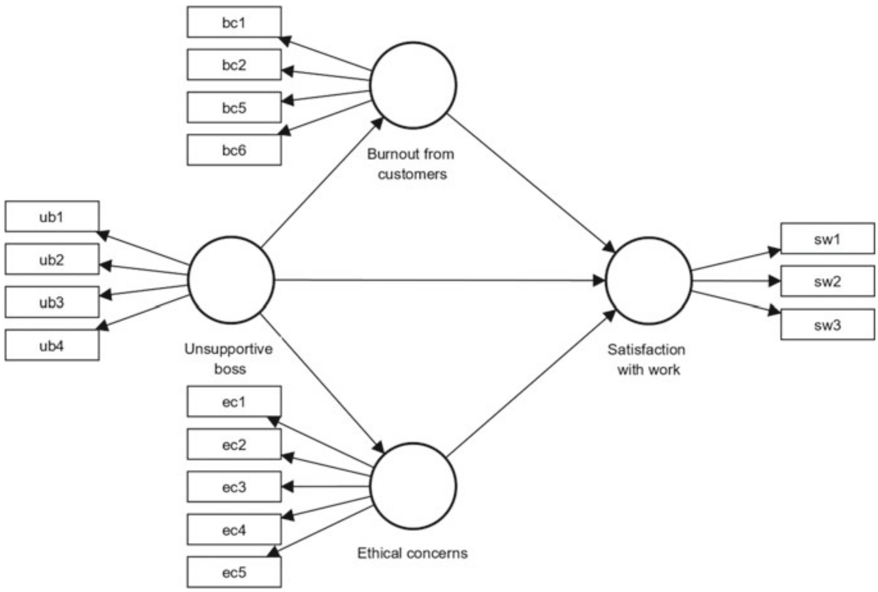

Fig. 8.2 Parallel mediation model in SmartPLS

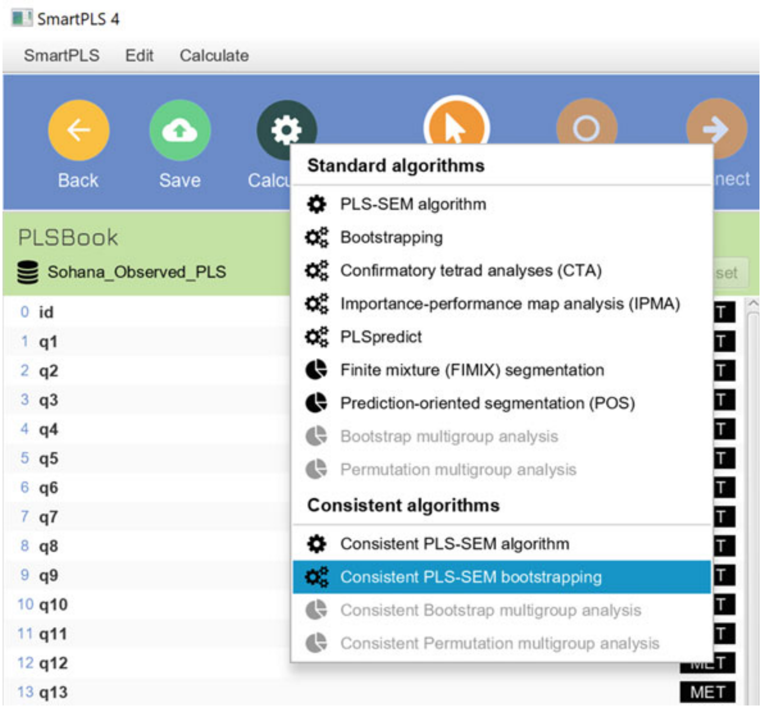

Fig. 8.3 Bootstrapping calculation option in SmartPLS

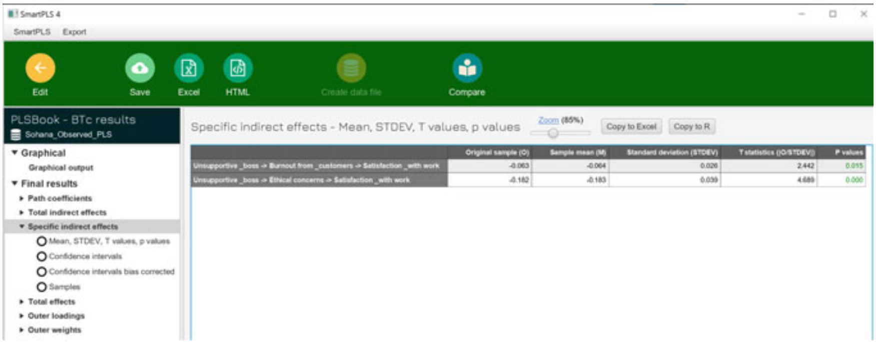

Fig. 8.4 Specific indirect effects output in SmartPLS

8.3.1 Operationalization of the Mediation Model

The model shown in Fig. 8.2 comes from an old but well-known dataset used and cited extensively in marketing and human resources research (e.g., Singh, 2000; Singh et al., 1994). The sample includes 377 customer service representatives from 18 service centers. The sample was 69% female. Most had completed high school or some college, were relatively young (31–35 years old), and earned less than $20,000 per year. Average tenure at their current organization was around 3–5 years. Managers at the company confirmed that their sample was representative of their employees (Singh et al., 1994, p. 562).

The variables chosen for this model was selected primarily to emphasize the statistical mediation effects, rather than for any theoretical contributions. Nevertheless, we may reasonably expect an unsupportive boss to have a negative direct effect on employees' satisfaction with work. When one has an unsupportive boss, one would not receive the support needed to execute one's job adequately. Being unable to perform due to a lack of support would likely be frustrating, and therefore dissatisfying. Similarly, we may reasonably assume that the main effect may be conveyed through mediators like burnout from customers and ethical concerns. Specifically, the less supportive one's boss is, the less one may be able to cope with difficult customers, and therefore the greater one's burnout from those customers. Burnout is inherently dissatisfying. Along these same lines, the less supportive one's boss is, the less one is likely to trust the boss. Lower trust in one's boss may be tied to increased concern that ethical issues may be occurring. When one works for a company (or boss) that one suspects of ethical violations, one would likely have increased uncertainty about future employment. Such uncertainty is naturally dissatisfying. Thus, ethical concerns and burnout from customers each distinctly mediate part of the negative effect an unsupportive boss has on satisfaction with work.

Finally, regarding the specification, reliability, and validity of the latent variables in Fig. 8.2, all were measured reflectively (Mode A) using the PLSc algorithm. All latent variables achieved adequate convergent validity (AVEs ranged from 0.449–0.715—burnout was low) and reliability (CRs ranged from 0.770–0.911). They also exhibited adequate discriminant validity with all HTMT ratios less than 0.850 (the greatest was 0.728).

8.3.2 *Specific Indirect Effects Analysis in SmartPLS*

To conduct specific indirect effects analysis on a parallel mediation model in[3] SmartPLS, one simply needs to do the following:

1. Start with a model that has multiple indirect paths from an independent variable to a dependent variable, as shown in Fig. 8.2.
2. Go to Calculate and select Consistent PLS Bootstrapping, as shown in Fig. 8.3. Continue with the default settings. Consistent PLS (PLSc) is used in this case because PLSc is capable of estimating latent factors.
3. Navigate to the "Specific Indirect Effects" output page in the "Final Results" section, as shown in Fig. 8.4 (*not* the "Total Indirect Effects" page).

The Specific Indirect Effects section has a row for every specified indirect effect, including serial mediated effects (e.g., $X \rightarrow M_1 \rightarrow M_2 \rightarrow M_n \rightarrow Y$) if applicable (there were none in this model). Thus, this approach can also test specific and partial indirect effects involved in serial mediation. Partial indirect effects in serial mediation refer to the part of the serial chain being tested. For example, if there are three mediators, it is possible to examine just the $X \rightarrow M_1 \rightarrow M_2$ indirect relationship.

8.4 Indirect Effect Sizes

8.4.1 *Some Considerations for Effect Sizes in General*

Effect sizes for direct effects[4] may range from small to medium to large, although there is on-going debate regarding the amplitude of effect sizes for meaningful implications (Cortina & Landis, 2009; Fidler & Cumming, 2018; Grissom & Kim, 2012). These debates are consistent on the position that effect sizes cannot be interpreted in isolation but should always consider context (Cortina & Landis, 2009; Hancock et al., 2018; Lance & Vandenberg, 2009). However, the type of context, phenomenon of interest, and nature of development of a given phenomenon over time can influence the interpretation associated with a specific effect size criterion (Fidler & Cumming, 2018; Grissom & Kim, 2012; Lance & Vandenberg, 2009). The narrative on effect

[3] The steps are the same in SmartPLS versions 3 or 4.

[4] We first introduce debates around effect sizes in general, which focus on direct effects. We subsequently discuss the debates around indirect effect sizes.

size tends to emphasize the erroneous default disregard of small effect sizes in favor of medium or large effect sizes for further investigation (Grissom & Kim, 2012). Consequently, Cortina and Landis (2009) emphasize that, even when an effect is found smaller than a "small" effect, it may still act as a signal (a non-zero effect), especially if the phenomenon is still in its embryonic phase. Lance and Vandenberg (2009) similarly contend that, contingent upon contexts, a small effect size can still signal substantial implications, but such implications may remain underexplored when the default focus is on medium or large effects.

An expectation of a zero effect is logical and reasonably affirms that an exogenous construct exhibits no effect on a phenomenon of interest (Hancock et al., 2018). However, a departure from zero should then represent an indication that a phenomenon of interest is noteworthy and could likely relay a large effect under other conditions or contexts (Lance & Vandenberg, 2009). For example, Cortina and Landis (2009) argued that in the condition of a heart attack occurrence, the variance explained by the consumption of aspirin can be less than 1/10 of 1%. However, due to its almost zero cost intervention, its importance cannot be undermined given that any non-zero effect has crucial implications. Thus, a small effect size is equally important to be reported, and upheld to foster meaningful theoretical, policy, and practical implications in any given investigation (Ogbeibu et al., 2021). Furthermore, a large or small effect in one context does not necessarily generalize to another context (Grissom & Kim, 2012). Thus, small effects in one context may still be valid predictors in other contexts, and large predictors in one context may need validation across contexts (Ferguson, 2009; Lance & Vandenberg, 2009).

One additional consideration is obtaining a larger effect such as 1 or greater, which can be a consequence of data estimation bias and methodological designs favorable to large sample sizes (Grissom & Kim, 2012). Likewise, conditions of artificially large variance of predictor constructs can complicate the understanding and interpretation of overly large effects (Cortina & Landis, 2009). Thus, one cannot necessarily conclude that a small effect is certainly not important and that a large effect is certainly important. Just as an effect size can be small but have substantial implications in a particular context, the reverse may be the case where a large effect may imply minor importance in another context (Ferguson, 2009; Lance & Vandenberg, 2009).

8.4.2 Local Effects Sizes

The extent to which a single predictor contributes to the explained variance of a dependent variable is known as the local effect size (Aiken et al., 1991). Effect size in multiple linear regression (and SEM) is signified as f^2 (Cohen, 2013; Selya et al., 2012). The local f^2 can be calculated[5] as the R^2 for the dependent variable in the

[5] $f^2 = \frac{R^2_{AB} - R^2_A}{1 - R^2_{AB}}$ where B represents the focal predictor and A represents all other predictors.

complete model minus the R^2 for the dependent variable when a selected independent variable is omitted from the model, divided by one minus the R^2 for the dependent variable for the complete model. The established f^2 target values from Aiken et al. (1991) are as follows:

- No effect: $f^2 < 0.020$
- Small effect: $f^2 \geq 0.020$
- Medium effect: $f^2 \geq 0.15$
- Large effect: $f^2 \geq 0.35$

Using Fig. 8.1b as an example, the dependent variable has three predictors that we can pretend explain 57% of its variance ($R^2 = 0.570$); however, each predictor is only responsible for a specific portion of the 57% total variance explained. Assessing effect sizes—rather than just *p*-values—can help the researcher avoid false positives by indicating that a particular predictor makes a significant contribution to the dependent variable simply because the *p*-value is below some established threshold. The f^2 reveals the true influence an independent variable has on a dependent variable regardless of the *p*-value. This is particularly helpful when sample sizes are large, because they deflate standard error and subsequent *p*-values and effectively raise any effect to the "significance" level. The f^2 is not influenced by sample size. Consequently, even if a *p*-value drops below the target threshold for *p*-values (e.g., $p < 0.05$), if the effect size is less than 0.020, then the hypothesis should not be considered supported (Sullivan & Feinn, 2012).

8.4.3 Indirect Effect Sizes

Effect sizes are influenced by the size of the regression coefficient. This is problematic because values of indirect effects are often small due to the method of calculation. Indirect effects are the product of two decimals. A decimal (less than 1) multiplied by another will always result in a number smaller than either original value. Thus, indirect effect coefficients are naturally small. Additionally, mediation models (particularly complex ones, such as parallel mediation) require both direct and indirect effects on the dependent variable and, therefore, more predicting effects (direct plus indirect) than nonmediated models (merely direct). This combined situation, in turn, deflates the f^2 (Lachowicz et al., 2018). Therefore, using Aiken's or Cohen's recommendations for effect size targets may inadvertently result in false negatives when applied to indirect effect sizes.

Others have noted this problem but have not provided any practical alternative. For example, some (Ferguson, 2009; MacKinnon et al., 2007) have recommended that meaningful indirect (v) effect sizes may just require a larger sample size (e.g., > 500) to reduce errors associated with the mediated effect. Alternatively, Agler and De Boeck (2017), Lowry and Gaskin (2014), and Ogbeibu and Gaskin (2023) suggest that even if an effect size is considered too small, as is often the case with indirect effect sizes, it can still be useful to indicate the signal of an effect, and these signals can still serve as support for future predictive theorizing (Hofman et al., 2017; Liengaard et al., 2020).

In an attempt to devise a solution to small v effect sizes, Lachowicz et al. (2018) suggest that researchers could *square* the specific v effects. However, this again reduces the size of the estimate (decimal * decimal). Ogbeibu et al. (2021) and Ogbeibu and Gaskin (2023) took this further by suggesting that the estimation of v effect sizes (v^2) should be compared against a halving of Cohen's (1992) effect size measure thresholds to compensate for inherently small v effect sizes. Thus, Cohen's (1992) effect size thresholds of 0.02 (small), 0.15 (medium), and 0.35 (large) would be reduced to *0.01 (small), 0.075 (medium)*, and *0.175 (large)* for evaluating the size of indirect effects. For further justification of these suggested thresholds, we point the reader to Ogbeibu et al. (2021) and Ogbeibu and Gaskin (2023).

However, while suggested thresholds by Ogbeibu et al. (2021) and Ogbeibu and Gaskin (2023) make it more feasible to observe small and medium effects, it is still likely to be quite rare to observe a large effect. For example, to reach the large effect using their suggestion of 0.175, we would need the sample mean estimates for the indirect effect to equal 0.418 ($0.418 \times 0.418 = 0.175$). But to achieve the sample mean of 0.418, the values of a and b (in Fig. 8.1a) must be greater than 0.646 ($0.646 \times 0.646 = 0.418$). Not only is this unlikely, observing coefficients a and b greater than 0.646 is probably an indication of multicollinearity. Thus, we suggest a more feasible guideline derived from a simple assumption that the coefficients a and b are small when 0.100, medium when 0.200, and large when 0.300 or greater. This translates into small v effect sizes of 0.01 (0.100×0.100), medium as 0.04 (0.200×0.200), and large as 0.09 (0.300×0.300). We next outline the approach to finding, calculating, and interpreting these effect sizes in SmartPLS.

8.4.4 Conducting Indirect Effect Size Analysis in SmartPLS

SmartPLS 4 does not currently support indirect effect size calculations. Therefore, we will use SmartPLS to obtain v values, use basic math to calculate v^2, and then compare it against halved traditional effect size thresholds. This process is as follows:

1. Start with a model that contains at least one indirect effect, such as the one previously shown in Fig. 8.2.
2. As before, go to "Calculate" and select "Consistent PLS-SEM Bootstrapping," as shown previously in Fig. 8.3. Continue with the default settings.
3. As before, navigate to the "Specific Indirect Effects" output page in the "Final Results" section, as shown previously in Fig. 8.4 (not the "Total Indirect Effects" page).
4. Calculate the indirect effect size v as the square of the specific indirect effect sample mean estimate. In the video demonstrating this, the sample mean estimates are –0.185 through ethical concerns and –0.065 through burnout from customers. The resulting v effect sizes are therefore $–0.185^2 = 0.034$ and $–0.065^2 = 0.004$.

Thus, the path through ethical concerns is a small effect (i.e., greater than 0.01 but less than 0.04), and the path through burnout from customers is less than a small effect (i.e., less than 0.01).

Given these results, despite observing a statistically significant specific indirect effect for both indirect paths, the evidence from the effect size estimation suggests that only one of these indirect paths has a meaningful (substantive) effect. Thus, if we were developing and testing a theory that included a hypothesis for each of these specific indirect paths, we might conclude that one of the hypotheses was supported, while the other is not supported by the evidence (Ogbeibu et al., 2021). However, decisions to accept or reject a mediation hypothesis based on indirect effect size should also be guided by the context and nature of investigation (Sullivan & Feinn, 2012). This is chiefly on the basis that values of indirect effects are often small, and obtaining useful v effect sizes may demand a sample size of at least 500 (Ferguson, 2009; Ogbeibu & Gaskin, 2023). Therefore, small indirect effect path values are likely to produce even less than small v effects, and in conditions where the phenomenon of interest is still in its embryonic phase, the potential sample population is challenging to access, or the context of investigation is largely underexplored, it may be unrealistic to expect a substantial v effects (Agler & De Boeck, 2017; Lowry & Gaskin, 2014; Ogbeibu & Gaskin, 2023). We therefore argue that specific indirect effect sizes $v^2 > 0.0$ (typifying a shift from a completely non-zero effect) and that have been obtained from a clearly representative sample size that is < 400 (Kock, 2018; Kock & Hadaya, 2018; Krejcie & Morgan, 1970; Ogbeibu & Gaskin, 2023) should provide sufficient support for their corresponding hypothesis to be accepted if $p < 0.05$, and there are strong theoretical and contextual justifications. Thus, significant, but less than small effect size may still provide a signal for theorizing (Hofman et al., 2017; Liengaard et al., 2020). Table 8.1 provides a guide to interpreting evidence for indirect effects hypotheses, given specific indirect effect sizes and p-values.

The following link will take you to a follow-along video for estimating and interpreting indirect effect sizes in SmartPLS: https://youtu.be/pS5coOTcP-U.

Table 8.1 Interpreting evidence for indirect effects hypotheses

	$p < 0.05$ ("significant")	$p > 0.05$ (too much error)
$v^2 > 0.01$ (effect observed)	Supported	Rejected
$v^2 < 0.01$ (less than a small effect)	**Supported** if $n < 400$ and research context and the phenomenon of interest remain underdeveloped Otherwise, **reject**	Rejected

8.5 Concluding Remarks and Future Research

Several important advances have been made in PLS-SEM methodology research. However, these developments have been slow to find their way to most researchers who use PLS—because such researchers are not always adept in arcane statistical knowledge and, often, the mathematics needed to understand these advances. An example of this issue is the important advances that have been made with PLS mediation analysis. In this chapter, we thus tried to advance the research practice of mediation by simplifying and providing tutorials and clarifications for three important aspects of mediation testing that are generally not leveraged by most behavioral and business researchers: we (1) articulate the different data collection approaches to address prediction mediation research, (2) explain and demonstrate how to estimate specific indirect effects in PLS, and (3) explain and demonstrate how to estimate and interpret specific indirect effect sizes in PLS.

Future endeavors in this effort may go beyond what we have offered here by examining models with serial mediation: mediation with more than one mediator in the same specific indirect path. Future research may also seek to better understand the role of time in mediation through longitudinal designs. Such designs are better suited to real prediction via stronger causal mechanisms. We have also not touched on specific versus net mediation when moderation is at play. Future research may shine a light on how the interpretation of specific indirect effects and effect sizes need to be adjusted when moderation is also present in the model.

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Chapter 9
Alternative Approaches to Higher Order PLS Path Modeling: A Discussion on Methodological Issues and Applications

Rosanna Cataldo, Maria Gabriella Grassia, and Carlo Natale Lauro

Abstract In the context of Partial Least Squares-Path Modeling (PLS-PM), higher-order constructs have enjoyed increasing popularity in the last few years in relation to the investigation of models with a high level of abstraction, particularly in cases where the building of a system of indicators depends on different levels of information. Higher-order constructs in PLS-PM are considered as explicit representations of multidimensional constructs which are related to other constructs at a higher level of abstraction, thereby mediating completely the influence received from, or exercised on, their underlying dimensions. This chapter investigates the status and evolution of research studies on higher-order constructs in PLS-PM and focuses attention on the potentiality of their recent methodological developments, specifically on how they can help researchers in the estimation of complex and multidimensional phenomena. Different approaches will be discussed and compared using a case study within a social context.

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9.1 Introduction

Partial-Least Squares-Path Modeling (PLS-PM) is a statistical approach for the modeling of complex multivariable relationships between observed and latent variables (Wold, 1974). From a formal point of view, PLS-PM consists of a system of simultaneous regression equations. It includes a set of statistical methodologies that allow for the estimation of a causal theoretical network of relationships linking complex latent concepts, each measured through a series of observable variables. Since its first formulation, this approach has enjoyed a growing popularity over the years in various sciences, becoming a very important and flexible statistical tool for soft modeling.

PLS-PM consists, principally, of two elements: the *measurement model* (also known as the outer model), which describes the relationships between each construct (the Latent Variable—LV) and its associated observed variables (also called indicators, items or manifest variables—MVs); and the *structural model* (also known as the inner model), which describes the causal-predictive relationships between the constructs (Fig. 9.1). In the figure, the oval indicates latent construct with reflective indicators, the hexagon indicates latent construct with composite indicators, the rectangles are MVs and the β represent path coefficients to be estimated.

In recent years, the number of publications on PLS-PM has increased significantly (Hair et al., 2017, 2019), including several books (Chin et al., 1998; Esposito Vinzi et al., 2010; Hair et al., 2021; Latan & Noonan, 2017) and articles that illustrate applications (Becker et al., 2012; Cataldo et al., 2021; Latan, 2018). Henseler (2020) and Cataldo et al. (2017) have proposed various methodological extensions and other researchers have performed a critical analysis and review of certain aspects of this approach (Chin, 1998; Hair et al., 2012, 2017; Jarvis et al., 2003; Lauro et al., 2018). Sarstedt et al. (2021) have reviewed many of the articles dealing with PLS-PM applications in different disciplines and have revealed how their usage has increased considerably, generating new and substantive knowledge. Indeed, PLS-PM has evolved considerably (Shiau et al., 2019) to include a wide range of features (Latan, 2018). These allow users to address new data structures, such as higher-order constructs (HOCs), which consider the hierarchical relationships among the

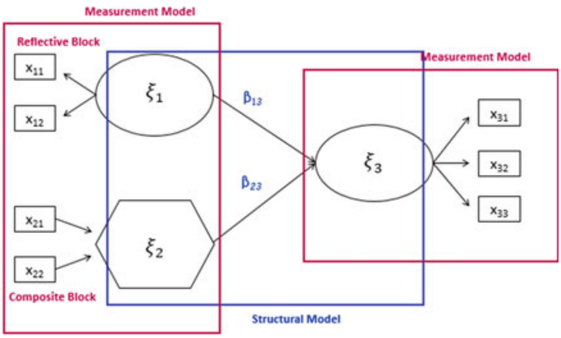


Fig. 9.1 PLS-PM: the structural model and measurement model

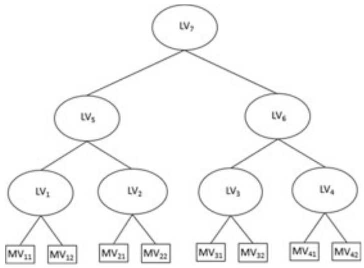


Fig. 9.2 Hierarchical LVs structure

constructs themselves, i.e., the subject of the present chapter. As a matter of fact, researchers (Cataldo et al., 2021; Funtowicz & Ravetz, 1990; Lauro et al., 2018; Saltelli, 2007) have recently been focusing their attention on the concept of a complex phenomenon, one which cannot be explained in terms of a single perspective. In such a case, it is necessary to consider a concept formed by different dimensions, each representing different aspects, which interact with each other (Fig. 9.2). The dimensions are not considered separately but are all integral parts of a single global concept.

Almost 40 years ago, Noonan and Wold (1983) claimed that PLS for hierarchical structures was in an early stage of development and research was still ongoing. For many years, hierarchical PLS-PM was scarcely considered by researchers, but starting from 2011 the number of papers expands significantly, thereby demonstrating that this new aspect of the model was starting to arouse the interest of researchers, especially, to address problems related to latent dimensions. Today there are many publications on this topic and some of them represent real points of reference for researchers. In order to provide an overview of these contributions on the subject of higher-order PLS-PM, we have undertaken a bibliometric study of international papers published between 1991 and 2021, retrieved from the Web of Science Database (https://www.webofscience.com/) using the keywords "Hierarchical" or "Higher-Order". Table 9.1 shows a summary of the most cited articles. A more detailed bibliometric analysis has also been carried out, which is included in the Appendix.

The articles have been sorted in terms of the total number of citations and normalized total citations (NTC). As can be observed, the study by Wetzels et al. (2009) has received the highest number of citations. The paper analyzes how PLS-PM can be used to assess a hierarchical construct model, showing guidelines for the construction of a hierarchical model. The second most highly cited work belongs to Becker et al. (2012), in which they focus their attention on second-order hierarchical LV models that include composite relationships. If we consider the ranking on the basis of the number of citations per year, the third most highly cited work is the article by Sarstedt et al. (2019) which, despite being published only in 2019, has received a huge number of citations. As a matter of fact, considering the ranking in terms of the NTC metric, this chapter comes first in the ranking, precisely because (despite being only recently published) it has received such a very high number of citations.

Table 9.1 Top manuscripts by number of citations

Authors	Paper	Source	TC	TCperYear	NTC
Wetzels et al. (2009)	Assessing using PLS path modeling hierarchical and empirical construct models: guidelines	*MIS Quarterly*	1928	137.71	5.55
Becker et al. (2012)	Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models	*Long range planning*	740	67.27	11.19
Akter et al. (2016)	How to improve firm performance using big data analytics capability and business strategy alignment?	*International Journal of Production Economics*	356	50.86	12.34
Sarstedt et al. (2019)	How to specify, estimate, and validate higher order constructs in PLS-SEM	*Australasian Marketing Journal* (AMJ)	255	63.75	16.55
Akter et al. (2011)	Trustworthiness in mHealth information services: an assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS)	*Journal of the American Society for Information Science and Technology*	164	13.67	6.94
Tenenhaus et al. (2015)	PLS methodology to study relationships between hedonic judgements and product characteristics	*Food quality and preference*	151	8.39	2.22

TC Total Citations; *TCperYear* Total Citations per Year; *NTC* Normalized Total Citations

Sarstedt et al. (2019) explain how to evaluate the results of HOCs in Partial-Least Squares-Structural Equation Modeling (PLS-SEM) using the two approaches known in the literature (the Repeated Indicators and the Two-Step Approaches).

There have been many advances since their first development and considerable research has been undertaken into the use of higher-order PLS-PM, with several applications developed. The large diffusion of these hierarchical models is linked to their usefulness and the countless advantages that such an approach can have (Edwards, 2001). Many researchers agree that these models, by reducing the number of relationships in the structural model, make PLS-PM more parsimonious and easier to understand (Becker et al., 2012; Edwards, 2001; Johnson et al., 2011; Polites et al., 2012; Sarstedt et al., 2019). Moreover, in situations characterized by collinearity among the constructs, a HOC can reduce such issues and may solve discriminant validity problems (Ringle et al., 2012).

The rest of this chapter is organized as follows: Sect. 9.2 consists of a focus on reflective and composite constructs; in Sect. 9.3 HOC path modeling is discussed and the different approaches proposed in the literature are considered with an in-depth analysis of the characteristics of each. Moreover, in this section some evidence on the choice of these approaches on the basis of their properties and characteristics is provided. The application of these approaches is shown by means of a case study in Sect. 9.4; and, finally, in Sect. 9.5, some concluding remarks are made and future studies are reported. Other results of a bibliometric analysis on scientific articles published on the subject are reported in the Appendix.

9.2 Reflective and Composite Constructs

To develop path models, researchers need to draw on both structural theory and measurement theory, which indicate the relationships between the elements of a path model (Sarstedt et al., 2021). The basic idea is that the complexity inside a system can be studied by taking into account the causal relationships among the constructs, each measured by several indicators.

Generally, there are two different ways to measure LVs: *reflective measurement*, in which the indicators are caused by the construct; and *composite-formative* (Henseler, 2020; Schuberth et al., 2020) (or simply composite) measurement (Bollen & Diamantopoulos, 2017; Henseler, 2017; Van Riel et al., 2017), in which the indicators cause the construct. The choice of whether to adopt a composite or reflective model is still an open question. The setting of a reflective rather than a composite construct substantially affects the identification and estimation of the model. Given the choice between developing a composite or reflective measure or between adopting an existing composite or reflective measure, which should be selected? We can attempt to answer this question by briefly discussing the characteristics of the two models. This choice represents an important moment for the researcher and, indeed, has been the focus of most discussion regarding reflective and composite measurement (Blalock & Blalock, 2017; Howell et al., 2007). Podsakoff et al. (2003) believe that some constructs are composite in nature and should not be modeled in a reflective way. According to Edwards and Bagozzi (2000), in some situations the constructs are usually viewed as the causes of their measures, with these measures being called reflective because *they represent reflections, or manifestations of a construct* (Fornell & Bookstein, 1982); in other situations, the measures are viewed as the causes of the constructs (Bagozzi & Fornell, 1982; Blalock & Blalock, 2017; Edwards & Bagozzi, 2000). Such measures are called composite (or formative), because the construct is formed by its measures (Fornell & Bookstein, 1982). Edwards and Bagozzi (2000) reason about the different conditions under which the measures should be modeled as composite or reflective by providing guidelines. In the same year, other researchers studied this topic; for example, Bollen and Ting (2000) propose an empirical test to determine whether indicators are more likely to be composite or reflective (Howell et al., 2007). Moreover, Jarvis et al. (2003) highlight that composite indicators are not interchangeable, while reflective indicators are mutually interchangeable. On this aspect, MacKenzie et al. (2005) emphasize that the reason for this interchangeability is related to the fact that reflective indicators should be highly correlated.

In fact, in the *reflective way*, each MV reflects the corresponding LV (Fig. 9.1). A block is defined as *reflective* if the LV is assumed to be a common factor that reflects itself in its respective MVs. This implies that, considering a matrix X of MVs partitioned in q blocks and x_{pq} the generic *p-th* (with p from *1* to P) of a *q-th* block,[1] the relationship between each MV x_{pq} and the corresponding LV ξ_q is modeled according to Eq. (9.1):

$$x_{pq} = \lambda_{pq}\xi_q + \epsilon_q \tag{9.1}$$

where λ_{pq} is the simple regression coefficient between the MV and LV, also called the *loading*. In the reflective case, the MVs should be highly correlated with each other, due to the fact that they are connected with the LV of which they are expressions. In other words, the block has to be homogeneous.

In the *composite case*, the LV is supposed to be generated by its own MVs (Fig. 9.1) according to Eq. (9.2):

$$\xi_q = \sum_{p=1}^{P_q} \omega_{pq} x_{pq} + \delta_q \tag{9.2}$$

where ω_{pq} are the *regression coefficients* of a multiple regression model, linking each MV x_{pq} to the corresponding LV ξ_q, and δ_q being the errors that represent the part of the LV not explained by the block of MVs.

The choice of whether to adopt a reflective or composite construct is not clear. The kind of measurement generally depends on the construct conceptualization, the aim of the research and the role of the construct in the model (Sarstedt et al., 2014).

[1] P_q is the number of MVs in the q-th block.

Table 9.2 Guidelines for choosing the measurement construct

Criterion	Decision	References
Causal priority between the indicator and the construct	From the construct to the indicators: reflective From the indicators to the construct: composite	Diamantopoulos and Winklhofer (2001)
Is the construct a trait explaining the indicators or rather a combination of the indicators	If trait: reflective If combination: composite	Fornell and Bookstein (1982)
Do the indicators represent consequences or causes of the construct?	If consequence: reflective If causes: composite	Rossiter (2002)
Is it necessarily true that if the assessment of the trait changes, all items will change in a similar manner (assuming they are equally coded)?	If yes: reflective If no: composite	Chin (1998)
Are the items mutually interchangeable?	If yes: reflective If no: composite	Jarvis et al. (2003)

Source Hair et al. (2021)

Hair et al. (2021) provide guidelines about the choice of appropriate measurement specification. Their framework is reported in Table 9.2.

As can be seen, the different authors shown in the table consider different criteria for choosing the type of relationship. For example, Diamantopoulos and Winklhofer (2001) focus their attention on the causal priority between the indicators and their constructs. Instead, Fornell and Bookstein (1982) analyze whether the construct is a trait that explains the indicators or is, rather, a composite combination of the indicators. Finally, Jarvis et al. (2003) study the interchangeability of the composite indicators. In addition to the aforementioned criteria, according to Bagozzi (2011), composite constructs have a place in research but their practical use is much more challenging. According to Bagozzi (2011), *researchers contemplating the use of composite measures and constructs should make explicit their ontological assumptions and carefully assess the theoretical and empirical meaningfulness of any model in this regard*. He states that the applicability of composite constructs *is restricted to a few narrowly defined models, unless one is willing to make a commitment to the ontology behind the approach and forgo the ontology and implications of the use of reflective measures exclusively*. For a detailed discussion of representations of composite models, see Bagozzi (2011). Ringle et al. (2012) in their critical review of all empirical studies using PLS-PM published in *MIS Quarterly*, find that 15%

of studies have inappropriately evaluated composite measurement models by using reflective evaluation criteria.

The above criteria focus on the type of first-order construct (between the MVs and the respective LV). However, it is important to note that conceptual definitions of constructs are often specified at a more abstract level, which sometimes include multiple composite and/or reflective first-order dimensions (Jarvis et al., 2003). In this case, it is important to consider the implications that choosing specific types of measurement model constructs have in the hierarchical structure model. Different types of measurement models in the hierarchical structure and their applications are discussed in Sect. 9.3.1, where each type of measurement model is linked to each type of structural model.

9.3 Relevance of HOC Path Modeling

Recently, important methodological research studies on PLS-PM have involved complex constructs at higher levels of abstraction. Researchers have pointed out that many complex phenomena are based on different levels of abstraction and that a high level of abstraction, when a dimension is manifold, lacks its own indicators and is described by various underlying constructs. This kind of model can be distinguished from unidimensional constructs, which are characterized by a single underlying dimension (Netemeyer et al., 2003).

The purpose of a hierarchical model is to synthesize the information of the various underlying blocks, thereby reducing complexity and increasing parsimony, as fewer paths need to be estimated (Becker et al., 2012). Many researchers argue that only by aggregating heterogeneous and different aspects is it possible to provide a complete understanding of a phenomenon (Edwards, 2001). Others, instead, are critical and question the theoretical utility as they argue that such constructs are ambiguous because a variation in these multidimensional constructs can imply variation in some or all of its dimensions (Cronbach, 1972). In this context, the use of hierarchical LV models has allowed researchers to extend the application of PLS-PM to more complex models (Becker et al., 2012), in which a set of relations expressed through equations is considered, thus becoming a very flexible way of investigating models with a high level of abstraction. It is a useful power tool and is now considered essential for analysis within the framework of this type of hierarchical model (Latan, 2018).

Nowadays, many constructs refer to a multidimensional reality, which cannot be synthesized with a single block. For example, in a social context, Cataldo et al. (2021) have proposed a methodological framework, estimated through higher-order PLS-PM for the sustainable developments goals (SDGs). In their work, the hierarchical relationships between these different LVs are considered and their connections to a higher-order global sustainability dimension estimated.

9.3.1 HOC PLS-PM Theoretical Framework and Its Different Types

HOCs in PLS-PM, also known as *hierarchical models* or *multidimensional constructs*, are considered as explicit representations of multidimensional constructs which exist at a higher level of abstraction and are related to other constructs at a different level of abstraction, completely mediating their influence from or on their underlying dimensions (Chin, 1998). Many theoretical and empirical studies (Cataldo et al., 2017; Edwards, 2001; Jarvis et al., 2003; Sarstedt et al., 2019; Wetzels et al., 2009) emphasize the usefulness of the hierarchical construct model, and many researchers argue that such models allow a greater theoretical parsimony and reduce the model complexity (Edwards, 2001; MacKenzie et al., 2005; Wetzels et al., 2009). Moreover, even in the presence of a high collinearity among the composite indicators, researchers can subdivide the set of indicators and establish separate constructs in a higher order structure (Hair et al., 2021).

Generally, regardless of the type of construction, HOC models have become a widely used method in many research fields. For example, Ringle et al. (2020) point out that these kinds of models are frequently used in human resource management (HRM), a field where the emergence of progressively more complex models underlines the critical importance of developing advanced analytical methods.

In the collection of international papers about hierarchical models shown in detail in the Appendix in this chapter, the HOC models are used widely in marketing and management research. Furthermore, we noticed that many researchers have used this approach in order to study the quality of life, satisfaction, expectation, behaviors, and perceptions. If we consider the macro-categories of fields of application of Table 9.12 in Appendix, almost 40% of the documents refer to the business area; the second area, by a long way, is that of social sciences with a percentage of 9% of documents, followed by computer science with 8% and the medical area with 7%; the fifth and last category is represented by science and technology with a percentage of 6%. Typically, HOC models provide a framework for researchers to model a construct on a more abstract dimension (referred to as an HOC), its more concrete sub-dimensions (referred to as lower-order constructs (LOCs)) and the different relationships between the HOC and the LOCs (reflective or composite relationships) (Becker et al., 2012; Edwards, 2001; Jarvis et al., 2003; Wetzels et al., 2009). Often, multidimensional constructs include combinations of composite and reflective measurements (Jarvis et al., 2003). This means that, both for the first-order constructs and the HOCs, the type of measurement model can and should be determined separately (van Riel et al., 2017). As shown by Becker et al. (2012), *a higher (or second)-order construct is a general concept that is either represented (reflective) or constituted (composite or formative) by its dimensions (lower (or first)-order constructs). Therefore, the relation between higher and lower order constructs is linked to the idea of existence of the hierarchical LV, as the higher order construct (the general concept) does not exist without its lower order constructs (dimensions).* If the higher order construct is reflective, the general concept is manifested by several specific dimensions, which are themselves latent (unobserved). If the higher order construct is composite, it is a combination of several specific (latent) dimensions in a general concept (Edwards, 2001; Wetzels et al., 2009). Edwards (2001) termed these two types of construct respectively *superordinate* and *aggregate*, instead Chin and Gopal (1995) and Law and Wong (1999) defined reflective model as *molecular model* and composite model as *molar model* (Law & Wong, 1999; Wetzels et al., 2009). According to Polites et al. (2012), it is important to carefully conceptualize the relationship not only between the first-order constructs and their indicators, but also between the LOCs and the HOC (van Riel et al., 2017).

In this respect, this research study refers to the four types of HOC, shown in Fig. 9.3 (Jarvis et al., 2003). These types of model consider two elements: the HOC, which captures the more abstract entity, and the LOC, which captures the sub-dimensions of the abstract entity. The difference between the types is related to the relationship between the LOCs and their elementary indicators (the measurement model specification) and the relationship between the HOC and the LOCs (the structural model specification) (Becker et al., 2012). One of the most popular choices in structural equation modeling among researchers is Reflective-Reflective Type I model (Afthanorhan, 2014). Lohmöller (2013) calls this type of model the "hierarchical common factor model", where the higher order construct represents the common factor of several specific factors (Afthanorhan, 2014). The Reflective-Reflective Type I model is most appropriate if the objective of the study is to find the common factor among several related, yet distinct, reflective constructs (Becker et al., 2012). The Reflective-Composite Type II model has become the most widely used in empirical applications currently being considered by researchers. According

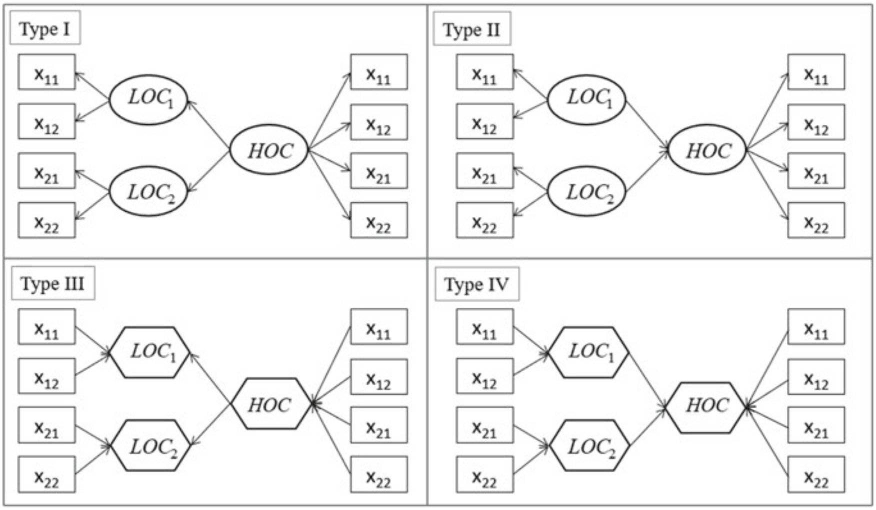


Fig. 9.3 Types of second-order constructs. LOC = Lower Order Construct; HOC = Higher Order Construct

to Chin et al. (1998) in this kind of model, the LOCs are selectively measured constructs that do not share a common cause but rather form a general concept that fully mediates the impact on subsequent endogenous variables (Crocetta et al., 2021). Different studies have been based on this type of construct (Becker et al., 2012; Crocetta et al., 2021). The Composite-Reflective Type III model is appropriate in those cases where the HOC is a common concept of several specific composite LOCs. Examples in the empirical literature are rather scarce, but Becker et al. (2012) argue that such an approach could be used in the corporate setting to measure performance. The Composite-Composite Type IV model is the least frequently implemented in PLS-PM but may be useful to structure a complex composite construct with many heterogeneous indicators into several sub-constructs.

Empirical concerns about the measurement model specification and the structural model have received far less attention from the mainstream education or psychology research compared to other research fields (Thien, 2020), particularly in information systems (Cenfetelli & Bassellier, 2009), business (Rigdon, 2014) and marketing (Jarvis et al., 2003). According to Edwards (2001) reflective constructs are common in personality and psychological research, while composite constructs are widespread in organizational behavior research. This consideration is also confirmed by a bibliometric analysis of the collection of international works published between 1991 and 2021 and retrieved from the Web of Science Database. Many papers published in the social and psychological fields use the reflective-composite HOC PLS-PM approach (Becker et al., 2012; Cataldo et al., 2021; Ringle et al., 2012), while those that operate in the business field use composite-composite HOC PLS-PM models (Becker et al., 2012; Jarvis et al., 2003; Petter et al., 2007).

Finally, van Riel et al. (2017) suggests that for composite constructs the classical PLS algorithm should be used, while for reflective constructs the PLS consistent algorithm (PLSc) should be used (Dijkstra & Henseler, 2015). van Riel et al. (2017) explains that *if the constructs are meant to be reflective, PLS generates inconsistent estimates, which may lead to flawed theoretical conclusions* (Henseler et al. 2014). *PLSc corrects inter-construct correlations for attenuation so that the estimates of path coefficients and loadings become consistent.*

9.3.2 Alternative Approaches for Higher-Order PLS-PM Estimation

One important decision regards determining how to operationalize the HOC constructs. PLS-PM requires all constructs to be attached to MVs, regardless of relationship type, to make the algorithm run. As observed variables (or indicators) to estimate the construct of the HOC do not exist, various methods to model the hierarchical LVs in PLS-SEM have been proposed in the literature (Becker et al., 2012). Within the framework of PLS-PM, the two main approaches suggested to estimate the HOCs models are the *Repeated Indicators Approach* (Lohmöller, 2013; Wetzels et al., 2009) and the *Two-Step Approach* (Hair et al., 2021). Recently, researchers have proposed some alternative approaches for the specification and estimation of this kind of model in PLS-PM in order to overcome some limitations and problems of traditional methods (Cataldo et al., 2017). All these approaches will be briefly described in the following subsections, each presented with a graph and related equations. For the sake of simplicity, both the graph and equations refer to a composite-composite scheme, being easy to extend them to other models previously considered.

9.3.2.1 The Repeated Indicators Approach

Within the context of PLS-PM, the most common approach proposed to estimate the HOCs model is the *Repeated Indicators Approach* (Sarstedt et al., 2019), the so-called *Hierarchical Component Model* (Wold, 1982) or *Super-block Approach* (Lohmöller, 2013; Tenenhaus et al., 2005) (Fig. 9.4).

The Repeated Indicator Approach consists of taking the indicators of the LOCs ξ_1^I and ξ_2^I and using them as the MVs of the HOC ξ^{II} (Sarstedt et al., 2019). The Repeated Indicators Approach can be explained by considering the following three equations in the composite external model:

$$\xi_j^{II} = \sum_{(q:\xi_q^I \rightarrow \xi_j^{II})} \beta_{qj} \xi_q^I + \zeta_j \tag{9.3}$$

$$\xi_q^I = \sum_{p=1}^{P_q} \omega_{pq} x_{pq} + \delta_q \tag{9.4}$$

$$\xi_j^{II} = \sum_{p=1}^{P_q} \omega_{pq} x_{pq} + \epsilon_j \tag{9.5}$$

where the vectors ξ_q^I, ξ_j^{II}, x, ζ, δ and ϵ indicate, respectively, the first-order and second-order LVs, the MVs, and the structural and measurement error terms. The vectors β_{qj} and ω_{pq} define the path coefficients connecting the LVs and the weights linking, respectively, the MVs to the first-order and second-order LVs. The structural or inner model in Eq. (9.3) specifies the relationships between the first-order and

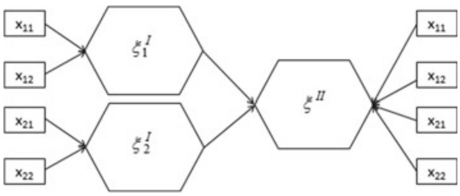


Fig. 9.4 HOC model building—the repeated indicators approach

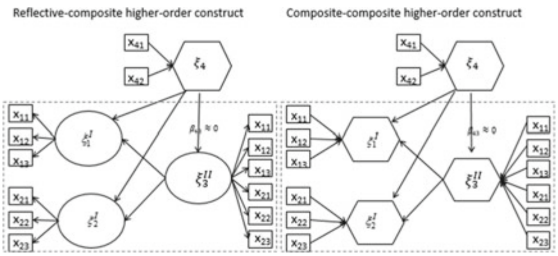


Fig. 9.5 Extended repeated indicators approach proposed by Ringle et al. (2012)

second-order LVs. Equations (9.4) and (9.5) denote the measurement models, where the MVs, measuring each first-order LV, are repeated in order to represent the HOC. In this way, the elementary indicators have a dual role: they are the measure of each dimension of the lower order and also of the construct of the higher order.

Given its constructive simplicity, this approach is widely used by researchers and its advantage is its ability to estimate all constructs simultaneously. Wold (1982) claims that this approach is generally better suited to reflective-reflective type models. Chin (2010) and Ringle et al. (2012), instead, argue that the Repeated Indicators Approach is often used in the reflective-composite type of model. Becker et al. (2012), however, think that this approach is more appropriate in the composite-composite type. In view of these considerations, it is important to emphasize that the choice of model depends on the research hypothesis that the researcher formulates at the beginning.

In this kind of approach, the interpretation of the relationships between the LOCs and the HOC must account for the bias of unequal numbers of indicators in the LOCs. Indeed, many researchers recommend this approach only in the case of an equal number of indicators per construct (Lohmöller, 2013; Ringle et al., 2012) although this hypothesis has not yet been tested in the literature. Finally, regardless of the model type, by relating indicators of the same type to each other through the PLS estimate with this approach, there is the possibility of a perceived effect of a possible distortion of the estimates. This can be a disadvantage of the Repeated Indicators Approach because the repeated use of the same indicators can cause artificially correlated residuals (Becker et al., 2012).

A possible solution has been suggested by Ringle et al. (2012), who, in *Appendix B: Hierarchical Component Models* to their article, *A Critical Look at the Use of PLS-SEM in "MIS Quarterly"*, proposed an alternative and very schematic version of the Repeated Indicators Approach, in which the higher construct is not directly affected by the other constructs in the model but is influenced only indirectly through the lower constructs. This type of model (Fig. 9.5), which was later given the name of the *Extended* Repeated Indicators Approach, was then developed by Sarstedt et al. (2019). In this alternative approach, the effect of a construct on a higher construct is thus viewed as being fully mediated by the lower constructs (Sarstedt et al., 2019; Van Riel et al., 2017).

9.3.2.2 The Hybrid Approach

Another option for modeling HOCs is the *Hybrid Approach* proposed by Wilson et al. (2007). The idea behind this approach is to randomly split all the MVs of the lower constructs so that half of their indicators are represented on their respective lower construct side and the other half on the higher constructs side. The MVs are assigned by random sampling. Thus, the Hybrid Approach uses half to estimate the lower construct and the other half to estimate the higher construct, thereby avoiding the repeated use of indicators in the model (Wilson, 2010). This approach has drawbacks in the case of a low number of indicators per LOC or in the case of dimensions with an unbalanced number of indicators. However, it presents the advantage of reducing the number of indicators when this number is high for each construct. Its applicability is limited in the case of reflective schemes that presume very related indicators. Regarding this approach, however, it still remains unclear how to proceed in cases where there is an odd number of indicators. Similarly, there are no clear guidelines in the literature on what type of construct to use in this approach. Wilson et al. (2007) in their simulation studied only reflective measurement models and it remains unclear whether their results can be generalized to PLS path models with composite measures.

9.3.2.3 The Two-Step Approach

The *Two-Step Approach*, or *Sequential LV score method*, was proposed by Ringle et al. (2012) as an alternative to the Repeated Indicators Approach. This approach was also called the *Two Stage Approach* or the *Disjoint Two-Stage Approach* by Sarstedt et al. (2019). As the name suggests, it consists of two steps (Sarstedt et al., 2019; Wetzels et al., 2009). It estimates the construct scores of the LOCs ξ_1^I and ξ_2^I in a first-step model without the presence of HOC ξ^{II} and, subsequently, in the second step, the PLS-PM analysis is performed using the first-step computed scores as indicators of the HOC ξ^{II} (Fig. 9.6) according to Eq. (9.6):

$$\xi_j^{II} = \sum_{p=1}^{P_q} \omega_{pj} \xi_q^I + \epsilon_j \tag{9.6}$$

Therefore, the aim of the first step is to obtain the LV scores for the first-order dimensions. In essence, the measurement of the first-order constructs is reduced to single items (van Riel et al., 2017) and in this step the HOC (and thus the relationship to the structural model) is not yet included. This aspect is considered instead in the second step (van Riel et al., 2017) and the single items obtained for each dimension in the first step will be the indicators of the HOC. In the literature, there are no examples of using this approach with more than two levels. This would be necessary in any case when the analysts have previously used factor scores prior to running further regression analyses in the structural model. This approach may prove to be useful

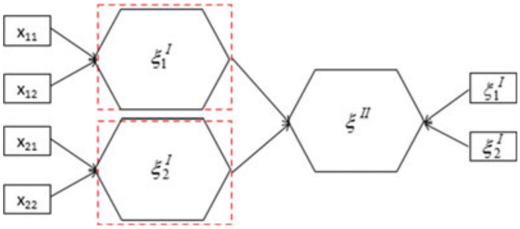


Fig. 9.6 HOC model building—the two-step approach

when estimating higher order models with composite indicators in the measurement model (Diamantopoulos & Winklhofer, 2001; Reinartz et al., 2004).

It has the advantage of estimating a more parsimonious model on the higher level analysis without needing the LOCs. On the downside, a clear disadvantage is that any construct investigated in the second step is not taken into account when estimating the LV scores in the first step.

According to Ringle et al. (2012) this approach is appropriate when the model involves a composite structural model, i.e., when the HOC is formed by its lower dimensions.

9.3.2.4 The Mixed Two-Step Approach

The *Mixed Two-Step Approach* has been proposed by Cataldo et al. (2017) as an alternative approach that computes the scores internally within the model rather than externally as in the step approach. The scores calculated with the classic two-step approach computed without the HOC accurately capture the structure of variability of the block so as to maximize the representativeness of the blocks. This makes sense if there is a high communality in each first order block, so especially in a reflective-composite model. However, in a path model where all the relationships among the LVs are considered, this approach is not recommended for prediction of the HOC. This procedure has also been called by Sarstedt et al. (2019) *the Embedded Two-Stage Approach*.

The approach begins with the implementation of the PLS-PM using the indicators of the LOCs as the MVs of the HOC, as in the Repeated Indicators Approach. In this way, the algorithm gives the scores of the LOCs. Thus, the scores of the blocks become indicators of the HOC according to Eq. (9.7), and the PLS-PM algorithm is run again (Fig. 9.7).

$$\xi_j^{II} = \sum_{p=1}^{P_q} \omega_{pj} ScoresPLS\xi_q^I + \epsilon_j \tag{9.7}$$

where *ScoresPLS* are the scores obtained by the PLS-PM algorithm with repeated indicators in the first step.

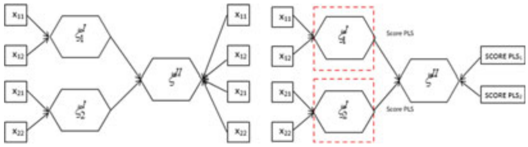


Fig. 9.7 HOC model building—the mixed two-step approach

In this way the scores are calculated considering the higher order dimension, which allows us to identify the LOC that is the best representative of its block and, at the same time, has the best predictive power in relation to the HOC (Crocetta et al., 2021).

Cataldo et al. (2017) investigated within the same simulation design, the performance of the classic Two-Step Approach and the Mixed Two-Step Approach in a reflective-composite Type II model. The aim was to compare these approaches using different sample sizes in order to understand the effect of the sample dimension. In this simulation, the Two-Step Approach heavily underestimated all the path coefficients linking the LOCs with the HOC for all sample sizes and the variability of the estimates was higher than in the Mixed Two-Step Approach. This result could be attributable to the noise reduction at the HOC level.

9.3.2.5 The PLS-Component Regression Approach

Both the Two-Step and the Mixed Two-Step approaches determine a single component that synthesizes the information of the first-order constructs. Choosing only the first component, the remaining portion of the variability of the block may not be taken into account (Cataldo et al., 2017). For this reason, the *PLS Component Regression Approach* has been proposed by Cataldo et al. (2017) and Crocetta et al. (2021) in order to overcome the problems related to the unique component of the first-order constructs, giving the possibility of choosing the number of components to be extracted according to empirical criteria (eigenvalues one or the percentage of explained variance) or according to an optimal criterion. In addition, since the aim of PLS-PM is to estimate the relationships between the LVs, this approach provides components that are at the same time representative of their blocks and predictive of the HOC. As can be seen in Fig. 9.8, it starts with an HOC formed of all the MVs of the LOCs. Next, PLS-Regression is applied in order to obtain h components for each block. For each h component model, the PRediction Error Sum of Squares (PRESS) index is obtained. First, PRESS decreases for a certain number of components; then, it begins to increase as the number of components increases. Obviously, the number of components giving the minimum PRESS is chosen.[2] Once h components have been obtained, they represent the indicators of the HOC according to Eq. (9.8) and the PLS-PM algorithm is performed (Cataldo et al., 2017).

[2] For a more detailed illustration see Ball (1963).

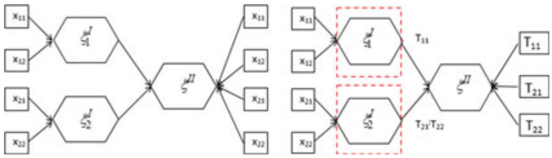


Fig. 9.8 HOC model building—the PLS-component regression approach

$$\xi_j^{II} = \sum_{h=1}^{H} \omega_h T_h^I + \delta_j \tag{9.8}$$

where T_h are the components obtained by the PLS-Regression.

This approach shows a higher diversity among path coefficients as it includes more information than the other mentioned approaches. As the sample size increases, PLS-Regression improves in terms of the estimates, becoming more stable than the others. Indeed, the authors suggest using this approach with a great number of MVs per LOC and in a composite-composite Type IV model, namely when we are faced with problems of heterogeneity of the data in each construct. In addition, in contrast to the Two-Step approach, this approach performs better in prediction because it is based on PLS-Regression, which represents a supervised method in comparison with, for example, principal component analysis (PCA), which does not use the responses for the construction of the new components.

9.3.3 Some Guidelines for Choosing the Best HOC Approach

After deciding on the model that best matched the researcher's hypothesis, the choice of a particular approach for its estimation mainly depends on its properties and characteristics. There are several factors to be taken into consideration, such as the number of variables, the number and type of relationships among the MVs and LVs, the communality and redundancy levels to be reached and the contribution expected. On the basis of the previous methodological discussion, taking into account at the same time the different operational situations, a concise synoptic framework has been presented in Table 9.3.

In choosing an approach to HOCs, the first objective is to find a methodology that is consistent with a hierarchical data structure. The aim of the various proposals is to summarize in a proper way the lower order dimensions and appropriately define their MVs and constructs associated with the higher order dimension. With the exception of the Repeated Indicators Approach, all the estimation methods may even result in a loss of information in exchange for the advantage of the enhanced explanatory and interpretative capacity of the HOC model. One desirable criterion is linked to a balance in the number of MVs for each lower or higher model dimension. Generally, the HOC PLS-PM approach, regardless of the type of relation on which the LOCs

Table 9.3 Requirements and properties of HOC estimation approaches

	Repeated indicators	Two-step	Hybrid	Mixed two step	PLS-component regression
Type of relations	R-R or R-C	R-C	R-R or R-C	R-C	R-C or C-C
Number of MVs	Few	Many	Many	Many	Many
Unbalanced number of MVs	No	Yes	No	Yes	Yes
Communality	High	High	High	High/Low	High/Low
Redundancy	High	High	High	High/Low	High/Low
Contributions expected diversification	Not relevant	Relevant	Not relevant	Relevant	Relevant

Type of relations: R= Reflective; C= Composite

and HOC are based, works well even when the number of MVs is not the same in all lower order dimensions.

According to the type of the relations, some methods are typically more adherent to an HOC scheme that contemplates reflective relationships at the first level and composite relationships at the second and higher level. For the Two-Step and Mixed Two-Step Approaches the aim is to obtain components that are as representative as possible of the first-order blocks and therefore the MVs of each first level block must be correlated with each other (a high communality). According to the number of MVs, it is advisable to use the Repeated Indicators Approach in a case of few variables in order to avoid model heaviness and high heterogeneity in the higher order dimension. Moreover, the aim of this approach, and of the Hybrid Approach, is not to synthesize the MVs but to process the available information. For this reason, these approaches are not affected by the unbalanced number of MVs. The communality must be high for those approaches that operate more commonly in the perspective of reflective-reflective relationships.

9.4 Application to Real Data: Comparison of the HOC PLS-PM Approaches

This empirical illustration is based on the construction of the Multidimensional Poverty Index construction, considered a crucial factor for monitoring poverty and advising nations with respect to immediate action. The very simple example presented in this section is aimed at showing the usage and computations of the different approaches and see the consequences on the path coefficient estimates and on the validation and interpretation of the model.

9.4.1 A Model-Based Multidimensional Poverty Index (MPI)

The global Multidimensional Poverty Index (MPI) was developed in 2010 by the Oxford Poverty and Human Development Initiative (OPHI) within the United Nations Development Program (UNDP, 2010) and has been published annually since then. The MPI uses 10 indicators to measure poverty considering various deprivations in three dimensions—health, education and standard of living—following the same dimensions and weights as the Human Development Index. It is an international measure of multidimensional poverty covering over 100 developing countries and it complements traditional monetary poverty measures by capturing the acute deprivations in health, education and living standards that a person faces simultaneously. More details about the general methodology can be found in Alkire and Jahan (2018). Programs for computing the MPI and its components for a large selection of countries with appropriate data are available at https://hdr.undp.org/.

This measure is based on the dual cut-off counting approach to poverty developed by Alkire et al. (2011). The Alkire-Foster (AF) method is a way of measuring multidimensional poverty as defined by the OPHI's Sabina Alkire and James Foster (Alkire et al., 2015). Building on the Foster-Greer-Thorbecke poverty measures (Foster et al., 2010), it involves counting the different types of deprivation that individuals experience at the same time, such as a lack of education or employment, poor health or poor living standards. The subsequent deprivation profiles are analyzed to identify the poorest countries. In this context, the multidimensional poverty is a complex phenomenon, devoid of its own indicators and described by various underlying constructs. Differently from the classic approach based on computing the average of normalized indicators associated to each dimension followed by a further average (usually geometric) of such syntheses, here we propose an MPI estimation using a model-based approach through a suitable higher-order PLS-PM, in which the hierarchical relationships between the different LVs are considered. The MPI can be, here, conceived as a second-order construct affected by the first-order LVs that are associated with the three dimensions measuring health, education and living standards (Fig. 9.9).

Although we have included all types of hierarchical LV models in our conceptual framework, in the empirical application we will focus on the reflective-composite hierarchical LV model. Each of these three dimensions was measured by MVs and the relationship between them and the respective LV was assumed to be reflective (every LV is the reflection of the MVs to which it is connected), with these three dimensions having an impact on the MPI in a composite way. This kind of reflective-composite modelization is a particularly important and widely adopted type of model, frequently used in research in the social sciences (Ringle et al., 2012), particularly in the construction of composite indicators.

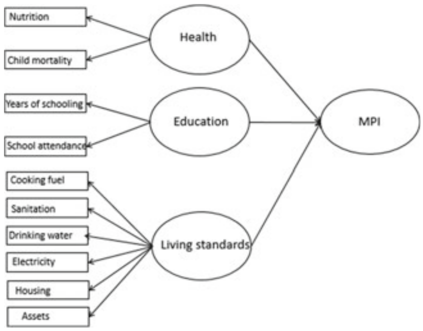


Fig. 9.9 MPI estimated through the higher order PLS-PM

As a matter of fact, this type of model-based approach to the construction of composite indicators as proposed by Lauro et al. (2018), has the advantage of being based on a weighted synthesis of the lower order LVs through their estimated impacts by means of PLS-PM. In this way, it is also possible to evaluate the importance of LOCs in defining the MPI composite indicator.

Moreover, the goal is not to find a factor common to these three dimensions, which are conceptually different from each other, but rather to study to what extent these three dimensions predict the MPI score, or to estimate the impacts they have on this index. For this reason, the higher order MPI is conceived as a dimension which depends on the three lower order dimensions according to a composite structural model (that describes the causal-predictive relationships between the LOC and HOC constructs), which in turn are reflected in a series of observed variables (MVs).

For this application we follow van Riel et al. (2017) suggestion, according to which for reflective constructs is used PLS consistent (PLSc) algorithm (Dijkstra & Henseler, 2015). The elementary indicators (MVs) are derived from the database of the United Nation Human Development Reports HDRs, updated to the last MPI 2021 report.[3]

9.4.2 *Analysis*

The MVs used in the present exercise are the same as those proposed in the MPI report and employed in building the MPI scores. Considering that the MVs have different scales, for comparative purposes they have been first normalized to a value between 0 and 1, where 0 is assigned to the country in the most favorable condition while 1 is assigned to the poorest country for each indicator.

[3] The analysis was performed using the SmartPLS statistical programming language (https://www.smartpls.com/) (Ringle et al., 2022) and the R programming language. The external commands to the package were manually implemented to obtain the different HOCs for the individual approaches. We are working on implementing a package that includes building HOCs automatically.

Table 9.4 shows the correlation matrix of the MVs. It generally reveals a high internal correlation in each block and a lower correlation between the blocks, which justify the choice of a second-order reflective-composite hierarchical model.

Before applying the PLS-PM approach, an exploratory PCA was performed in order to analyze the relationship between the indicators inside each dimension. In Fig. 9.10 the scree-plot, the so-called PCA correlation circle, and the table of eigenvalues of each dimension are shown.

A correlation matrix is useful for calculating the eigenvalues for the choice of synthesis factors and therefore for the graphical representation on a factorial plane. The eigenvalues represent a measure of the variability of the axes, the second-order blocks therefore corresponding to those eigenvectors (corresponding to the largest eigenvalues of the correlation matrix) that maximize the variability of the points projected into the new reference system. The three most popular methods for choosing factors are the "eigenvalue-one"; the "scree test"; and the "rate of inertia" or "variability explained". According to the first criterion, those factors are chosen whose eigenvalues are greater than or equal to one. Since the initial variables are normalized (therefore with unit variance) it would not make sense to consider eigenvalues lower than one because they would explain less, in terms of variability, than any of the initial variables would. The second criterion, also known as the "maximum fall of the eigenvalues", is based on the non-regularity of the eigenvalues on a histogram. For eigenvalues decreasing on a regular basis we have a cloud of points of a more or less spherical shape while, due to irregularities in the histogram, we move away from the situation of sphericity and the cloud takes on a "shape". We therefore choose those factors whose eigenvalues come before the regularization of the histogram. Finally, the inertia rate highlights the variability explained by the eigenvalues. The criterion requires that we choose those eigenvalues which allow us to reach a percentage of explained variability close to or greater than 75% of the total. On the basis of the three criteria described above, it is evident that the first component explains the most variability of the MVs. By projecting the original indicators onto the plane spanned by the first two principal components, we can notice that the first factor is strongly correlated with all the MVs for each dimension and so, for each dimension, there is an underlying measure that summarizes the variables analyzed.

Table 9.5 shows the main descriptive measures of the three dimensions considered. For a more detailed discussion on these indexes see Tenenhaus et al. (2005) and Dijkstra and Henseler (2015).

The internal consistency of each construct is assessed through the composite reliability and Cronbach's alpha, which are the most commonly used quality criteria for the measurement model. Values higher than 0.7 are usually considered as symptoms of unidimensionality, as happens in our case study for health, education and living standards. Another widely used index in PLS literature is the communality index, which measures the amount of MV variability explained by the corresponding LV. It is very high in our example, allowing us to assess the representativity of the different LOCs, as a consequence of the high correlations among their own MVs thereby confirming the results of the PCA. At this point it is possible to specify the HOCs according to the different approaches considered previously.

Table 9.4 Correlation between indicators

	Health		Education		Living standards					
	Nutrition	Mortality	School	Attendance	Fuel	Sanitation	Water	Electricity	Housing	Assets
Nutrition	1.00									
Mortality	0.86	1.00								
School	0.86	0.87	1.00							
Attendance	0.87	0.87	0.91	1.00						
Fuel	0.95	0.86	0.93	0.89	1.00					
Sanitation	0.94	0.86	0.92	0.89	0.97	1.00				
Water	0.92	0.78	0.87	0.83	0.95	0.96	1.00			
Electricity	0.92	0.83	0.89	0.85	0.97	0.96	0.96	1.00		
Housing	0.94	0.82	0.91	0.87	0.97	0.96	0.95	0.95	1.00	
Assets	0.82	0.65	0.77	0.69	0.87	0.86	0.91	0.89	0.89	1.00

Mortality: child mortality; school: years of schooling; attendance: school attendance; fuel: cooking fuel; water: drinking water

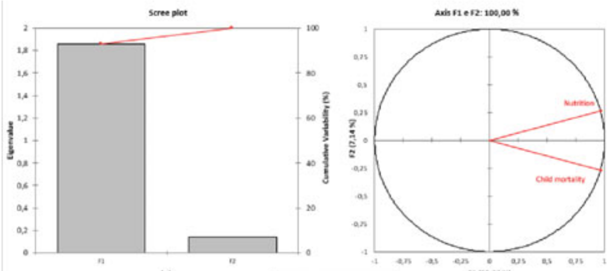


Table of eigenvalues:

	F1	F2
Eigenvalues	1,857	0,143
Variability (%)	92,860	7,140
Cumulative%	92,860	100,000

(a) Health

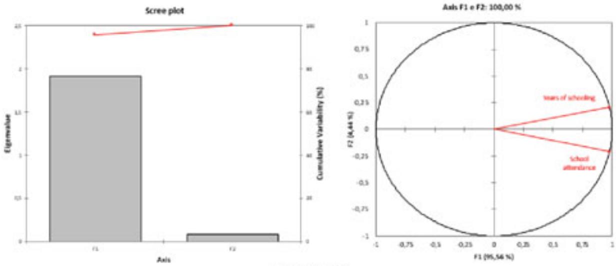


Table of eigenvalues:

	F1	F2
Eigenvalues	1,911	0,089
Variability (%)	95,563	4,437
Cumulative%	95,563	100,000

(b) Education

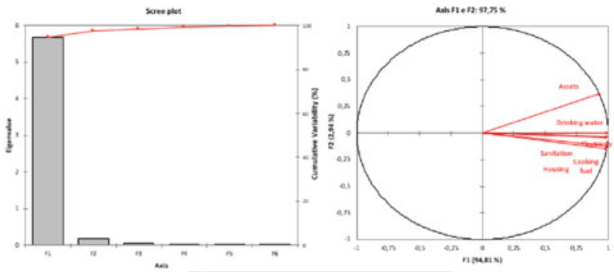


Table of eigenvalues:

	F1	F2	F3	F4	F5	F6
Eigenvalues	5,688	0,176	0,050	0,038	0,030	0,017
Variability (%)	94,807	2,939	0,837	0,633	0,506	0,278
Cumulative%	94,807	97,746	98,583	99,216	99,722	100,000

(c) Living standards

Fig. 9.10 Scree-plot and correlation circle of the three MPI dimensions

Table 9.5 Descriptive measures of the first-order dimensions

	Health	Education	Living standards
Cronbach's alpha	0.923	0.954	0.989
Composite reliability	0.963	0.977	0.991
Communality	0.929	0.956	0.948

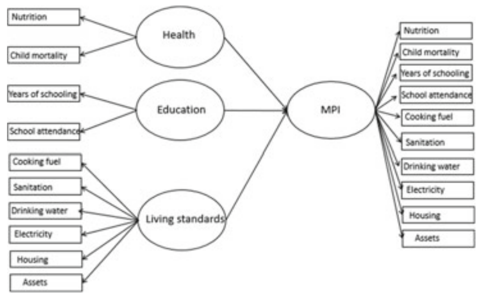


Fig. 9.11 The MPI dimension according to the repeated indicators Approach

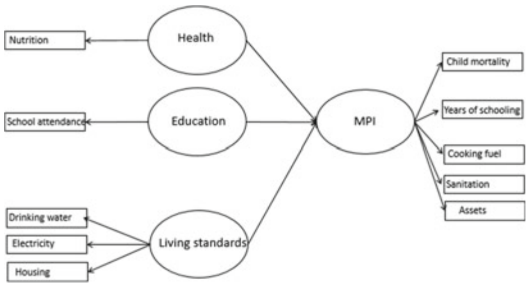


Fig. 9.12 The MPI dimension according to the hybrid approach

The Repeated Indicators Approach. In the Repeated Indicators Approach all the indicators of the three dimensions are assigned to the LV MPI, as shown in Fig. 9.11. In this case, the different number of MVs of each block could affect the interpretation. A stronger relationship between the MPI and living standards construct can emerge from this kind of set-up since they share a large number of indicators in the HOC construct.

The Hybrid Approach. With the Hybrid approach, on the other hand, we randomly split all the MVs of the three dimensions, so that half of their indicators are represented on their respective first-order construct side and the other half on the second-order construct side, as shown in Fig. 9.12.

In the case of few variables, as in this example, the results depend on the selection made. Any defect could be corrected by summarizing the estimated models for various alternative choices, or for a greater number of variables, by a random sampling in the blocks. A limit case occurs when the dimension is made up of only two MVs as in the case of education. In this case the lower-dimension will be represented by only a single MV. Baumgartner and Homburg (1996) underlines that *the single-item*

Table 9.6 Measures of the first principal component dimensions of the two-step approach

		Eigenvalue	Percentage	Cumulative percentage
Health	First PCA component	1.857	92.86	92.86
	Second PCA component	0.143	7.14	100.00
Education	First PCA component	1.911	95.56	95.56
	Second PCA component	0.088	4.44	100.00
Living standards	First PCA component	5.688	94.80	92.80
	Second PCA component	0.176	2.94	100.00

constructs are not recommended because they ignore the unreliability of measurement, precisely one of the problems PLS-PM was designed to avoid (Petrescu, 2013). Furthermore, Petrescu (2013) claims that *in most circumstances any single indicator is usually biased and requires the use of multiple indicators* (Anderson & Gerbing, 1988; Bergkvist & Rossiter, 2007; Campbell & Fiske, 1959). In accordance to Hayduk (1987) a variance with more than 40% or 50% can lead to estimation problems for the structural model. For a detailed discussion of using single-item indicators in structural equation models, see Petrescu (2013), which provides recommendations on circumstances when single-item indicators can be used and their modeling in SEM in order to prevent reliability and validity issues.

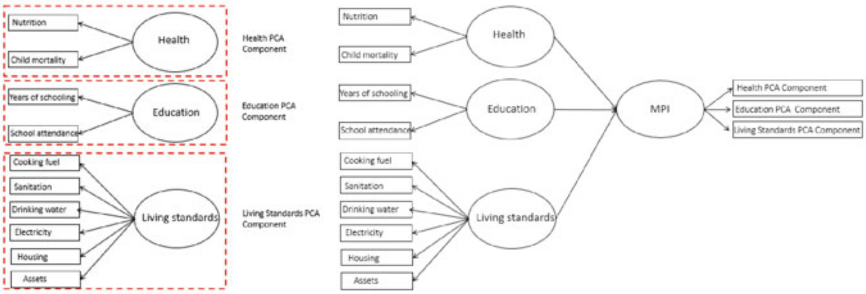
The Two-Step Approach. If we want to specify the MPI according to the Two-Step Approach, we first need to obtain a PCA component of the first-order dimensions, in accordance with Table 9.6.

With this approach we obtain three PCA components in the first step, one for each dimension, which will represent the MVs of the MPI dimensions in the second step (Fig. 9.13).

These three PCA components summarize the information of the first-order construct and represent the components that maximize the representativeness of these blocks.

The Mixed Two-Step Approach. According to this approach, first, an MPI dimension is formed by all the MVs of the three dimensions and the PLS-PM algorithm is performed. Next, the scores for each block obtained in the first step of the algorithm are used as the MVs of the MPI block and the PLS-PM algorithm is performed again (Fig. 9.14).

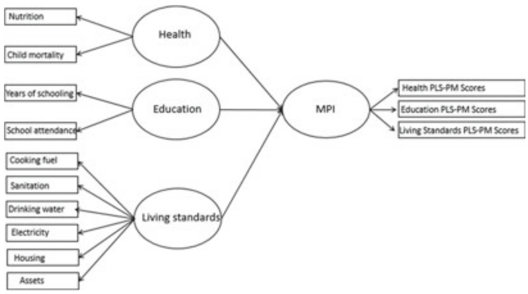
The PLS-Component Regression Approach. The last analyzed approach consists in considering, firstly, the MPI dimension formed by all the MVs of the three dimensions. The second step consists in applying the PLS-Regression, which pre-



(a) First Step (b) Second Step

Fig. 9.13 The MPI dimension according to the two-step approach

Fig. 9.14 The MPI dimension according to the mixed two-step approach



supposes that the common information carried by the LOCs and the HOC can be summarized in more than one latent component. Therefore, a crucial issue in the PLS-Regression is the definition of the number H of components to retain. In PLS Regression the explicative ability of the model (measured in terms of the R^2 index) increases as the number of the components increases. By contrast, the predictive ability of the model, i.e., the explicative ability of the model referred to units that have not been considered in its construction (the validation set), begins to decrease at some point as the number of components increases. This means that the model overfits the data, and the extraction of the components has to stop. In order to measure the marginal contribution of the *h-th* component to the predictive power of the model the Q^2 index is used: the *h-th* component is retained if $Q^2_h \geq 0.0975$ (Nengsih et al., 2019; Tenenhaus, 1998).

Looking at Table 9.7 we notice that, on the basis of the Q^2 criterion, two components are selected for the health dimension, while for education a single component exceeds the threshold and for the living standards dimension there are two components that exceed the criterion. These five components will represent the MVs of the MPI block. Therefore, the model to which the PLS-PM algorithm will be applied is the one shown in Fig. 9.15.

Table 9.7 Component selection based on the Q^2 criterion of the PLS-component regression approach

	T1	T2	T3	T4	T5	T6
Health	**0.8239**	**0.2138**				
Education	**0.8098**	0.040				
Living standards	**0.8797**	**0.3428**	0.0514	0.033	0.0233	0.0044

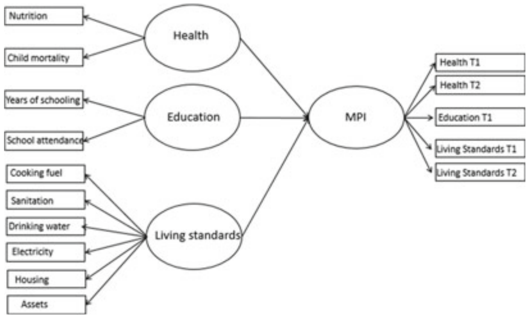


Fig. 9.15 The MPI dimension according to the PLS-component regression approach

Table 9.8 Assessment measures for each analyzed approach

	Repeated indicators	Hybrid	Two step	Mixed two step	PLS-component regression
MVs	10	5	3	3	5
ρ_A	0.972	0. 932	0.970	0.988	0.988
Composite reliability	0.972	0. 931	0.970	0.970	0.855
AVE	0.776	0.772	0.915	0.916	0.611
GoF	0.961	0.941	0.971	0.972	0.914

In accordance with this approach, if we consider not just a single component but also more than one for each block, each dimension becomes even more important in terms of its predictive capability.

Once the MPI dimension has been defined according to the different approaches outlined in the literature, it is important to consider some synthesis and quality measures of the model, in terms of reliability and construct validity (in Table 9.8) and the path coefficients and the Contribution to R^2 (in Table 9.9). For reflective measurement constructs, composite reliability, convergent validity (AVE: Average Variance Extracted—the dominant measure of convergent validity) and global goodness-of-fit (GoF) should be evaluated. ρ_A of Dijkstra and Henseler (2015) should be considered to evaluate whether the construct scores reliably represent the underlying construct.

Table 9.9 Impact of the dimensions on the MPI for each analyzed approach

		Repeated indicator	Hybrid	Two-step	Mixed two step	PLS-component regression
Health	Impact	0.105	0.103	0.344	0.339	0.187
	Contribution to R^2	10.244	8.957	31.132	32.944	18.173
Education	Impact	0.309	0.260	0.420	0.442	0.396
	Contribution to R^2	30.147	22.609	38.009	42.954	38.484
Living standard	Impact	0.611	0.787	0.341	0.248	0.446
	Contribution to R^2	59.609	68.434	30.859	24.102	43.343

For the second-order MPI construct, the average, composite reliability and convergent validity of the different measurement models exceed the conventional acceptability threshold of 0.7 for all approaches, with the exception of the AVE of the PLS-Component Regression, which is calculated taking into account only one dimension. For all approaches, ρ_A of Dijkstra and Henseler (2015) is larger than 0.707 and it can be regarded as reasonable, as more than 50% of the variance in the construct scores can be explained by the latent variable. At the same time, for all assessment measures, values are presented that are slightly lower than the other approaches considered. This depends on the type of modeling considered that rest on the extraction of more components and use a reflective-composite relationship for both the model levels. In Table 9.8 the GoF criterion is reported. Although this approach has been proposed for PLS path modeling, it mainly serves a diagnostic purpose and is not used for formal testing (Tenenhaus et al., 2005). In the different approaches considered, the GoF is generally high (greater than 0.90) as it is in all the models that replicate the MVs of the previous level (the Repeated Indicators Approach). This situation depends on the two components that enter the calculation of the GoF, namely the geometric average of the communalities and the average of the R^2 indexes of the structural models of the hierarchical path model (just one in our two hierarchical orders). The first component in the case of adopting a reflective approach in the external model can only be higher because, as observed, the MVs are highly correlated. As regards the R^2 of the unique structural model, to the extent that the elementary indicators of the explanatory LV LOCs are the same as those of the high-level variable or high representative synthesis, the R^2 coefficient can only be 1 or close to unity. For these reasons, the average between these two quantities (both very close to unity) results in high values, as we have found in this case study. If the unidimensional condition is no longer valid, in which case a composite model is preferable, this index may be more indicative of the explanatory and predictive quality of the model. Note that the lowest values are for the Hybrid and PLS-Component Regression approaches for the reasons discussed above.

In Table 9.9, we observe that the Repeated Indicators and PLS-Component Regression approaches offer, in terms of path coefficients and contributions to R^2, a clearer interpretation of the role played by the different dimensions in defining the Multidimensional Poverty Composite Indicator than the Two-Step and Mixed Two-Step approaches. The very low number of MVs for the health and education dimensions means that it is not possible to differentiate their contribution in the Repeated Indicators approach. Similarly, the results in the Hybrid approach strongly depend on the sampled variables (just one for the first two dimensions).

9.5 Some Key Findings

This chapter was written with the idea to provide the community with a general guideline of HOC in PLS-PM. HOCs estimated according to PLS-PM have been analyzed, initially in general terms, focusing attention on the potentiality of the recent development of this methodology and on how it can help researchers in the estimation of complex and multidimensional phenomena based on a hierarchical relationship. Special attention has then been paid to the different estimation approaches proposed in literature.

A general overview of the works dealing with this issue has been carried out through a bibliometric analysis of articles published on the Web of Science database.

Hierarchical models are, in fact, a very recent innovation. Since their debut on the PLS-PM scene, the only known and widely used approach addressing this type of model has been the Repeated Indicators Approach. Even today this approach is extensively used in HOC studies despite having several disadvantages. Its main advantage is related to its ease of implementation. Only recently have researchers proposed new approaches and started to discuss how these approaches work and under what circumstances it is preferable to use one approach rather than another.

However, to date, there has been no exhaustive analysis that takes into account all the implications of the different approaches. In this chapter, the authors have tried to summarize and focus attention only on some aspects that are considered of major importance for the choice of the approach to be used. The choice of a particular approach principally depends on its properties and characteristics. There are several factors to take into consideration, such as the number of variables and the number and type of the relationship among the MVs and LVs. The real problem for researchers is that to date there is no clear and precise guideline on how to use these models, or clear indications on what to consider. For these reasons, a concise synoptic framework has been constructed and presented in the Sect. 9.3.3 with the aim of providing some guidelines to help researchers in their choice of estimation approach to follow in specific situations.

In any case, HOC modeling depends on the research questions and hypothesis, as well as on the consequent modeling choices of the researcher. Therefore, with any change in the model parameters, the results will change. Moreover, it is essential to define correctly the theoretical framework with an appropriate measurement model because errors of specification at this stage lead to problematic results.

Further simulation studies on these hierarchical models should be conducted in order to take into account simultaneous changes in the above characteristics and criteria or in consideration of the HOC data structure and hypothesis. Furthermore, the recent advances in PLS-PM literature, such as consistent estimation (Dijkstra & Henseler, 2015) and redundancy optimization in order to improve the model predictivity (Dolce et al., 2018), should also be considered to evaluate their benefits in relation to HOC modeling. In addition, the use of new data should be tested in HOC modeling, for example ordinal and categorical variables (Russolillo, 2012) and quantile composite variables (Davino et al., 2017).

Appendix: A Bibliometric Review of Higher Order PLS-PM

In order to perform an overview of the contributions of PLS-PM to case of a hierarchical relationship among LVs, a bibliometric study of international papers on the subject has been conducted.

The analysis of the literature has been performed using the Bibliometrix R-Tool (Aria & Cuccurullo, 2017), a recent R-package which facilitates a complete bibliometric analysis employing specific tools for both bibliometric and scientometric quantitative research. With the aim of understanding how the research on hierarchical PLS-PM issues has evolved, data were retrieved from the Web of Science's (WOS) database of the Institute for Scientific Information (ISI), which is recognized as covering a broad range of relevant journals and peer-reviewed articles of high quality (Skute et al., 2019).

We extracted documents published between 1991 and 2021 (incl.) according to the following topics:

- "Hierarchical" and "PLS Path Modeling" or "Partial-Least Squares-Path Modeling" or "PLS-PM" or "PLS-SEM";
- "Higher order" and "PLS Path Modeling" or "Partial-Least Squares-Path Modeling" or "PLS-PM" or "PLS-SEM"; and
- "second order" and "PLS Path Modeling" or "Partial-Least Squares-Path Modeling" or "PLS-PM" or "PLS-SEM"

The data were downloaded on 10th March 2022. This process resulted in a final sample of 518 articles, relating to 357 sources (journal, books, etc.). Table 9.10 shows the main information relating to the bibliographic data frame.

The annual scientific production in this research area is shown in Fig. 9.16. Comparing the quantity of publications over the past thirty years, it is evident that initially the increase in the number of publications was very small, emphasizing the fact that for many years hierarchical PLS-PM was not taken much into consideration by researchers. In 2001 the first works on this topic began to appear, the number

Table 9.10 Main information about the bibliographic data frame

Time	1993:2021	Annual percentage	15.06
Sources	357	Growth rate	
Article	518		
		Keywords	
Average years from publication	4.62	Author's keywords (DE)	2,089
Average citations per documents	18.94	Keywords plus (ID)	1,516
Average citations per year per doc	2.899		
References	28,910		
Authors		*Author collaboration*	
Authors	1,471	Single-authored documents	44
Author appearances	1678	Documents per author	0.35
Authors of single-authored documents	37	Authors per document	2.84
Authors of multi-authored documents	1,434	Co-authors per documents	3.24
		Collaboration index	3.03

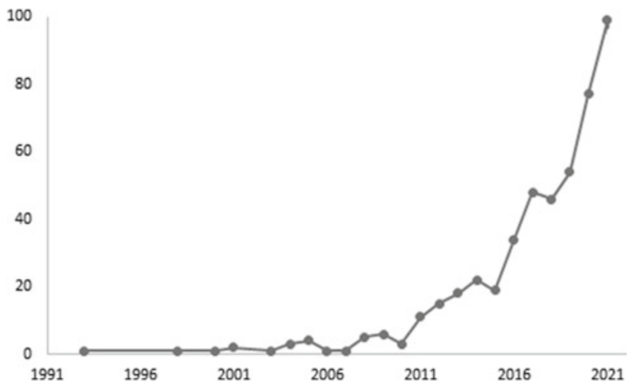


Fig. 9.16 Growth trajectory of the literature on hierarchical PLS-PM, 1993–2021 ($n = 518$)

Table 9.11 Top ten most important countries in terms of publications and citations

	Country	TC	AC
1	Netherlands	2078	159.85
2	Germany	1256	78.50
3	Australia	1001	37.07
4	USA	710	32.27
5	France	707	30.74
6	Spain	698	16.62
7	UK	585	30.79
8	China	527	9.94
9	Malaysia	401	6.08
10	Italy	318	9.64

TC Total Citation; *AC* Average Article Citations

expanding significantly from 2011, thereby demonstrating that this new aspect of the model was starting to arouse the interest of researchers, above all to address and solve problems related to latent dimensions. In particular, starting from 2015 we notice an exponential growth, with researchers paying far more attention to this development of the PLS model and, above all, proposing new and alternative approaches for the estimation of these models. In the last year, 2022, the number of publications is very low because, obviously, the research concerned only the first two months of the year. Generally, the annual percentage growth rate of the HOC PLS-PM contributions over the thirty years of analysis is equal to 15.06%.

As can be seen from the trend of publications over time, PLS-PM has enjoyed increasing popularity over the years for the measurement of concepts that depend on different aspects and that are based on different types of relationships.

Looking at the authorship pattern, the documents were written by 1,471 researchers, with an average value of 0.35 documents per author. Only 2.5% of these documents were written by a single author. Instead, almost all the documents were written by multiple co-authors (97.5%), emphasizing the need for collaborations between authors, even from different countries and/or belonging to different research domains. From the index "authors per document", it is possible to state that each document was written on average by 2.84 authors, therefore almost three authors per article. This ratio evaluates the extent to which scholars publish single-authored or co-authored publications, a statistic which can also be seen as a proxy for the average size of the research team (Aria et al., 2020). This finding is also confirmed by another index, "co-authors per document", which considers the number of times an author appeared in the collection of data, namely 3.24. From both these two measures there emerges an average number of authors for each article equal to 3. The last measure that substantially confirms the results obtained from the previous two metrics is the collaboration index which is equal to 3.03.

The countries are listed and sorted by the number of citations. As you can observe in Table 9.11, the Netherlands is in first place for citations, followed by Germany.

Table 9.12 Subject category of documents collected

Subject category	Percentage (%)
Business	36
Social Science	9
Computer Science	8
Medical	7
Science and Technology	6

Finally, we have considered the fields of application of HOC PLS-PM. It can be seen in Table 9.12, which shows a summary of the first five subject categories, hierarchical models are widely applied in business.

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Chapter 10
How to Apply Necessary Condition Analysis in PLS-SEM

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Abstract This chapter illustrates the application of necessary condition analysis (NCA) in the context of partial least squares structural equation modeling (PLS-SEM). We demonstrate the joint use of the two methods using the standard software application SmartPLS 4, which incorporates PLS-SEM and the core NCA computation capabilities, and we offer background information on the key steps and interpretations associated with the combined application. We introduce the fundamentals of necessity logic and NCA, outlining key differences to PLS-SEM and its underlying logic. Using a recently published guideline and an illustrative example of the combined application of the two methods, the chapter provides guidance on generating results and interpreting *must-have* and *should-have* factors in the PLS-SEM context, enabling researchers to identify necessary conditions that may underlie their significant but also nonsignificant structural model relationships. The consideration of both must-have and should-have factors through the joint use of PLS-SEM and NCA is a unique way of assessing causality that may advance research in multiple fields. Our approach contributes to the further diffusion of the two logics in research

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applications. Our guidelines and systematic application of the two methods will assist researchers in exploiting these analyses' valuable potentials in their own studies.

10.1 Introduction

When applying PLS-SEM, researchers explicitly or implicitly refer to an additive sufficiency logic or net effects thinking. They interpret their PLS-SEM findings using expressions such as *X increases Y* or *a higher X leads to a higher Y*. According to this logic or thinking, each antecedent construct in a structural model is sufficient (but not necessary) for producing changes in the dependent construct. That is, a given condition is able to produce a given outcome, but not all instances in which the outcome manifests include the presence of the condition (sufficiency logic) (Swartz, 1997). Likewise, each antecedent construct is assumed to influence the outcome. These effects can be added, and the non-overlapping contribution of each antecedent to the explained variance in the outcome is the net effect (Ragin, 2006). This means that single constructs can compensate for one another (Richter et al., 2020b, 2022; Swartz, 1997). For instance, in their study, Richter et al. (2021) used PLS-SEM to analyze the antecedents of high performance in multicultural teams, and hypothesized that the cultural intelligence of the team leader, and the cultural intelligence of team members are positively associated with the performance of the team. That is, a higher team leader cultural intelligence and/or higher team member cultural intelligence are assumed to cause higher team performance. Similarly, in PLS-SEM studies on the sources of competitive advantage, each antecedent is assumed to contribute to higher performance, and the absence of one source can be compensated for by another source (Castillo-Apraiz et al., 2020; Gudergan et al., 2012; Richter et al., 2019). Likewise, in studies that seek to understand the factors that lead to a stronger intention to use certain technology (Lin & Lin, 2019; Mathieson, 1991), researchers assume that a greater enjoyment of using the technology leads to higher technology use. That is, the enjoyment of using a technology is referred to as a should-have factor for technology use.

While in the past years this logic has been dominant in many fields, researchers recently began to consider the proposed relationships from a necessity logic (Bokrantz & Dul, 2022; Fainshmidt et al., 2020; Hauff et al., 2021; Kardell et al., 2022; Richter & Hauff, 2022; Richter et al., 2020a, 2022). A necessity logic implies that an antecedent construct is necessary but not sufficient for a dependent construct. Researchers who refer to this logic use expressions such as *X is necessary for Y* or *X is needed for Y*. The dependent construct or outcome can only be achieved if the necessary cause is in place or is at a certain level. Notably, a necessary condition cannot be compensated for by other antecedent constructs; that is, its absence will prevent the outcome from existing (Dul, 2016). For instance, while according to a sufficiency logic or net effects thinking, the absence of enjoyment of a technology could be compensated for by other determinants, this would not be the case for antecedent constructs that are necessary. If we for instance assume that the perceived usefulness of a technology is a necessary condition for technology use, the technology will not be used if the necessary cause is not in place, i.e., there will be no technology use without a positive evaluation of its usefulness. The perceived usefulness is a must-have factor for technology use. Necessity logic can be tested by using necessary condition analysis (NCA) (Dul, 2020). For instance, in their study on the performance of multicultural teams, Richter et al. (2021) further hypothesized that a team's mean cultural intelligence is a necessary condition for high team performance. That is, the team will be unable to achieve high performance if its members are not culturally intelligent—at least to a certain degree. For this reason, the authors complemented their PLS-SEM analysis with an NCA so as to gain a more in-depth understanding of the studied phenomena. In view of the NCA findings, they demonstrated that a certain level of cultural intelligence among team members is necessary for high-performing multicultural teams (a must-have factor). Using additional findings from PLS-SEM, they demonstrated that increasing the average cultural intelligence of team members drives team performance (a should-have factor). The value of considering and testing both must-have and should-have factors using NCA and PLS-SEM to understand the associations between antecedent and dependent constructs has been acknowledged as a unique and previously unrecognized way of assessing causality (Bergh et al., 2022) and has been rapidly adopted in first studies in various business research fields (Bolívar et al., 2022; Lee & Jeong, 2021; Richter et al., 2021). Further, a combined approach to analyzing data from both a should-have and a must-have perspective helps to avoid some limitations that stem from assumptions inherent to each standalone method, enhances problematization, and informs researchers, practitioners, and policymakers in a more comprehensive and meticulous way (Koay et al., 2022; Lee & Jeong, 2021; Sukhov et al., 2022; Walraven et al., 2022).

Richter et al. (2020b) provided a step-by-step guideline on how to complement PLS-SEM and NCA and how to interpret findings generated from a combined use of both methods. They also offered the relevant code to be used in the open-source software R to perform NCA in their article's appendix. However, more recently, NCA has been implemented into the software SmartPLS 4 (Ringle et al., 2022), which is popular among the PLS-SEM community owing to its ease of use (Memon et al., 2021; Sarstedt & Cheah, 2019) and can therefore be a key aid in combining these two logics in empirical studies. In this chapter, we demonstrate the joint use of PLS-SEM and NCA using the software SmartPLS 4 (Ringle et al., 2022). We will first introduce the fundamentals of necessity logic and NCA (in comparison to the fundamentals of PLS-SEM) and will then demonstrate their combined use following the steps outlined in Richter et al. (2020b) and their illustration in the technology acceptance field of study.

10.2 Fundamentals of Necessity Logic and NCA

A necessity logic implies that an antecedent construct is necessary but not sufficient for an outcome; i.e., if the necessary cause is not in place, the outcome will not materialize (Goertz, 2017). Accordingly, the necessary condition—being a constraint, a bottleneck, or a critical factor—must be satisfied in order to achieve a certain outcome. Other factors cannot compensate for the absence of a necessary condition. We may, for instance, assume that the perceived usefulness of a technology is a precondition for its use. There will be no technology use without perceived usefulness. Other aspects of the technology such as its ease of use cannot compensate the absence of perceived usefulness. To express this necessity in theoretical statements or hypotheses, researchers use expressions such as *X is needed for Y*, *X is a precondition for Y*, or *Y requires X* (Dul, 2016, 2020).

Researchers who acknowledge this logic can test it using NCA, which can identify the extent of a necessary condition that needs to be satisfied in order to achieve a certain level of a desired outcome. Thus, the method does not seek to explain how changes in an antecedent construct change an outcome (as is the underlying idea in PLS-SEM); instead, it analyzes whether an outcome does not occur if certain conditions are not in place. By using NCA, we can for instance identify the necessary extent of perceived usefulness of a technology to achieve a certain level of technology usage or we can identify the cultural intelligence quotient that is critical for high performance in multicultural teams. Thus, researchers can identify the must-have factors that need to be present, in addition to the should-have factors, in their SEM.

NCA does not impose specific requirements on the data or measurement other than the standard requirements in empirical studies. Thus, an NCA can be extended to unobservable, latent concepts—such as user satisfaction, usage intention, and perceived usefulness by using scores for these constructs (Dul, 2020). NCA itself does not compute these scores. To test necessities in the SEM context, an NCA needs to be done on the scores (e.g., as obtained by PLS-SEM) of the involved constructs that will represent the dependent and independent variables in the NCA. NCA's focus is—other than in the typical PLS-SEM estimation—on single conditions that are necessary for an outcome. Thus, NCA is a bivariate technique—if more than one necessary condition is analyzed, this is called a *multiple NCA* or a *multiple bivariate NCA* (Dul, 2022b). The necessity association found between a condition X_1 and an outcome Y in a multiple bivariate NCA does not depend on other conditions in the estimation. That is, adding a further condition X_2 to the model does not change the estimated association between X_1 and Y (i.e., the effect of X_1 on Y does not depend on the antecedent X_2 and the correlation between X_1 and X_2).

Rather than analyzing average relationships between dependent and independent variables, NCA reveals areas in scatter plots of dependent and independent variables that denote the presence of a necessary condition. While PLS-SEM establishes a linear function through the center of relevant data points, NCA uncovers a ceiling line on top of the data. The ceiling line separates the area with observations from the area without observations (C; also called the ceiling zone). The larger the empty area

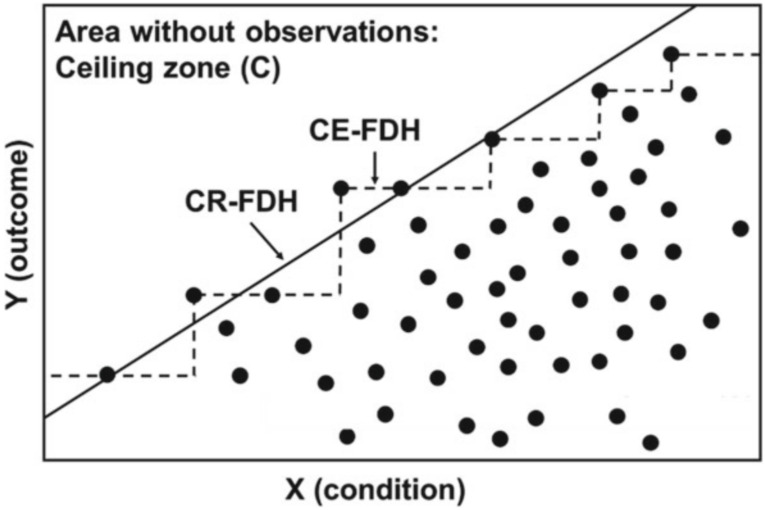

Fig. 10.1 Ceiling lines example

is relative to the total area (S; also called the scope), the larger the constraint that X puts on Y (Dul et al., 2020). There are commonly two default ceiling lines. One is the ceiling envelopment—free disposal hull (CE-FDH) line, which is a nondecreasing, stepwise linear line (step function), as shown in Fig. 10.1. Another is the ceiling regression—free disposal hull (CR-FDH) line, which is a simple linear regression line through the data points of the CE-FDH line (Fig. 10.1). The CE-FDH ceiling line is recommended for discrete data, or when the pattern of observations near the ceiling line is irregular; i.e., the border between the empty area and area with observations shows a more irregular pattern. The CR-FDH line is recommended for continuous data, or when the pattern of observations near the ceiling line is approximately linear, or when theory suggests that the ceiling line is straight (Dul, 2020).

The ceiling line specifies the minimum level of X that is necessary to achieve a certain level of Y. To grasp this concept, consider Fig. 10.2, which shows an example of an NCA ceiling line chart from a SmartPLS output. In this example, when the independent variable X has a level below 3.0, the CE-FDH ceiling line shows no observation of 4.0 or larger for the dependent variable Y. Thus, the independent variable X must have at least a level of 3.0 to achieve a level of 4.0 for the dependent variable Y. This NCA finding differs from the interpretation of linear regression, resembling PLS-SEM, where an increase in the independent variable leads on average to an increase of the dependent variable.

A bottleneck table is another way to illustrate the NCA results. In such a table, the first column shows the dependent variable or the outcome, while the next column represents (and any additional columns represent) the condition(s) that must be satisfied in order to achieve the outcome. That is, they represent the necessary levels of the independent variables for the outcome. The results of both the outcome and the

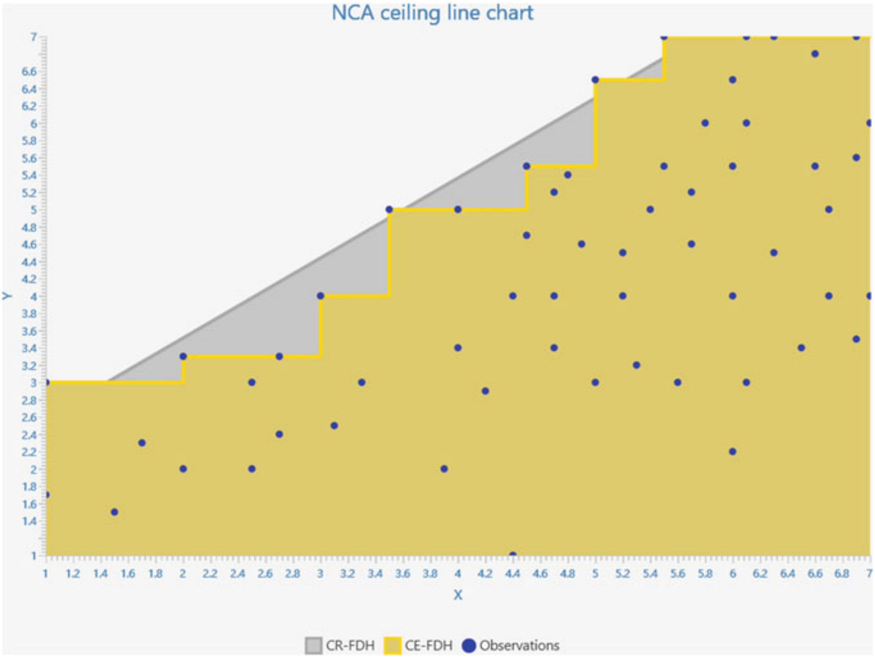

Fig. 10.2 Example of an NCA ceiling line chart in SmartPLS

condition(s) may refer to the actual values, the percentage values of the range, or the percentiles. When applying an NCA in a PLS-SEM context, the actual values (and their transformations, such as percentage ranges or percentiles) can take different forms depending on the construct scores used, such as standardized latent variable scores (we will further discuss this aspect in the research application below).

Table 10.1 is an illustrative bottleneck table that refers to the above example. It presents the same relationships as the ceiling line in Fig. 10.2. For instance, Table 10.1 shows that, in order to achieve a level of 4.0 for the dependent variable Y (second column), the independent variable X must achieve a level of 3.0 (third column). Furthermore, NN indicates that the independent variable is not necessary for this level of the dependent variable. For instance, there is no necessary level of X to accomplish a Y outcome level of 2.8 (or lower) in this example. However, for higher outcome levels of Y, the condition X becomes necessary as expressed by the results in Table 10.1. The visualization in the below table provides further information: the first column lists the percentage ranges for the outcome, which is a default visualization often used in NCA. It expresses the values of Y in percentages of their ranges (in which 0 corresponds to the lowest observed value, and 100 to the highest observed value). For instance, to achieve an outcome level of 50% (first column), which is indicated by an actual value of 4.0 on our 7-point scale (second column), X needs to be at a level of 3.0 (third column).

Table 10.1 Bottleneck table (CE-FDH)

Y in percentage ranges (%)	Y in actual values	X in actual values	X in counts	X in percentiles
0	1.0	NN	0	0
10	1.6	NN	0	0
20	2.2	NN	0	0
30	2.8	NN	0	0
40	3.4	3.0	10	16.7
50	4.0	3.0	10	16.7
60	4.6	3.5	13	21.7
70	5.2	4.5	20	33.3
80	5.8	5.0	27	45.0
90	6.4	5.0	27	45.0
100	7.0	5.5	33	55.0

Note NN = a result is not available and thus does not represent a necessary condition

In addition, Table 10.1 presents X in counts (fourth column) and in percentiles (fifth column). Displaying X in the bottleneck table in terms of counts focuses on the number of cases (i.e., the observations) that do not meet the necessary level of X to accomplish a certain level of Y. For instance, when considering an outcome level of 5.2 for the dependent variable Y, we find that 20 cases do not achieve the necessary level of X (i.e., a level for X of at least 4.5) to accomplish Y's desired outcome level of 5.2. Similarly, the percentile option displays the percentage of cases that do not meet the necessary level of X to accomplish a certain level of Y. We see for instance that the 20 cases that did not achieve a level of 4.5 correspond to 33.3% of all cases. In a multiple NCA, this result is helpful to select important necessary conditions where many cases do not achieve certain levels (Dul, 2020, 2022b).

The key NCA parameters are the necessity effect size (d) and its significance, which indicate whether a variable or construct is a necessary condition. The value d is calculated by dividing the area without observations (the ceiling zone C) by the total area that contains or could contain observations (the scope S) as per the boundaries outlined by the minimum and maximum theoretical or empirical values of X and Y (Dul et al., 2020). Thus, by definition, d ranges between $0 \leq d \leq 1$. Dul (2016) suggested that

- $0 < d < 0.1$ can be characterized as a small effect,
- $0.1 \leq d < 0.3$ as a medium effect,
- $0.3 \leq d < 0.5$ as a large effect, and
- $d \geq 0.5$ as a very large effect.

In line with these suggestions, previous studies have used the threshold of $d = 0.1$ to accept necessity hypotheses (e.g., Van der Valk et al., 2016). Thus, an effect size of 0.1 and higher is required to consider a variable a necessary condition. However, the absolute magnitude of d only indicates the meaningfulness of the effect size from a practical perspective. Accordingly, researchers should also evaluate the statistical significance of the necessity effect size using NCA's (approximate) permutation test. If the *p*-value is low enough (e.g., $p < 0.05$), the result can be considered statistically significant and a necessity hypothesis can be appraised (Dul, 2020).

Considering the above calculation of the effect size in an NCA, the necessity effect size should not be confused with the effect sizes produced in PLS-SEM, which measure the relative impact of an antecedent construct on an outcome in terms of explanatory power. For instance, the f^2 effect sizes in PLS-SEM measure the changes in R^2 when a specified antecedent construct is omitted from the model (Hair et al., 2022).

10.3 Research Application

To illustrate the combined use of PLS-SEM and NCA, we draw on the extended technology acceptance model (TAM), as used in Richter et al. (2020b). Likewise, we build on the step-by-step guideline in Richter et al. (2020b)—Sect. A7 in the Appendix shows an adapted version of the guideline. As we will use SmartPLS 4 (Ringle et al., 2022), some of the previously outlined steps (e.g., data transfers between software packages) are no longer necessary.

As we focus on the implementation of NCA, we will only briefly review the extended TAM, as discussed in Richter et al. (2020b). In doing so, we will not repeat the basic steps to perform a PLS-SEM in SmartPLS, as these have been documented extensively (for instance in Hair et al., 2022; Sarstedt et al., 2022b). The dataset is available as part of Richter et al.'s (2023) data article.

10.3.1 The Conceptual Model, Data, PLS-SEM Analyses, and Evaluation (Steps 1–4)

The extended TAM under consideration consists of two endogenous constructs: the *behavioral intention* to adopt a technology, which leads to the actual *technology use* (e.g., Ajzen, 1991; Davis et al., 1989; Sheppard et al., 1988; Turner et al., 2010). It has four key exogenous constructs that antecede *behavioral intention* and *technology use*: *compatibility*, which reports the technology's fit with a customer's lifestyle and values (Rogers, 2003), perceived *usefulness* and perceived *ease of use* (Moore & Benbasat, 1991), and *emotional value*, which measures whether customers enjoy or have positive feelings about a product's use (Sheth et al., 1991). For more details on the theoretical underpinnings of the proposed relationships, see Richter et al. (2020b).

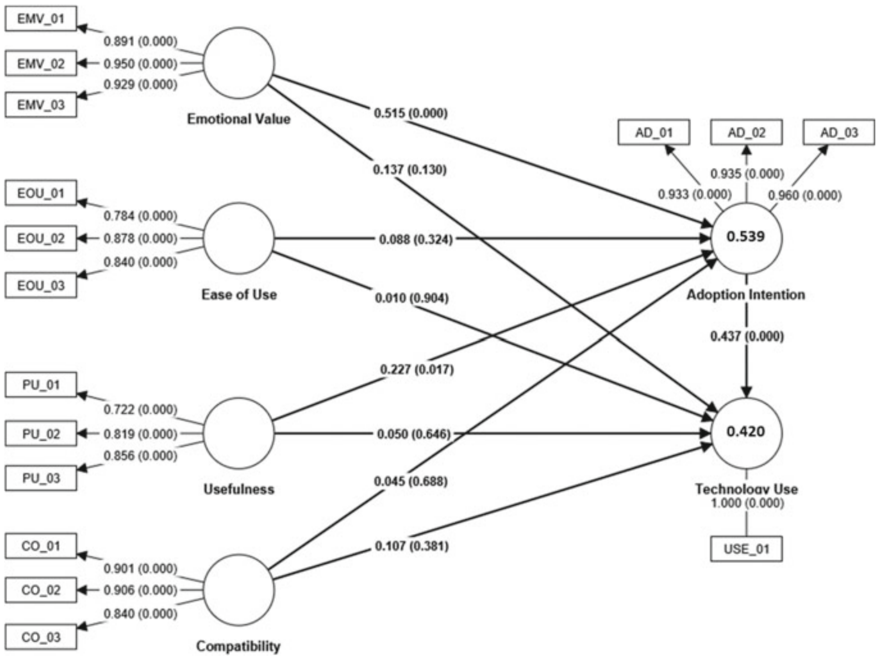

Fig. 10.3 Conceptual model and the PLS-SEM results

The sample comprises adopters of e-book readers in France ($N = 174$), whose responses were collected via an online survey. The target construct *technology use* was measured with a single item and on a 7-point Likert scale; the remaining constructs used reflective measurements and 5-point Likert scales (for more information on the sample and descriptive statistics, see Sect. A1 in the Appendix and Richter et al. (2020b)). The model estimation drew on the SmartPLS software. The measurement and structural models demonstrated appropriate statistical quality among the standard assessment criteria (e.g., Hair et al., 2019); Richter et al. (2020b) reported the corresponding results (see Sects. A2, A3, and A4 in the Appendix). Figure 10.3 visualizes the conceptual model and includes the estimated path coefficients, their significance levels, and the R^2-values of dependent constructs.

10.3.2 Extraction of Scores (Step 5)

To test necessities in the context of PLS-SEM, we recommend using the latent variable scores of PLS-SEM, since their generation considers the context of the structural model. That is, we run the NCA on the latent variable scores that we need to extract from the PLS-SEM estimations.

For this purpose, we use the PLS-SEM algorithm to estimate the extended TAM (see Fig. 10.3). In SmartPLS 4, we open the model and click on 'Calculate' → 'PLS-SEM algorithm.' We can use the default options, which will produce standardized latent variable scores for our constructs. The standardized construct scores are estimated based on standardized indicator data that has been *z*-transformed (i.e., the mean is deducted from each data point and the result is divided by the standard deviation) (for further information see Sarstedt & Mooi, 2019). Owing to the transformation of the data, the resulting standardized construct scores (see Fig. 10.4, left; which can be found by navigating to 'Final results' → 'Latent variables' → 'Scores' after running the algorithm) always have a mean value of 0 and a standard deviation of 1. Alternatively, we can change the results type in the PLS-SEM algorithm menu from standardized to unstandardized. In this case, the original indicator data are not standardized before the estimation, but the original values of the indicators are used. In our example, all indicators used for the antecedent constructs in the model have unitary interval scales (ranging from 1 to 5 and from 1 to 7 for the single outcome indicator of the construct *technology use*) (with 1 = low ratings for all indicators). In this case, as all indicators of a construct are measured on the same scale, the interpretation of the unstandardized latent variable scores is straightforward (see Fig. 10.4, right), which would not be the case if differently scaled indicators were used to measure a construct. Both the standardized and unstandardized latent variables scores will produce the same NCA parameters. However, the bottleneck levels will differ owing to the different scales that are involved. In the following, we therefore will draw on the unstandardized latent variable scores. Thus, we select the corresponding option next to the menu option 'Type of results,' tick the box next to 'Open report', and initiate the model estimation by clicking on 'Start calculation.'

After convergence, SmartPLS opens the report with the estimation results in a tabular format. The tabular presentation contains the latent variable scores (presented in Fig. 10.4) under 'Final results' → 'Latent variables' → 'Scores.'

While the subsequent NCA occurs in the SmartPLS 4 software environment, we still need to create a data file that contains the latent variable scores. For this purpose, in the results report view, click on the symbol with the label 'Create data file' (in

Latent variables - Scores

	Adoption Intention	Compatibility
0	-2.120	-0.528
1	0.505	-0.144
2	0.133	-0.144
3	1.260	1.359
4	0.133	0.614
5	-0.265	0.230
6	0.133	0.217
7	-0.994	-1.299
8	-0.582	-2.812
9	1.260	-1.273
10	-0.224	0.614

Latent variables - Scores

	Adoption Intention	Compatibility
0	2.000	3.000
1	4.329	3.336
2	4.000	3.336
3	5.000	4.652
4	4.000	4.000
5	3.647	3.664
6	4.000	3.652
7	3.000	2.325
8	3.365	1.000
9	5.000	2.348
10	3.683	4.000

Fig. 10.4 Latent variable scoresstandardized (left, including menu) and unstandardized (right)

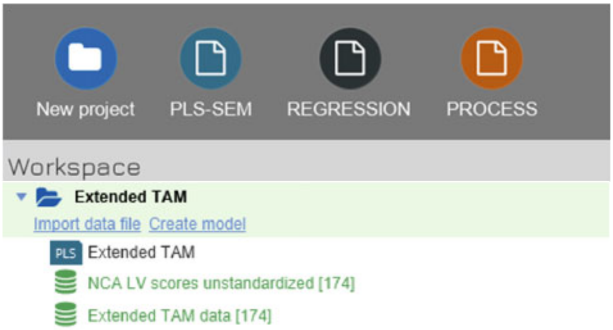

Fig. 10.5 Datasets for necessary condition analysis in the workspace view

the top menu). In the dialog that follows, change the file name in ‘NCA LV scores unstandardized’ (or standardized if you aim to use standardized scores, e.g., owing to different scales involved), and under the ‘Select columns’ option, check only the box next to ‘Latent variable scores.’ Next, click on the ‘Create’ button and return to the SmartPLS workspace view by clicking two times on the arrow symbol with the labels ‘Edit’ and ‘Back.’ In the SmartPLS workspace view, the new dataset with the name ‘NCA LV scores unstandardized’ appears, as shown in Fig. 10.5.

Double-click on the created dataset to open the data view. The report that opens includes the descriptive statistics for the six latent variables (i.e., ‘LV scores—Adoption Intention’ to ‘LV scores—Usefulness’): the number of missing values (in our case, 0), the mean and standard deviation, and the observed minimum (Observed Min) and maximum (Observed Max) values—as well as further information on for instance the kurtosis and skewness of scores (for an extract of the descriptive statistics for the unstandardized scores, see Fig. 10.6).

Using survey data, an indicator’s minimum and maximum can refer to the theoretical minimum and maximum values (e.g., 1 and 5 when using a 5-point scale) or to the empirical minimum and maximum values that result from the sample data (e.g., 2 and 5, because no respondent had evaluated the indicator below 2). Other scales that were used may not have a theoretical minimum or maximum.

Name	No.	Type	Missings	Mean	Median	Scale min	Scale max	Observed min	Observed max
LV scores - Adoption Intention	1	MET	0	3.882	4.000	1.000	5.000	1.000	5.000
LV scores - Compatibility	2	MET	0	3.462	3.652	1.000	5.000	1.000	5.000
LV scores - Ease of Use	3	MET	0	4.026	4.000	1.675	5.000	1.675	5.000
LV scores - Emotional Value	4	MET	0	3.807	4.000	1.000	5.000	1.000	5.000
LV scores - Technology Use	5	MET	0	3.983	4.000	1.000	7.000	1.000	7.000
LV scores - Usefulness	6	MET	0	3.570	3.648	1.000	5.000	1.000	5.000

Fig. 10.6 Descriptives: latent variable scoresunstandardized

In our sample all our respondents have used the full scale from 1 to 5 and from 1 to 7, respectively. Still, when we refer to the descriptive statistics of the unstandardized latent variable scores (see Fig. 10.6), we see that the observed minimum for the *ease of use* construct was 1.675, because no respondent evaluated all three *ease of use* indicators simultaneously on the lowest level. In PLS-SEM, there are options to re-scale the scores of variables (e.g., to reflect the theoretical range of values), which you may be familiar with if you use importance-performance map analyses. We refrained from further transformations (and therewith automatically use the empirical minimum and maximum values). If you opt for this in your project too, we recommend that you develop an understanding of the empirical range of values involved in your data by looking at the descriptive statistics (as in Fig. 10.6).

Currently, the SmartPLS software only searches for empty spaces in a scatter plot's upper left-hand corner. That is, it tests whether the presence of an antecedent construct is necessary for the presence of Y. Theoretically, there may be other forms of necessity that can be formulated, such as that the absence of the antecedent construct is necessary for the presence of the outcome. If true, this would be visible in an empty space in the upper right-hand corner. NCA is not limited to situations where the presence of a condition is necessary for the presence of an outcome but can also be applied to different combinations of the presence and absence of the condition and the outcome. However, to test for other combinations, you will need to flip the coding of your scales to ensure that testing for an empty space in the upper left-hand corner fits your conceptual thinking. Thus, researchers need to ensure that the coding of their variables corresponds to the analytical procedure that was implemented. For instance, if one of the antecedent constructs was *difficulty of use* (instead of *ease of use*) measured with indicators from 1 = not difficult at all to 5 = very difficult, you would most likely test for the necessity of the absence of the antecedent construct for the presence of the outcome. You would test whether the absence of difficulty of use is necessary for (the presence of) *adoption intention* or *technology use*. To enable this, you would need to flip the scale of the difficulty of use indicator to 1 = very difficult to 5 = not difficult at all. Thus, you would ensure that looking for an empty space in the upper left-hand corner fits your conceptual thinking.

10.3.3 Run the Necessary Condition Analysis (Step 6)

The NCA functionalities are found in SmartPLS 4 under the menu item regression in the workspace view (to which you may navigate by clicking on the 'back' arrow). The NCAs are performed individually for different outcome variables; in our case we need two NCAs, one for *adoption intention* and one for *technology use*. For this purpose, we left click on our extended TAM project in the workspace view and then click on the button with the label 'Regression' in the menu bar.[1] In the dialog that

[1] Alternatively, you can right-click on the TAM project and select the 'New REGRESSION model' option from the dialog that opens.

opens, we first insert 'NCA for extended TAM' under file name and then click on the 'Save' button. SmartPLS will automatically switch to the modeling window.

In the menu on the left-hand side (above the indicators), we need to select the dataset that we seek to use for the NCA. To select the 'NCA LV scores unstandardized' dataset, click on 'Select dataset;' the selected dataset will appear in the green box (above the indicators). After selecting this dataset, the unstandardized latent variable scores are shown as variables in the left-hand menu.

We will illustrate the next steps for the target construct *adoption intention* (and will comment on relevant differences for repeating these steps for the target construct *technology use* without re-doing the routines). After selecting the dataset with the unstandardized latent variable scores, we drag and drop the dependent variable 'LV scores—Adoption Intention' onto the modeling window. We then select the independent variables to be included in the NCA, namely, 'LV scores—Compatibility,' 'LV scores—Emotional Value,' 'LV scores—Usefulness and 'LV scores—Ease of Use' and drag and drop them on the dependent construct 'LV scores—Adoption intention.' This yields the model shown in Fig. 10.7 in the modeling window (first without results presented). Please note that the arrangement of the dependent construct (left or right) does not matter for the estimation; what is relevant is the direction of the arrows from the independent variables to the dependent variable. Also, we can ignore the intercept in the figure; it just illustrates the generic regression model setup in SmartPLS. If you replicate the model for the dependent variable *technology use* (later), you will follow the same steps, except for having an additional independent variable, namely, 'LV scores—Adoption Intention' which is then as the other independent variables associated with the 'LV scores—Technology Use.'

To run the NCA for the model shown in Fig. 10.7, we click on the wheel symbol 'Calculate' in the menu bar and select the option 'Necessary condition analysis (NCA)'.[2] A dialog opens that shows the variables in the model, and their observed minimum and maximum values (as commented on earlier). When clicking on the 'Start calculation' button, the analysis is done using the defaults settings. Before initiating the calculation, we can also adapt the steps for the bottleneck tables to be produced. Specifically, we can increase or decrease the number of entries in the bottleneck table. If we use the default of 10, we start with 0% and have a difference of 10 percentage points between the rows in the bottleneck table (i.e., 11 results rows after the header). In contrast, a value of 20 would increase the number of rows and would produce a table with a distance of 5 percentage points, while 5 would reduce the number of rows to 6 with a distance of 20 percentage points. We want to display the bottleneck table in such a way that it represents the scale of our outcome construct. Since *adoption intention* was measured on a 5-point scale we set the value to 4 and click on the 'Start calculation' button (and ensure that the box next to 'Open report' has been ticked).

In the screen that opens, we navigate to 'Final results' on the left-hand-side and click on 'Ceiling line effect size overview' to request the table shown in Fig. 10.8.

[2] Alternatively, you can choose 'Calculate → Necessary condition analysis (NCA)' in the menu bar.

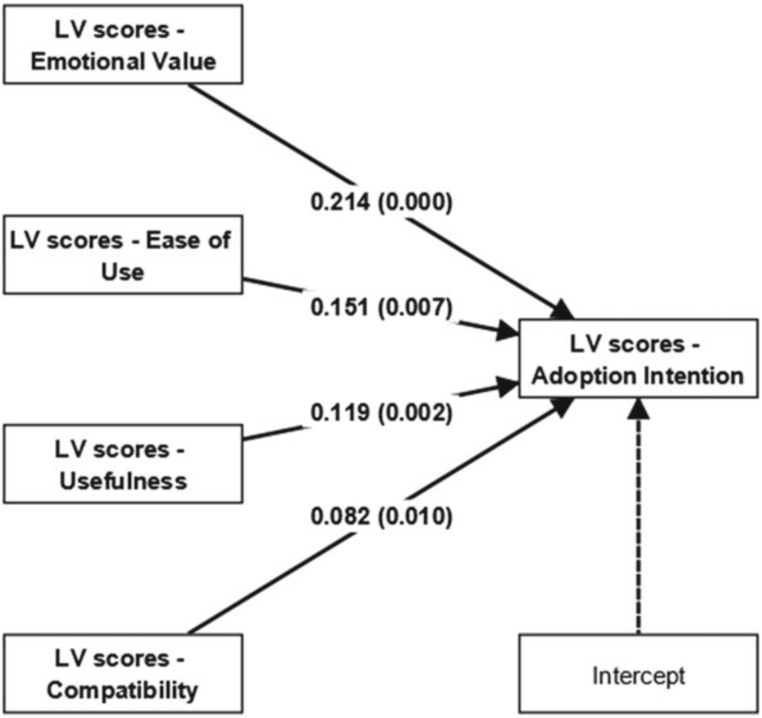

Fig. 10.7 NCA model and results for adoption intention in SmartPLS 4. *Note* CE-FDH effect sizes and *p*-values are displayed for each condition

Per default, the tables always present both the effect sizes based on the CE-FDH and the CR-FDH ceiling lines.

To support the decision on the ceiling line to choose, we can evaluate the ceiling accuracy. The ceiling accuracy represents the number of observations that are on or below the ceiling line divided by the total number of observations, multiplied by 100. A higher accuracy indicates that a lower number of observations is above the CR-FDH ceiling line. While the accuracy of the CE-FDH ceiling line is per definition 100%, the accuracy of the CR-FDH can be less than 100%. There is no specific rule regarding the acceptable level of accuracy. However, a comparison of the

Fig. 10.8 Ceiling line effect size overview for adoption intention

	CE-FDH	CR-FDH
LV scores - Compatibility	0.082	0.041
LV scores - Ease of Use	0.151	0.101
LV scores - Emotional Value	0.214	0.191
LV scores - Usefulness	0.119	0.079

	Effect size	Obs. above ceiling	Accuracy	Slope	Intercept
LV scores - Compatibility	0.041	0.000	100.000	0.760	3.240
LV scores - Ease of Use	0.101	2.000	98.851	6.024	-9.108
LV scores - Emotional Value	0.191	7.000	95.977	0.812	1.962
LV scores - Usefulness	0.079	3.000	98.276	6.368	-5.369

Fig. 10.9 CR-FDH details for adoption intention

estimated accuracy with a benchmark value (e.g., 95%) can help assess the quality of the generated solution (Dul, 2020). Thus, the 100% coverage accuracy of the CE-FDH is not a meaningful selection criterion, since this value is met by definition. In contrast, a low ceiling accuracy for a CR-FDH line indicates that the data pattern is not linear, and researchers are advised to select a nonlinear ceiling line, such as the CE-FDH. We find information on the ceiling accuracy in the results report under 'Final results' → 'Ceiling lines – details' → 'CE-FDH' respectively 'CR-FDH.' The report (Fig. 10.9) indicates the lowest ceiling accuracy for the CR-FDH ceiling line in our example at 95.977 for *emotional value*. It has 7 observations on or above the ceiling line, meaning that the remaining 167 of the total 174 observations are within the ceiling line, resulting in an accuracy of 95.977% (167 divided by 174). Even though these results indicate a satisfactory accuracy for the CR-FDH ceiling line, we decided to focus on the CE-FDH ceiling line as did Richter et al. (2020b).

While the magnitudes of the effect sizes indicate the effects' relevance, we will need the statistical significance of the effect sizes for a full interpretation later. For this purpose, a permutation test[3] is used. To initiate the permutation test, click on the arrow symbol with the label 'Edit' in the menu bar to return to the modeling window, which shows the model for the NCA (Fig. 10.7). Then select 'Calculate' → 'NCA permutation' in the menu and run the analysis. Ensure that the permutations are set to 10,000 and that a 0.05 significance level is applied. Before initiating the analysis by clicking on 'Start calculation,' check the box next to 'Open report.' In the results report that opens, go to 'Final results' → 'Ceiling line effect size overview' to see the effect sizes already reported (in the column 'Original effect size') and the *p*-values (in the column 'Permutation *p*-value') for the CE-FDH (and CR-FDH ceiling) line (for the CE-FDH ceiling line, see Fig. 10.10).

With these outputs, we have generated the core parameters. For the later interpretation, the bottleneck tables are useful. To access the bottleneck tables, we return to the NCA results or re-run the NCA. The bottleneck table for the CE-FDH ceiling line is found under 'Final results' → 'Bottleneck tables—CE-FDH' (Fig. 10.11). Since we set the number of steps for the bottleneck table to 4, it has a total of 5 rows, starting from a level of 0% that corresponds to the minimum level of *adoption intention* (i.e., 1), and ending at a maximum level of 100% (i.e., 5). Each row of the table represents a particular level of *adoption intention* that can be achieved if the necessary threshold level of each antecedent construct is met. By clicking on

[3] Note that bootstrapping approaches are not advised for NCA (for further explanation, see Dul et al., 2020).

	Original effect size	95.0%	Permutation p value
LV scores - Compatibility	0.082	0.055	0.009
LV scores - Ease of Use	0.151	0.116	0.009
LV scores - Emotional Value	0.214	0.103	0.000
LV scores - Usefulness	0.119	0.080	0.003

Fig. 10.10 CE-FDH ceiling line effect size overview (including significance for adoption intention). *Note* We used the fixed seed option for the permutation in SmartPLS. If you use the random seed option you can get slightly different results, as permutation involves a random process

	LV scores - Adoption Intention	LV scores - Compatibility	LV scores - Ease of Use	LV scores - Emotional value	LV scores - Usefulness
0.000%	1.000	NN	NN	NN	NN
25.000%	2.000	NN	2.015	NN	1.372
50.000%	3.000	NN	2.339	NN	1.372
75.000%	4.000	NN	2.339	2.660	1.628
100.000%	5.000	2.316	2.339	2.986	1.628

Fig. 10.11 CE-FDH bottleneck table for adoption intention (actual values)

'Counts' or 'Percentiles' the bottleneck table shows the number or percentage of cases that do not meet the necessary levels of the antecedents to accomplish a certain level of *adoption intention* (Figs. 10.12 and 10.13).

The values in the bottleneck table correspond to the ceiling line. Figure 10.14 shows the ceiling line chart for the relationship between the antecedent construct *ease of use* and the outcome *adoption intention*. We can find this output under 'Final results' → 'NCA charts' → 'LV scores—Ease of Use.' For instance, a level of 2.015 of *ease of use* is necessary for the intention to adopt to even manifest.

With these outputs, we have generated all the relevant results needed to turn to the evaluation of the structural model relationships and their interpretation for *adoption intention*. The routines to generate the outputs for *technology use* are the same, except

	LV scores - Adoption Intention	LV scores - Compatibility	LV scores - Ease of Use	LV scores - Emotional Value	LV scores - Usefulness
0.000%	1.000	0.000	0.000	0.000	0.000
25.000%	2.000	0.000	1.000	0.000	2.000
50.000%	3.000	0.000	2.000	0.000	2.000
75.000%	4.000	0.000	2.000	9.000	3.000
100.000%	5.000	11.000	2.000	10.000	3.000

Fig. 10.12 CE-FDH bottleneck table for adoption intention (counts)

	LV scores - Adoption Intention	LV scores - Compatibility	LV scores - Ease of Use	LV scores - Emotional Value	LV scores - Usefulness
0.000%	1.000	0.000	0.000	0.000	0.000
25.000%	2.000	0.000	0.575	0.000	1.149
50.000%	3.000	0.000	1.149	0.000	1.149
75.000%	4.000	0.000	1.149	5.172	1.724
100.000%	5.000	6.322	1.149	5.747	1.724

Fig. 10.13 CE-FDH bottleneck table for adoption intention (percentiles)

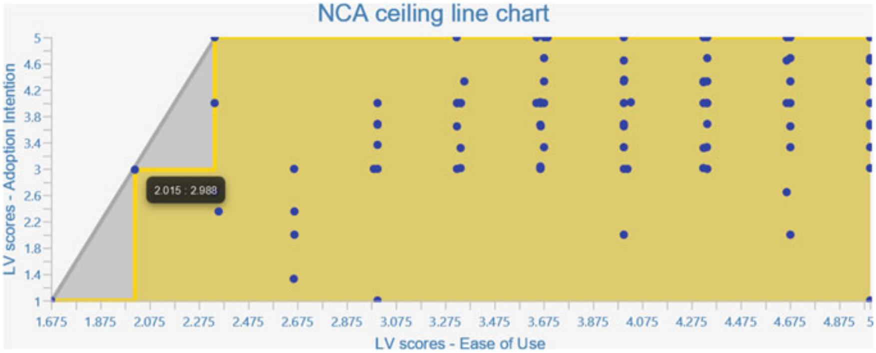

Fig. 10.14 Ceiling line charts for ease of use and adoption intention

for that you will need to include the latent variable scores for *adoption intention* ('LV scores—Adoption Intention') as a further independent variable in the model and to use *technology use* as a dependent construct ('LV scores—Technology Use').

10.3.4 Evaluate the Structural Model Relationships (Step 7)

We can now start evaluating the relationships in the structural model, both from a necessity perspective and a 'net effects' thinking or 'additive sufficiency' logic. We start the evaluation by assessing the PLS-SEM results in the structural model, for which we follow the standard routines as outlined in the PLS-SEM literature (Hair et al., 2017, 2019, 2022).

First, we check the inner model for collinearity issues using the Variance Inflation Factor (VIF).[4] In our example, the VIFs are all well-below the defined critical level of 5, with the highest inner VIF having a value of 3.054. Second, we shift our focus on the R^2-values of the dependent constructs, which indicated that our extended TAM has a relatively high explanatory power for both *adoption intention* and *technology use*, with values of 0.539 and 0.420, respectively (see Fig. 10.3). We complement this evaluation by assessing the model's predictive power by running the PLSpredict procedure (Shmueli et al., 2016, 2019). The derived Q^2 values are all above zero; furthermore, the PLS-SEM predictions' root mean squared error (RMSE) and mean absolute error (MAE) values are smaller than those of the linear model (LM) benchmark for all indicators of *adoption intention* and *technology use*. For further information on the prediction errors, see Sect. A3 in the Appendix and Richter et al. (2020b). Third, we evaluated the significance and size of the structural model relationships (see Fig. 10.3 and Sect. A4 in the Appendix) (results are derived using the percentile bootstrapping procedure with 5,000 subsamples). It is useful to get

[4] You may have done this intuitively before extracting the scores for the NCA (since this is part of the typical assessment of structural models in PLS-SEM, we report this here).

an overview of significant should-have factors for the outcomes. Also, here, we will focus on the findings for adoption intention: *Emotional value* has a significant effect on *adoption intention* (0.515; $p < 0.05$), and perceived *usefulness* has a significant effect on *adoption intention* (0.227; $p < 0.05$). The f^2 effect sizes support these findings (see Sect. A4 in the Appendix). For the remaining relationships, we did not find significant path coefficients in the structural model. These findings provide us with an overview over the relevant should-have factors; we now turn to the evaluation of must-have factors from the necessity perspective.

To evaluate the structural model relationships from a necessity perspective, we need to check the accuracy of the ceiling line (if going for other than the CE-FDH ceiling line) and to evaluate the key NCA parameters produced in the last step. We opted for the CE-FDH ceiling line in our illustrative example, which per definition has an accuracy of 100%. Thus, we continue with an evaluation of whether the necessity effect size d is equal to or higher than 0.1 and is statistically significant with an alpha level of 0.05 to indicate whether a construct is a necessary condition. Following this procedure, we find that *emotional value* (d = 0.214; $p < 0.05$), perceived *usefulness* (d = 0.119; $p < 0.05$) and *ease of use* (d = 0.151; $p < 0.05$) are necessary conditions for *adoption intention*. *Compatibility*, even though having a significant effect ($p < 0.05$) does not have a substantial effect (d = 0.082; i.e., small effect size of <0.1) and is therefore not a meaningful necessary condition for *adoption intention* (see also Sect. A5 in the Appendix). The bottleneck tables generated provide relevant levels of these antecedent constructs that are necessary to achieve specific outcome levels of interest. These can be used to enrich the interpretations in the next step.

10.3.5 Interpret the Findings (Step 8)

Following from the above, we identified both must-have and should-have factors for *adoption intention* and *technology use*. We can use an interpretation grid that has been proposed in previous guidelines to aid our interpretation (see Richter et al., 2020b). Therein, three scenarios are outlined that focus on an antecedent construct being a should-have and a must-have factor (Scenario 1), a should-have but not a must-have factor (Scenario 2), and a must-have but not a should-have factor. We plugged the results of our illustrative example for *adoption intention* into these scenarios, including an additional scenario (Scenario 4) that an antecedent is neither a should-have nor a must-have factor (see Table 10.2 and Sect. A6 in the Appendix). In the last column, we also offer an example of how to interpret the results for *adoption intention* to assist the translation of empirical findings into meaningful interpretations.

As becomes clear, our illustrative example demonstrates three of these four possible scenarios for *adoption intention*: *Emotional value* and perceived *usefulness* are both significant determinants (as per the PLS-SEM results) and necessary conditions (as per the NCA results) for *adoption intention*. *Ease of use* is not a significant determinant of *adoption intention* (as per the PLS-SEM results), but a necessary condition for a technology to be adopted (as per the NCA results). Finally,

Table 10.2 Scenarios to interpret findings for adoption intention (adapted from Richter et al., 2020b)

Scenario	PLS-SEM results	PLS_SEM (paths; *p*-value)	NCA results	NCA (d; *p*-value)	Conclusions	Interpretation illustrative example
1: Exogenous construct is a …	significant determinant	*Emotional value* (0.515; $p <$ 0.05); Perceived *usefulness* (0.227; $p <$ 0.05)	and an NC	*Emotional value* (0.214; $p <$ 0.05); Perceived *usefulness* (0.119; $p <$ 0.05)	On average, an increase in the exogenous construct will increase the outcome However, a certain level (see the NCA bottleneck tables) of the exogenous construct is necessary for the outcome to manifest	On average, an increase in the *emotional value* and the perceived *usefulness* of a technology will increase its adoption Also, a technology needs to have certain minimum levels of *emotional value* and perceived *usefulness* to be adopted
2: Exogenous construct is a …	significant determinant	n.a.	but not an NC	n.a.	On average, an increase in the exogenous construct will increase the outcome; no minimum level of the construct is needed to ensure that the outcome will manifest	n.a.
3: Exogenous construct is a …	nonsignificant determinant	*Ease of use* (0.088; $p >$ 0.05)	but an NC	*Ease of use* (0.151; $p <$ 0.05)	A certain level (see the NCA bottleneck tables) of the exogenous construct is necessary for the outcome to manifest However, a further increase is not recommended, since it will not increase the outcome any further	A technology needs to have a certain minimum level of *ease of use* to be adopted A further increase of *ease of use* will on average not further increase the *adoption intention*
4: Exogenous construct is a …	nonsignificant determinant	*Compatibility* (0.045; $p >$ 0.05)	and not an NC	*Compatibility* (0.082; $p <$ 0.05)	A change in the exogenous construct will not significantly influence the outcome; there is no necessary level of the antecedent to ensure that the outcome will manifest	*Compatibility* is neither a must-have nor a should-have factor for the *adoption intention* of a technology

Note NC = necessary condition; n.a. = not applicable *compatibility* is not a significant determinant (as per the PLS-SEM results), and not a relevant necessary condition (as per the NCA results) for *adoption intention* (owing to its low effect size).

These findings can be used to accept or reject theoretical hypotheses outlined at the beginning of the project and/or to develop theoretical implications. In our illustrative example, the statistical analyses provide empirical support for some of the theoretical ideas that are incorporated in the TAM and its extensions (e.g., Sheth et al., 1991; Venkatesh & Bala, 2008; Venkatesh et al., 2012), namely for the relevance of *emotional value* and perceived *usefulness*. *Ease of use* and *compatibility* do not have a significant impact on *adoption intention*; these findings contradict research hypotheses that researchers may have outlined with reference to identifying should-have factors (Hu et al., 1999; Subramanian, 1994). Richter et al. (2020b) highlighted that there are theoretical arguments in the literature to posit that the *compatibility* and the perceived *usefulness* of a technology may represent necessary conditions in the context of technology acceptance. Building on the findings of this illustrative example, these necessity ideas were supported for perceived *usefulness* (but not supported for *compatibility* and adoption intention).

The results contribute to further theory-building from both a sufficiency and a necessity perspective. More importantly, complementing the two perspectives offers relevant additional insights: Finding a nonsignificant relationship in a structural model for an antecedent construct does not necessarily mean that it is not relevant for the outcome. While we found that *ease of use* is not a significant should-have factor for a technology's adoption, it is a must-have antecedent. That is, we need to have a certain minimum level of *ease of use* in order for *adoption intention* to materialize.

In addition to these theoretical implications, these findings can also be used to derive key implications informing business practitioners on whether a further investment in a given driver of technology adoption is warranted or useless, which is contingent on the necessary conditions being met, as specified in the bottleneck tables.

Following from the bottleneck table created for *adoption intention* (Fig. 10.11), we can conclude that, in order to achieve a 75% level of *adoption intention* (i.e., a value of 4 on a scale of 1–5), the *emotional value* must have at least a value of 2.660, the perceived *usefulness* a value of 1.628, and the *ease of use* a value of 2.339. If a respondent exhibits a condition (i.e., *emotional value*, perceived *usefulness,* and *ease of use*) at a value lower than the specified threshold, this respondent cannot achieve the corresponding level of the target *adoption intention*. Interpreting the percentiles (Fig. 10.13) offers further insights. We see for instance that 5.2% (i.e., 9 cases; see Fig. 10.12) did not achieve the required *emotional value* level for a 75% *adoption intention*.

10.4 Discussion and Conclusion

In this chapter, we combined the use of PLS-SEM and NCA. For this purpose, we first introduced necessity logic and the fundamentals of NCA, in contrast to the logic implied by standard PLS-SEM analyses. Specifically, the interpretation of relationships between antecedent and outcome constructs in PLS-SEM reveals should-have antecedent constructs that may be able to produce a change in an outcome. However, these may not be necessary. The absence of the antecedent construct could be compensated for by other variables. In contrast, a necessity logic implies that an outcome, or a certain level of an outcome, can only be achieved if the necessary antecedent construct is in place or is at a certain level. NCA enables the identification of these necessary conditions in datasets. Rather than analyzing average relationships between constructs, the NCA reveals empty areas in scatter plots that denote the presence of a necessary condition. NCA can easily be applied to unobservable, latent concepts by computing composite scores of the indicators used to measure these concepts. The composite scores of PLS-SEM are especially useful, because their generation considers the context of the structural model, which represents the underlying theory and corresponds to the idea to test necessities in the context of PLS-SEM. Thus, researchers are able to reveal must-have antecedent constructs that need to be in place in order for an outcome to materialize.

While the combined use of the two methods has been acknowledged as a new way of thinking about causalities, it may be perceived as cumbersome by researchers with a lower affinity to use software packages such as R.[5] In the PLS-SEM community, SmartPLS has become one of the standard software packages for applying this method (Sarstedt et al., 2022a). The capability of the new version of the software to identify necessities in the software environment can therewith be a strong driver of a further diffusion of the combined use of PLS-SEM and NCA. A second contribution of this chapter was to offer a tutorial on how to generate the relevant findings on necessary relationships in structural models using a standard software package, a conceptual model, and an illustrative example introduced in earlier research. As the software is continually updated, there may be further capabilities to carry out NCA studies in future releases; likewise, there may be further capabilities to perform NCA that are or may become available in the software R (first). Still, we are confident that this illustration will further contribute to the diffusion of the combined use of PLS-SEM and NCA.

Finally, we enriched our application by further background information that should support the interpretation of parameters and findings generated in PLS-SEM and NCA. This chapter also offers further assistance to interpret findings of the two methods, even when using other software packages, such as R. The research application illustrates the relevance and potential value of complementing PLS-SEM results

[5] Researchers who prefer to use the software R, however, will find further information on how to implement both NCA and PLS-SEM in R here: Dul (2020); Dul (2022b); Hair et al. (2021). Also, there are various online resources and video tutorials to implement the methods in R, see for instance here: Richter (2022); Dul (2022a); Bokrantz et al. (2022).

with those of an NCA. Both analytical approaches are essential for getting a comprehensive understanding of the must-have and should-have factors for an outcome. When encountering nonsignificant effects that fail to support hypothesized relationships in studies that seek to identify should-have antecedent constructs, researchers often contemplate what to do with these. Even though being theoretically plausible, in many empirical studies, such nonsignificant relationships are discarded in spite of a priori well-established arguments for their inclusion in a given model. Such actions may be a precedent for making incorrect decisions as, while not fulfilling the requirements for a should-have factor, these seemingly nonsignificant effects may still be crucial to a model once a necessity logic is introduced into the analytical equation.

Acknowledgements This chapter uses the statistical software SmartPLS (https://www.smartpls.com/). Ringle acknowledges a financial interest in SmartPLS.

Data Availability The dataset is available as part of Richter et al.'s (2023) data article.

Appendix

A1: Data Description

Latent variable (measurement adapted from)	Indicator		Mean	Range [min; max]	S.D.	Excess kurtosis	Skewness
Emotional value, reflective (Sweeney & Soutar, 2001)	EMV_01	Enjoyment	3.902	[1; 5]	0.842	1.942	−1.036
	EMV_02	Pleasure	3.724	[1; 5]	0.887	0.940	−0.675
	EMV_03	Relaxation	3.799	[1; 5]	0.877	1.465	−0.933
Ease of use, reflective (Moore & Benbasat, 1991)	EOU_01	Learning duration	4.011	[1; 5]	0.988	0.800	−0.996
	EOU_02	Operation	4.092	[1; 5]	0.811	0.798	−0.822
	EOU_03	Menu navigation	3.971	[1; 5]	0.867	1.201	−0.904
Perceived usefulness, reflective (Antón et al., 2013; Moore & Benbasat, 1991)	PU_01	General advantage	3.753	[1; 5]	0.923	0.566	−0.768
	PU_02	Practical application	3.397	[1; 5]	0.970	−0.176	−0.296
	PU_03	Improvement of reading	3.598	[1; 5]	1.055	−0.106	−0.585

(continued)

(continued)

Latent variable (measurement adapted from)	Indicator		Mean	Range [min; max]	S.D.	Excess kurtosis	Skewness
Compatibility, reflective (Huang & Hsieh, 2012; Moore & Benbasat, 1991)	CO_01	Reading behavior	3.299	[1; 5]	0.996	−0.238	−0.419
	CO_02	Consumption pattern	3.427	[1; 5]	0.991	0.259	−0.646
	CO_03	Reading needs	3.655	[1; 5]	0.992	0.430	−0.829
Adoption intention, reflective (Venkatesh et al., 2012)	AD_01	Future usage	4.023	[1; 5]	0.928	1.210	−1.046
	AD_02	Daily usage	3.776	[1; 5]	0.972	0.360	−0.712
	AD_03	Frequent usage	3.845	[1; 5]	0.925	0.869	−0.785
Technology use, single item (Venkatesh et al., 2012)	USE_01	E-books	3.983	[1; 7]	1.610	−0.894	−0.063

A2: Results of the Reflective Measurement Models

Latent variable	Indicators	Loadings >0.70	Indicator reliability >0.50	AVE >0.50	Composite reliability 0.70–0.95	Cronbach's alpha 0.70–0.95	Rho A 0.70–0.95	HTMT 95% CI[6] does not include 1
Emotional value	EMV_01	0.891	0.794	0.853	0.946	0.914	0.917	Yes
	EMV_02	0.950	0.903					
	EMV_03	0.929	0.863					
Ease of use	EOU_01	0.784	0.615	0.697	0.873	0.783	0.783	Yes
	EOU_02	0.878	0.771					
	EOU_03	0.840	0.706					
Perceived usefulness	PU_01	0.722	0.521	0.642	0.842	0.723	0.753	Yes
	PU_02	0.819	0.671					
	PU_03	0.856	0.737					
Compatibility	CO_01	0.901	0.812	0.779	0.914	0.858	0.859	Yes
	CO_02	0.906	0.821					
	CO_03	0.840	0.706					
Adoption intention	AD_01	0.933	0.870	0.889	0.960	0.938	0.939	Yes
	AD_02	0.935	0.874					
	AD_03	0.960	0.922					

[6] Confidence interval. HTMT values based on absolute correlations (Ringle et al., 2023).

A3: Results from PLSpredict

Dependent constructs' indicators	PLS-SEM			LM		PLS-SEM - LM	
	RMSE	MAE	Q^2_{predict}	RMSE	MAE	RMSE	MAE
AD_01	0.692	0.524	0.451	0.712	0.530	−0.020	−0.006
AD_02	0.756	0.560	0.401	0.804	0.596	−0.048	−0.036
AD_03	0.688	0.521	0.454	0.727	0.555	−0.039	−0.034
USE_01	1.371	1.118	0.287	1.415	1.154	−0.044	−0.036

Note $PLS_{predict}$ results are based on three folds

A4: Results of the Structural Model

Regression path	Path coefficient	95% CI[7]	Significant ($p < 0.05$)?	f^2 effect sizes	Total effects	95% CI (total effects)
Emotional value → Adoption intention	0.515	[0.349; 0.656]	Yes	0.336		
Emotional value → Technology use	0.137	[−0.045; 0.316]	No	0.014	0.362	[0.200; 0.521]
Ease of use → Adoption intention	0.088	[−0.063; 0.292]	No	0.012		
Ease of use → Technology use	0.010	[−0.167; 0.170]	No	0.000	0.049	[−0.110; 0.215]
Perceived usefulness → Adoption intention	0.227	[−0.028; 0.396]	Yes	0.044		
Perceived usefulness → Technology use	0.050	[−0.178; 0.255]	No	0.002	0.149	[−0.075; 0.357]
Compatibility → Adoption intention	0.045	[−0.162; 0.272]	No	0.001		
Compatibility → Technology use	0.107	[−0.133; 0.343]	No	0.006	0.127	[−0.108; 0.365]
Adoption intention → Technology use	0.437	[0.268; 0.609]	Yes	0.152		

[7] Confidence interval.

A5: Results of the NCA

Construct	Adoption intention		Technology use	
	CE-FDH	*p*-value	CE-FDH	*p*-value
Emotional value	0.214	0.000	0.331	0.000
Ease of use	0.151	0.009	0.235	0.018
Perceived usefulness	0.119	0.003	0.243	0.001
Compatibility	0.082	0.009	0.211	0.000
Adoption intention			0.294	0.000

A6: Results Overview: PLS-SEM and NCA

Construct	Adoption intention		Technology use	
	Total effects (PLS-SEM)	CE-FDH effect sizes (NCA)	Total effects (PLS-SEM)	CE-FDH effect sizes (NCA)
Emotional value	0.515^{***}	0.214^{***}	0.362^{***}	0.331^{***}
Ease of use	0.088	0.151^{**}	0.049	0.235^{*}
Perceived usefulness	0.227^{*}	0.119^{**}	0.149	0.243^{**}
Compatibility	0.045	0.082^{*}	0.127	0.211^{***}
Adoption intention			0.437^{***}	0.294^{***}

Note * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

A7: Guidelines for the Combined Use of PLS-SEM and NCA

Step 1	Specify the research objective and the theoretical background
Outline hypotheses along a sufficiency and a necessity logic *(for the latter, see Bokrantz & Dul, 2022; Richter & Hauff, 2022)	
Step 2	Prepare and check the data
• *Sample size*: Follow the guidelines on sample size outlined in a PLS-SEM context, for instance, by referring to published power tables (Hair et al., 2022) • *Data distribution*: Report information on the data distribution (Hair et al., 2012) • *Outliers*: Perform an outlier analysis following common guidelines, for instance, by looking at observations that show a z-score >3 *and following the outlier analysis in (Sarstedt & Mooi, 2019) • *Measurement level/coding of scales*: Use metric or quasi-metric data (i.e., interval-scaled, such as Likert scales); ensure that the direction of the scale/coding corresponds to the theoretically assumed relationships, otherwise revert or flip the scale	
Step 3	Run the PLS-SEM analysis
Use PLS-SEM to estimate the latent variable scores, structural model relationships and their significance (Hair et al., 2022)	
Step 4	Evaluate the reliability and the validity of the measurement models
• Make use of the assessment guidelines in the PLS-SEM context to evaluate the quality of measurement models (Hair et al., 2019, 2022). For reflective constructs, evaluate loadings, Cronbach's α/composite reliability/ρ_A, average variance extracted and heterotrait-monotrait ratio. For formative constructs, do a redundancy analysis, evaluate the variance inflation factors, and the significance and relevance of the indicator weights. If required, make improvements (Hair et al., 2022)	
Step 5	*Extract the latent variable scores
• Generate the latent variable scores for all constructs by running the PLS-SEM algorithm. In doing so, select the results type, i.e., either standardized or unstandardized, depending on the measurement scales used for constructs • Create a new dataset containing the (standardized or unstandardized) latent variable scores	
Step 6	Run the NCA
• *Run the NCA in SmartPLS (use 10,000 permutations) (Dul, 2020) • Analyze hypothesized relationships or explore all relations: Dependent = endogenous latent variable score(s); independent = preceding latent variable scores and indicator scores for formative indicators; repeat for all endogenous constructs • *Select the ceiling line based on the theory or the data pattern (Dul, 2020)	
Step 7	Evaluate the structural model
• *After evaluating the VIFs of the inner model, evaluate the PLS-SEM model along the standard assessment criteria, most importantly the coefficient of determination (R^2), the statistical significance and relevance of the path coefficients, and the predictive power (Hair et al., 2019, 2022; Shmueli et al., 2019) • Evaluate the necessity effect size d and its statistical significance (Dul, 2016, 2020) • Check the accuracy of the ceiling line (if going for other than the CE-FDH)	
Step 8	Interpret the findings

Note We marked updates to the guideline by Richter et al. (2020b) with a *

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Part III
Applications

Chapter 11
New Insights for Public Diplomacy Using PLS-SEM to Analyze the Polyphony of Voices: Value Drivers of the Country Image in Western European and BRICS Countries

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Abstract For the successful public diplomacy of a nation-state, it is essential to thoroughly analyze the country image in strategically relevant countries and develop coherent communication strategies that take into consideration the polyphony of voices raised by different countries when fostering a good country image abroad. In our study, we apply the five-dimensional country image measurement scale to data collected in cooperation with the Federal Department of Foreign Affairs in Switzerland (Presence Switzerland). Specifically, we analyze the similarities and differences among the (drivers of) country image in neighboring and close countries (France, Germany, Italy, and the United Kingdom) and those with a significant geographical distance from Switzerland (Brazil, Russia, China, and South Africa). We also conduct a cluster analysis, resulting in a Western European cluster and a BR(I)CS cluster. Based on the news values theory and stereotypes, we empirically test and confirm our hypothesis that countries differ in their image of other countries regarding geographical, cultural, and political proximity to the target country. Finally, we discuss potential benefits for public diplomacy when applying PLS-SEM and developing coherent communication strategies.

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11.1 Introduction

How a country is perceived abroad depends on a variety of influencing factors, such as whether the country and/or its products, politicians, and people are well known, discussed diversely in the media, or strongly advertised as a tourist destination. The country image, defined as a subjective stakeholder attitude toward a country, comprising beliefs and feelings in functional, normative, natural, cultural, and emotional dimensions, is one of the most important target constructs in public diplomacy and international public relations. However, in order to understand the key components that shape a country image abroad, it is necessary to measure the so-called "value drivers" of the country image and analyze the cognitive country image dimensions with respect to the country's economic performance and government system, social norms and values, cultural aspects, and nature and scenery. Recent research on country images has validated a five-dimensional scale to measure country images across different cultures, applying a covariance-based structural equation modeling (CB-SEM) approach to the scale development process. The CB-SEM approach delivers insights into which dimensions of the country image become relevant and have the greatest influence on the formation of the country image. However, as we aim to analyze which items or "value drivers" in each of the country image dimensions are the most influential and significantly contribute to explaining the construct, we draw on the partial least squares-structural equation modeling (PLS-SEM) approach (Wold, 1982), which is particularly useful for analyzing formative measurement models (Sarstedt et al., 2023).

For public diplomacy, it is essential to analyze the country image in strategically relevant countries to develop coherent communication strategies that consider the polyphony of voices raised by different countries when fostering a good country image. With such an image being seen as an instrument for soft power (Nye, 2008), it is necessary for public diplomacy practitioners to know which attitudes about the home country have become prevalent among which foreign publics, and which voices become influential in shaping the formation of the country image. The same holds true for international PR, as this knowledge is also essential for the strategic communication of globally operating organizations when selling products and positioning themselves in international markets abroad. While analyzing each strategic country individually allows for the development of fine-tuned communication strategies, it can also be an advantage, with respect to cost-saving arguments, to aggregate countries with similar attitudes and develop communication strategies and campaigns that can be applied in all of them. Here, a cluster analysis can help to identify groups that show a similar attitude pattern.

Therefore, the overall research questions of this study are:

RQ1: How can the value drivers of the cognitive country image dimensions be analyzed using PLS-SEM?

RQ2: How can we identify groups with similar and disparate attitudes towards a country?

To answer these research questions, we will apply the newly validated five-dimensional country image measurement scale (Ingenhoff, 2017) with PLS-SEM among eight countries and analyze the differences and similarities between them in building a country image.

In the following, we present the country image construct, specifying its dimensions and items. We then examine the overall measurement model including all countries, followed by a cluster analysis to investigate differing groups with similar attitudes among the countries. Finally, we analyze the groups' differences and similarities. The results form the basis for developing a public diplomacy strategy clustered toward countries with similar attitudes.

11.2 Literature Review: The Formation of the Country Image

11.2.1 A Multidisciplinary Research Field

A multitude of different research fields have already addressed the causes and effects of country images, such as business studies (Kühn, 1993; Martin & Eroglu, 1993; Wang & Lamb, 1983), social psychology (Cottam, 1977; Cuddy et al., 2007; David & Bar-Tal, 2009; Herrmann et al., 1997), political science (Leonard et al., 2002; Schatz & Levine, 2010; Vickers, 2004), and communication sciences (Albritton & Manheim, 1985; Golan & Wanta, 2003; Kunczik, 2003). In the following, we will discuss a prominent conceptualization of country image and its relationships with related concepts.

11.2.2 Developing a Country Image Measurement Based on Identity, Attitude, and Reputation Theory

Buhmann and Ingenhoff (2015a) applied a public relations perspective and suggested a four-dimensional model of country image, based on (a) the concept of national identity by Smith (1987); (b) the attitude theory of reasoned action and the theory of planned behavior by Ajzen (1991), specifying the country image as a set of beliefs (cognitive component) and emotions (affective component) toward the image object; and (c) the model of reputation as a multidimensional construct, as suggested by Ingenhoff and Sommer (2007) and Eisenegger and Imhof (2008). The cognitive component consists of multiple specific evaluations regarding a broad set of attributes, while the affective component refers to a general judgment regarding the likeability and attractiveness of the image object (Bergler, 2008). Buhmann and Ingenhoff (2015a) concluded that the cognitive components have to be specified as formative constructs, while the affective component was measured as a reflective construct. So far, the four-dimensional model has only been preliminarily tested with small-scale student samples.

11.2.3 From 4D to 5D Model of Country Image

The first study with representative survey data from 16 countries (Ingenhoff, 2017), showed that 5 country image dimensions can be differentiated when measuring country images: (1) the *functional* judgments as to how strong the country is perceived to be in terms of its apparent competitiveness (economy, business, innovation, science, etc.) and the effectiveness of its government; (2) the *normative* aspects addressing the evaluation of the integrity and morality of a country as reflected in its norms and values and its government, as well as the social and ecological responsibilities of a country; the (former) aesthetic dimension, which is split into (3) a *cultural* dimension reflecting cultural assets and traditions made by mankind, and (4) a *natural* dimension capturing beliefs regarding the beauty of the country's nature; and, finally, (5) the emotional dimension reflecting the general feelings toward and attractiveness and fascination of a country. As a result, the basic model was redefined to a five-dimensional model, defining country images as "a stakeholder's attitude towards a nation and its state, comprising of specific beliefs as *cognitive* components in a *functional*, a *normative*, a *cultural*, and a *natural* dimension, as well as general feelings in an *emotional* dimension."

11.2.4 The Weakening Influence of the Functional Dimension

We are interested in determining which dimension has the strongest impact on forming the country image and which value drivers can account for this effect. Country images are formed by knowledge about a country; while this can be based on personal impressions and contacts, it is very often (solely) based on media coverage. More than 50 years ago, Galtung and Ruge (1965, p. 64) had already stated that "the regularity, ubiquity and perseverance of news media will in any case make them first-rate competitors for the number-one position as international image-former." Today, we receive daily news and reports about what is going on in different countries. However, as we can observe, there are ongoing huge structural changes in media systems all over the world, with new intermediaries like Facebook and Google profiting from advertising revenues, resulting in lower revenues for quality media, a decreasing overall media quality, and people being less willing to pay for high-quality news (Forschungsinstitut, 2017; Schranz & Eisenegger, 2016). As a consequence, we find that the broader public is less informed about functional aspects like political issues, innovations, and market positions. That result might be mirrored in our second hypothesis:

H1: The functional dimension has the weakest impact on the emotional dimension.

11.2.5 The Role of Stereotypes and Prejudices

Instead, attitudes toward a country are predominantly based on stereotypes and prejudices drawn from socialization, advertising, movies, travel literature, and textbooks, as well as from mediated symbols and key landmarks (Chen et al., 2016; Cuddy et al., 2009; Dovidioet al., 2010; Gkritzali et al., 2016). Stereotypes are "associations and beliefs about the characteristics and attributes of a group and its members that shape how people think about and respond to the group" (Dovidio et al., 2010, p. 8) in order to reduce complexity (Halkias et al., 2016). They are usually understood as "the content of an assumed set of characteristics associated with a particular social group" (Biernat & Dovidio, 2000, p. 89). As Fiske (2017, p. 791) found, attributes such as ethnicity, race, and religion (and, therefore, also differing countries) show "cultural variation in their stereotype content, supporting their being responses to particular cultural contexts, apparent accidents of history." Other studies have also shown that stereotypes differ cross-culturally, with most using the stereotype content model (SCM) (Cuddy et al., 2009; Durante et al., 2017), as culture has an effect on cognitive processes (Nisbett et al, 2001) and forms ideologies through which prejudices become legitimized (Crandall et al., 2001; Glick & Fiske, 2001). Thus, stereotypes can differ from country to country in terms of which dimensions the country will be reduced to. For Switzerland, the stereotypes are mostly positive: beautiful landscapes, chocolate, cheese, wine, and watches (Bender et al., 2013; Kym, 2010; Rindisbacher, 2010). These stereotypes have also been confirmed by Feige et al., (2016), who found that the themes most associated with Switzerland are chocolate, cheese, banks, watches, and landscapes with mountains and lakes. These stereotypes mostly refer to the cultural and natural dimensions. Thus, we conclude:

H2: The natural and cultural dimensions have the strongest impact on the emotional dimension.

11.2.6 The Role of Proximity

Secondary to the media system as an explanatory factor in the information and knowledge gained about a country; the proximity of the evaluated country also makes a difference. In terms of the news values theory, geographical proximity is a factor that plays an important role in assessing information about a country abroad (Eilders, 2006; Galtung & Ruge, 1965; Haynes Jr, 1984). The news values theory explains which factors promote the dissemination of an event in the media. The proximity factor demonstrates how events that take place in a country with geographical, cultural, or political proximity are more likely to be portrayed in the news than other events (Staab, 1990). As Galtung and Ruge (1965) concluded, a "distant nation will have to produce events that capture attention particularly easily in order to be recorded." Thus, countries that are located in near geographical proximity, have a similar culture, or are politically close are more likely to learn more about each other through the media and, therefore, are better able to establish more substantiated knowledge. This might explain why we receive more information and, therefore, have much more detailed knowledge about neighboring/close countries than geographically, culturally, and politically distant countries.

H3: Proximity has an effect on the perceived country image.

In contrast, for distant countries, attitudes and beliefs regarding the target country are mainly formed based on stereotypes (Cuddy et al., 2009), as already stated in H1. Since a stereotype is a "shortcut which simplifies an individual's interaction with a complex environment" (Herz & Diamantopoulos, 2013, p. 402), complexity-reducing stereotypes are used to construct an attitude about a country despite a lack of knowledge of the complexity of the different dimensions of the country. Thus, for Switzerland, we assume:

H4: Countries located geographically further away or with less cultural or political proximity are more impacted by the aesthetic (natural and cultural) dimension than countries that are closer.

11.3 Methodology

11.3.1 Data

In collaboration with the Swiss Federal Department of Foreign Affairs (FDFA, Presence Switzerland), an international market research institute was commissioned to conduct surveys representative with respect to gender, age, and regions on the country image of Switzerland in neighboring or close countries (France ($n = 501$), Germany ($n = 503$), Italy ($n = 526$), and the United Kingdom ($n = 500$)) and countries with a significant geographical distance from Switzerland (Brazil ($n = 500$), Russia ($n = 506$), China ($n = 504$), and South Africa ($n = 522$)). All questionnaires were translated and re-translated for validation in the respective languages of each country, with local diplomats of the country involved to ensure correct wording. The total sample included 4062 persons, 2070 women and 1992 men, between the ages of 18 and 69 years (Mean (M) = 39.8, Standard Deviation (SD) = 13.3).

11.3.2 Measures

The operationalization was based on the survey instrument developed by (Ingenhoff, 2017), consisting of 9 items for the functional dimension, 10 for the normative dimension, 6 for the cultural dimension, and 2 for the natural dimension. The affective component of the model (emotional dimension) is measured with three items. The items were rated on a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). To avoid side effects, the items in the survey were randomized.

11.3.3 Data Analysis

To test for the differential impact of the country image's cognitive dimensions on the emotional dimension, we used PLS-SEM. PLS is a causal-predictive approach to SEM, which emphasizes prediction in estimating models that have been derived based on theory and logic (Cho et al., 2022, 2023; Hair et al., 2019a). As such, the method can identify the key value drivers, which presents valuable insights for both academic research and practitioners (Hair et al., 2011; Sarstedt & Danks, 2022). Another key advantage of PLS-SEM is that the method readily incorporates formatively specified constructs where the indicators are conceived as jointly forming the constructs (Sarstedt et al., 2016). The understanding and use of PLS-SEM has increased in recent years, especially in business research disciplines (Hair et al., 2012, 2020; Henseler et al., 2009; Sarstedt et al., 2022a, 2022b; Sharma et al., 2023b). However, in communication research, PLS-SEM has rarely been applied. This is surprising considering that the field often relies on complex models whose estimation seeks to offer actionable recommendations to practitioners. In line with the Sarstedt et al.'s (2016) recommendations (see also Hair et al., 2019b), our model estimation draws on the standard PLS-SEM algorithm using the standard settings as implemented in the SmartPLS 4 software (Ringle et al., 2022), which we used for model estimation.

11.4 Results

11.4.1 All Countries

11.4.1.1 PLS-SEM Model Evaluation

To check the quality of the model, we first evaluated the reflective measurement models (Hair et al., 2019a; Ringle et al., 2023). Table 11.1 shows the indicator loadings as well as the Cronbach's α, the Rho_A, the composite reliability, and the Average Variance Extracted (AVE) for the reflectively measured emotional dimension of a country image. The results show that the reflective items all have significant loadings

Table 11.1 Indicator loadings (all countries)

	All countries		
	Loadings	S.E.	*t*-value
Edrawnto	0.86	0.01	69.50**
Efascina	0.86	0.01	89.45**
Elikabil	0.86	0.01	78.30**
Cronbach's α	0.82		
Rho_A	0.82		
Composite Reliability	0.89		
AVE	0.73		
N	4062		

Note * $p \leq 0.05$; ** $p \leq 0.01$

larger than 0.7 and that the construct measure exhibits sufficient levels of internal consistency, reliability, and convergent validity.

In the next step, we evaluated the formative measurement models (Hair et al., 2019a). To check the convergent validity of the formative measurement models, we ran a redundancy analysis by correlating each set of formative indicators with a global single item that captures each dimension's salient elements (Cheah et al., 2018). We find that each item is correlated substantially (i.e., > 0.70) and significantly with the corresponding single item, providing support for the measures' convergent validity. To rule out collinearity issues, we considered the measurement models' VIF values (Hair et al., 2022). All values are lower than 3, providing support that collinearity does not substantially impact the indicator weight estimates (Table 11.2). In the next step, we ran bootstrapping (10,000 subsamples; Becker et al., 2023) to assess the formative indicator weights' significance (Table 11.2). We find two items with nonsignificant weights (feducati: 'Switzerland provides great opportunities for education' and finvesto: "Switzerland is an investor-friendly country"). However, as their loadings are larger than 0.50 and significant, these indicators have a strong absolute contribution to the construct. Looking at the indicator weights, we find that the cuisine, history, tradition, and Swiss products, as well as the solidarity and tolerance of Switzerland, seem to be the most important factors in forming the image of Switzerland for all countries overall. The items of the natural dimension have to be interpreted carefully, as there are only two items forming this construct.

After evaluating the measurement models, we next assessed the structural model (Hair et al., 2019a). To rule out potential collinearity issues among the exogenous constructs, we first considered the structural model's VIF values (Table 11.3). We find that all VIF values are below 3, suggesting that the path coefficient estimates are not negatively affected by any collinearity.

Table 11.3 also shows that all path coefficient estimates are significant and positive. The cultural dimension, in particular, has an extremely strong impact on the emotional dimension. In line with Buhmann and Ingenhoff (2015a), the normative dimension also has a strong impact on the emotional dimension of a country's image.

Table 11.2 Indicator weights (all countries)

		All Countries			
		weights	*t*-value	S.E.	VIF
Cultural	Aecharism	0.09	3.02**	0.03	1.81
	Aeculinar	0.30	8.97**	0.03	1.56
	Aeculture	0.16	4.54**	0.04	1.98
	Aehistory	0.31	8.76**	0.04	1.72
	Aetraditi	0.30	8.14**	0.04	1.32
	Fsportst	0.10	3.64**	0.03	1.64
Natural	Aepresnat	0.73	26.35**	0.03	1.32
	Aescenery	0.41	11.63**	0.03	1.32
Functional	Feducati	-0.03	1.08	0.03	1.74
	Fglobeco	0.24	6.11**	0.04	1.56
	Fgovernd	0.21	5.88**	0.04	1.41
	Finnovat	0.14	4.17**	0.03	1.63
	Finvesto	0.05	1.64	0.03	1.51
	Fproduct	0.41	10.29**	0.04	1.51
	Fscience	0.09	3.04**	0.03	1.58
	Fworkpla	0.22	5.76**	0.04	1.56
Normative	Nforeign	0.26	6.92**	0.04	1.74
	Nfutgene	0.12	3.29**	0.04	1.66
	Nprotenv	0.17	4.81**	0.04	1.56
	Nsolidar	0.35	8.66**	0.04	1.81
	Ntoleran	0.35	7.72**	0.04	1.91
N		4062			

Note $*p \leq 0.05$; $** p \leq 0.01$

Table 11.3 Structural model results (all countries)

	All countries			
	Path coefficient	*t*-values	S.E.	VIF
Cultural Dimension ➔ Emotional	0.44	24.186**	0.02	2.24
Functional Dimension ➔ Emotional	0.11	5.961**	0.02	2.27
Natural Dimension ➔ Emotional	0.17	11.54**	0.01	1.60
Normative Dimension ➔ Emotional	0.21	11.61**	0.02	2.26
R^2_{adj}	0.62			
N	4062			

Note $*p \leq 0.05$; $** p \leq 0.01$

Table 11.4 $PLS_{predict}$ results (all countries)

	All countries		
		MAE	
	Q^2	PLS-SEM	LM
Edrawnto	0.396	0.600	0.597
Efascina	0.469	0.524	0.522
Elikabil	0.481	0.514	0.515

In summary, all exogenous constructs contribute significantly to the endogenous construct.

Examining the model's explanatory power, we find that the dimensions explain 62% of the emotional dimension's variance ($R^2 = 0.62$), which can be considered highly satisfactory in light of the model's complexity. Complementing the assessment of the models' explanatory power (Hair & Sarstedt, 2021; Hair et al., 2019b; Sarstedt et al., 2021), we then evaluated the model's predictive power using Shmueli et al., (2016) $PLS_{predict}$ procedure. We find that all the endogenous construct's indicators have Q^2 values larger than zero. Interpreting the prediction errors, we find that these are highly asymmetrically distributed. We therefore focus on the interpretation of the MAE values of the endogenous construct's indicators . Comparing the MAE values from the PLS-SEM (Shmueli et al., 2019) analysis with those generated by the naive linear benchmark model, we find that the PLS path model produces smaller MAE values in one of the three indicators (Table 11.4), suggesting that the model has a low predictive power. This result is not surprising, considering the limited complexity of the model (i.e., only two layers of constructs). Results from running the cross-validated predictive ability test (CVPAT; Sharma et al., 2023a) confirm this finding. The model significantly beats the indicator average, but not the linear model benchmark.

The results of the path coefficients (Table 11.3 and Fig. 11.1) show that all paths (functional dimension: $\beta = 0.011$, $p = 0.000$; normative dimension: $\beta = 0.021$, $p = 0.000$; cultural dimension: $\beta = 0.044$, $p = 0.000$; natural dimension: $\beta = 0.017$, $p = 0.000$) have a significant positive effect on the emotional dimension.

The first hypothesis states that the functional dimension has the smallest effect on the emotional dimension. This hypothesis can be confirmed.

The second hypothesis indicates that the cultural and natural dimensions have the highest effect on the emotional dimension. While the cultural dimension has the highest impact on the emotional dimension, the natural dimension has a slightly smaller effect than the normative dimension in this overall model. Therefore, the third hypothesis can only be partially confirmed for the cultural dimension being the most influential variable. Figure 11.1 shows the overall model, with the formative constructs displayed as hexagons, and the reflective construct as an oval (see Cho et al, 2022).

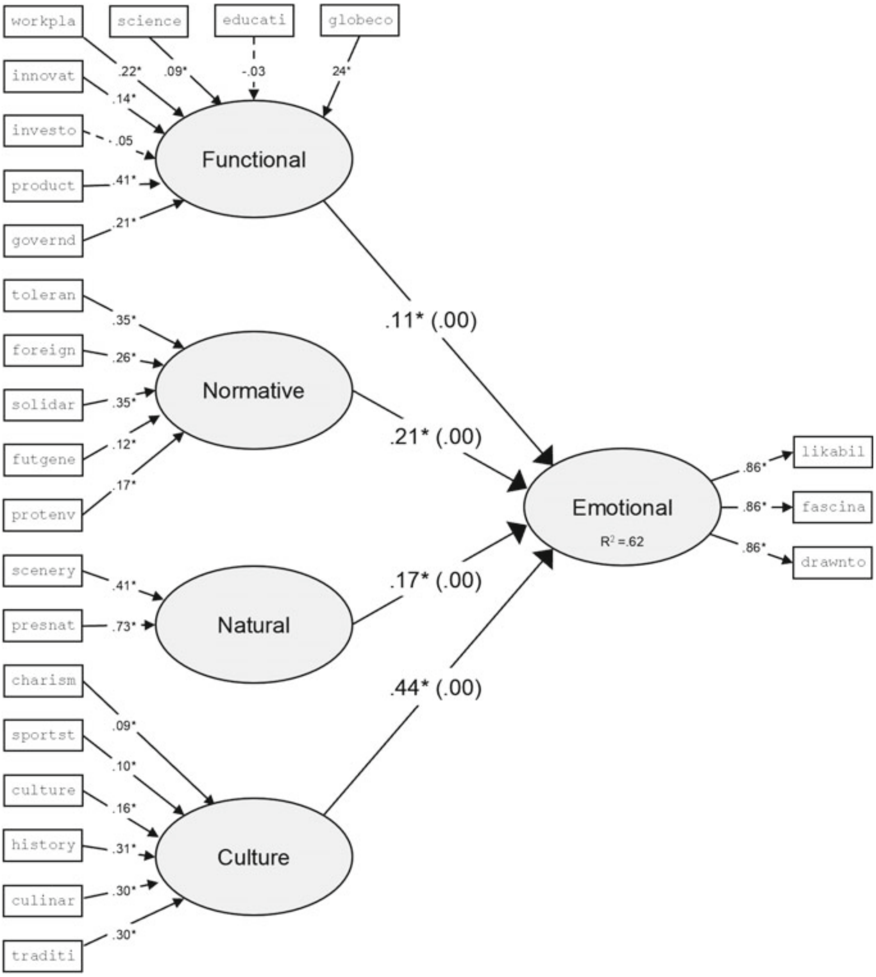

Fig. 11.1 PLS-SEM results (all countries)

11.4.2 Cluster Analysis

In the next step, we ran a combination of hierarchical clustering and *k*-means clustering to identify groups of countries that are homogeneous with regard to their country image of Switzerland on the ground of the five dimensions. Specifically, we applied the Ward's method with Euclidean distances to identify a suitable number of clusters and identify cluster centroids that we used to derive a starting partition for *k*-means clustering (Hair et al., 2014; Punj & Stewart, 1983; Sarstedt & Mooi, 2019).

The dendrogram of the agglomerative hierarchical analysis (Fig. 11.2) indicates a two-cluster solution. This result is also supported by the elbow criterion (Fig. 11.3).

Table 11.5 shows the Euclidean distances of the countries, which quantify the similarities and distances between the countries in terms of the dimensions. For example, Brazil has a much smaller distance to China (0.075) compared to Germany (1.240).

Illustrating the countries in the two affective and cognitive country image dimensions, these cluster affiliations and the distances can be clearly seen (Fig. 11.4). It is

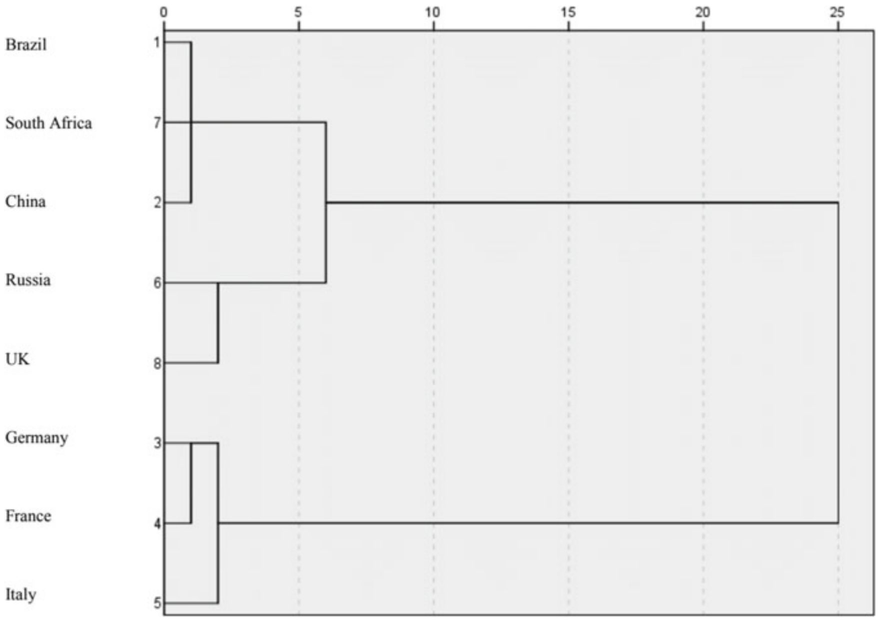

Fig. 11.2 Dendrogram (Ward's method)—Rescaled distance cluster combine

Fig. 11.3 Elbow Criterion—Distances versus number of clusters

Table 11.5 Euclidean distance matrix

	Squared euclidean distance							
	Brazil	China	Germany	France	Italy	South Africa	Russia	UK
Brazil								
China	0.075							
Germany	1.240	1.357						
France	0.715	0.769	0.089					
Italy	1.103	1.129	0.156	0.117				
South Africa	0.171	0.163	0.693	0.321	0.559			
Russia	0.011	0.069	1.199	0.686	1.041	0.121		
UK	0.504	0.425	0.380	0.133	0.292	0.182	0.468	

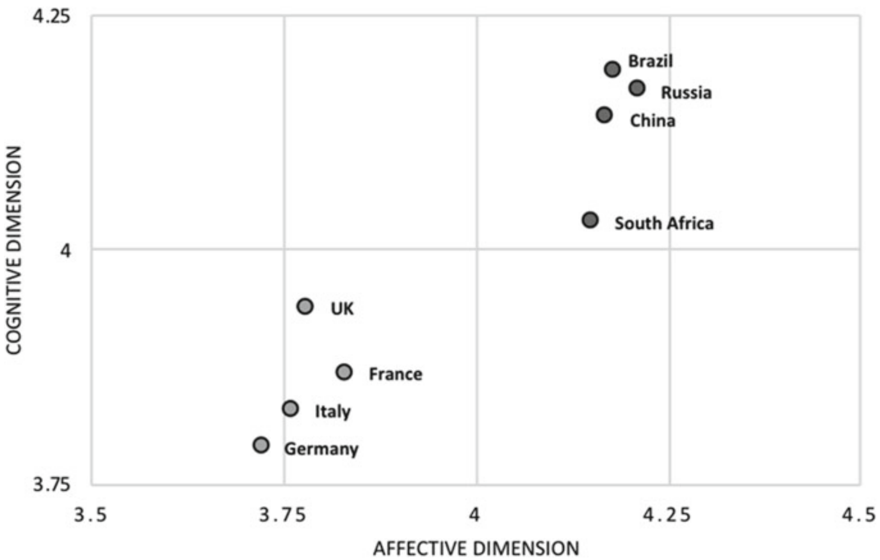

Fig. 11.4 Cluster affiliation in affective and cognitive country image dimensions (k-means)

interesting to note that the further a country is geographically, culturally, and politically from Switzerland, the higher it is rated on the two dimensions. The lowest means are from the three nearest countries that share both a border and partial linguistics as well as history with Switzerland. The UK, which is in geographical and historical proximity to Switzerland compared to the more distant countries, also ranks Switzerland lower than those countries do.

Thus, with the cluster analysis, the eight countries can be statistically and logically grouped into two clusters: (1) Brazil, China, Russia, and South Africa (the countries that are geographically, culturally, and politically far away from Switzerland) and (2) Germany, France, Italy, and the UK (the countries that are geographically, culturally,

Table 11.6 *t*-test differences between the BRICS and Western Europe in their judgment of the different dimensions of the image of Switzerland

	BRICS		Western Europe		*t* (4062)	*p*	Cohen's *d*
	M	*SD*	*M*	*SD*			
Functional	4.1	0.63	3.9	0.62	7.58	0.567	0.320
Normative	4.0	0.68	3.6	0.75	18.50	0.000	0.559
Culture	4.0	0.68	3.7	0.73	15.36	0.003	0.425
Nature	4.4	0.67	4.6	0.67	2.97	0.313	−0.299
Emotional	4.2	0.78	3.8	0.88	14.68	0.000	0.481

and politically close to Switzerland). Examining the countries within the clusters, we can hereafter refer to them as (1) the BRICS countries (i.e., countries belonging to the association of five major emerging national economies, either leading developing or newly industrialized countries: Brazil, Russia, (India)),[1] China, and South Africa, and (2) Western Europe. The two clusters were then tested for their differences by conducting a *t*-test. The results in Table 11.6 show that the two groups differ significantly ($p < 0.001$) for three of the five dimensions (normative, culture, and emotional dimensions). Thus, the clustering of the countries into these two groups concerning their image of Switzerland supports our previous theoretical elaborations (Table 11.6).

Having identified significantly clustered groups of countries, the image of Switzerland in these groups can be approached to see how they differ. To compare and analyze the value drivers of the country images of the two groups of countries, we evaluated each PLS path model individually.

11.4.3 PLS-SEM Model Evaluation (Per Cluster)

To check the quality of the two different models, we applied the same criteria as for the analysis of the complete dataset. Table 11.7 shows that all indicator loadings, as well as the Cronbach's α, Rho_A, composite reliability, and AVE, have good values for both models (BRICS and Western Europe), providing support for the reflective measurement models' reliability and validity.

The formative measurement model assessment results confirm that neither of the indicators is subject to collinearity, as evidenced by VIF values below 3 (Table 11.8). Checking for the indicator weights (Table 11.8), we find some differences compared to the complete dataset. While all items contribute significantly to the formative constructs for the BRICS countries, there are two nonsignificant items for Western Europe (finvesto: "Switzerland is an investor-friendly country" and fscience: "Switzerland is recognized internationally as a significant location for science and

[1] India was not in our sample for this study.

Table 11.7 Indicator loadings (BRICS and Western Europe)

	BRICS			Western Europe		
	Loadings	s.e	*t*-value	Loadings	S.E.	*t*-value
Edrawnto	0.84	0.01	84.91**	0.85	0.01	97.57**
Efascina	0.84	0.01	84.60**	0.85	0.01	110.04**
Elikabil	0.86	0.01	101.12**	0.87	0.01	122.43**
Cronbach's α	0.80			0.82		
Rho_A	0.80			0.82		
Composite Reliability	0.88			0.89		
AVE	0.71			0.73		
N	2032			2030		

Note $^*p \leq 0.05$; $^{**}\ p \leq 0.01$

research"), one of which is different from the two nonsignificant items of the complete dataset. However, as with the complete dataset, the corresponding indicators have significant loadings larger than 0.5, providing support for their absolute contribution. The most important items for the cultural dimension are traditions, cuisine, and history (especially for the BRICS countries). For the Western European countries, charismatic personalities also have a high weight. The items for the natural dimension cannot be analyzed further since there are only two. The functional dimension differs between the two groups: While the government, products, and Switzerland as a workplace have the strongest impact on the perceived image of Switzerland for the BRICS countries, the Western European countries emphasized the innovativeness of Switzerland, alongside the government. The BRICS countries form their normative dimension of the image of Switzerland mostly from the care for future generations, solidarity, and protection of the environment. For the Western European countries, the strongest effect on the normative dimension is formed by the solidarity of Switzerland, closely followed by the care for future generations.

Table 11.9 documents the path coefficients of the two models along with the exogenous constructs' VIF values. We find no elevated levels of collinearity in either of the models. Considering the path coefficient estimates, we find that all are positive and significant for both models. It is interesting to see that for both groups of countries, the cultural dimension has the strongest impact on the emotional dimension. But aside from that, the country images of the two groups are completely different. For the BRICS countries, the natural dimension is extremely strong, while the functional and normative dimensions have a small effect on the emotional dimension. The Western European countries, on the other hand, build their image of Switzerland largely via the cultural dimension. In contrast to the BRICS countries, the normative dimension has the second strongest impact on the emotional dimension for the Western European countries.

Finally, assessing the models' explanatory power, we find that the exogenous constructs explain a significant share of the emotional dimension's variance,

Table 11.8 Indicator weights (BRICS and Western Europe)

		BRICS				Western Europe			
		weights	*t*-value	S.E.	VIF	weights	*t*-value	S.E.	VIF
Cultural	Aecharism	0.15	3.82**	0.04	1.71	0.22	7.06**	0.03	1.76
	Aeculinar	0.27	7.66**	0.04	1.55	0.23	7.58**	0.03	1.54
	Aeculture	0.13	3.25**	0.04	1.84	0.11	3.43**	0.03	1.96
	Aehistory	0.31	8.10**	0.04	1.66	0.20	6.79**	0.03	1.68
	Aetraditi	0.36	9.44**	0.04	1.62	0.45	15.24**	0.03	1.80
	Fsportst	0.10	2.58**	0.04	1.58	0.07	2.28*	0.03	1.61
Nature	Aepresnat	0.63	17.30**	0.04	1.31	0.74	22.44**	0.03	1.33
	Aescenery	0.53	14.06**	0.04	1.31	0.40	9.58**	0.04	1.33
Functional	Feducati	0.12	2.76**	0.0 5	1.74	0.10	2.37*	0.04	1.71
	Fglobeco	0.14	3.42**	0.04	1.52	0.08	1.99*	0.04	1.57
	Fgovernd	0.30	6.80**	0.04	1.42	0.40	9.40**	0.04	1.39
	Finnovat	0.17	3.86**	0.04	1.64	0.41	8.96**	0.05	1.63
	Finvesto	0.09	2.13*	0.04	1.55	0.01	0.19	0.04	1.49
	Fproduct	0.26	6.31**	0.04	1.47	0.17	3.99**	0.04	1.54
	Fscience	0.11	2.49*	0.04	1.55	0.02	0.35	0.04	1.62
	Fworkpla	0.23	5.56**	0.04	1.63	0.19	4.14**	0.04	1.55
Normative	Nforeign	0.10	2.66**	0.04	1.45	0.12	3.11**	0.04	1.81
	Nfutgene	0.39	8.90**	0.04	1.67	0.39	9.69**	0.04	1.58
	Nprotenv	0.30	6.66**	0.04	1.66	0.21	5.29**	0.04	1.47
	Nsolidar	0.30	7.03**	0.04	1.74	0.40	9.48**	0.04	1.72
	Ntoleran	0.19	4.82**	0.04	1.63	0.19	4.49**	0.04	1.96
N		2032				2030			

Note $*p \leq 0.05$; $** \, p \leq 0.01$

Table 11.9 Structural model results (BRICS and Western Europe)

	BRICS			Western Europe		
	Path coefficient	*t*-values	S.E.	Path coefficient	*t*-values	S.E.
Cultural ➔ Emotional	0.37	13.54**	0.03	0.47	19.91**	0.02
Functional ➔ Emotional	0.16	5.40**	0.03	0.10	4.35**	0.02
Nature ➔ Emotional	0.21	9.08**	0.02	0.16	8.88**	0.02
Normative ➔ Emotional	0.16	5.62**	0.03	0.19	8.03**	0.02
R^2_{adj}	0.59			0.61		
N	2032			2030		

Note $*p \leq 0.05$; $** \, p \leq 0.01$

Table 11.10 $PLS_{predict}$ results (BRICS and Western Europe)

	BRICS			Western Europe		
	MAE			MAE		
	Q^2	PLS-SEM	LM	Q^2	PLS-SEM	LM
edrawnto	0.370	0.541	0.534	0.388	0.640	0.638
efascina	0.442	0.486	0.482	0.463	0.557	0.558
elikabil	0.444	0.500	0.503	0.484	0.528	0.526

with R^2 values of 59% for BRICS and 61% for Western Europe (Table 11.9). Finally, the $PLS_{predict}$ results suggest that both models have a low predictive power (Table 11.10). The results from the CVPAT analyses (Sharma et al., 2023a) confirm this finding. Both models significantly beat the indicator average benchmark, but not the linear model benchmark.

Overall, these results suggest satisfactory degrees of explanatory and predictive power in terms of Switzerland's image for both BRICS and Western Europe. Figures 11.5 and 11.6 illustrate the two models.

11.4.4 Comparisons Between BRICS and Western Europe

To compare the image of Switzerland between these two groups of countries, a multigroup analysis is typically a useful tool. However, as Henseler et al., (2016) MICOM analysis did not offer support for the measures' partial invariance, probably due to the different perceptions of the constructs in these different countries, we followed Henseler et al., (2016) and only considered the cluster-specific effects separately. The cultural dimension has a high impact on the emotional dimension for the Western European countries. For the BRICS countries, the natural and the emotional dimensions show a substantial effect.

These results imply that history and nature seem to be highly important to the BRICS countries in forming an image of Switzerland. At the same time, for Western Europeans, the countries' functional items, in particular, like the government and innovativeness of Switzerland, are extremely relevant in forming their image. This might be the case due to the BRICS countries having less concrete information about Switzerland because the media reports less about distant countries. In this situation, people rely more on aspects like the scenery and what they have heard about a country's history in order to form an opinion about that country. These results confirm hypotheses three and four, that proximity has an effect on the perceived country image, and that countries that are located further away with a more different culture and politics are more impacted by the cultural and natural dimensions than geographically, culturally, and politically closer countries.

In Table 11.11, the results of a second *t*-test show that the two groups of countries differ significantly in the number of people who have actually visited Switzerland [*t*

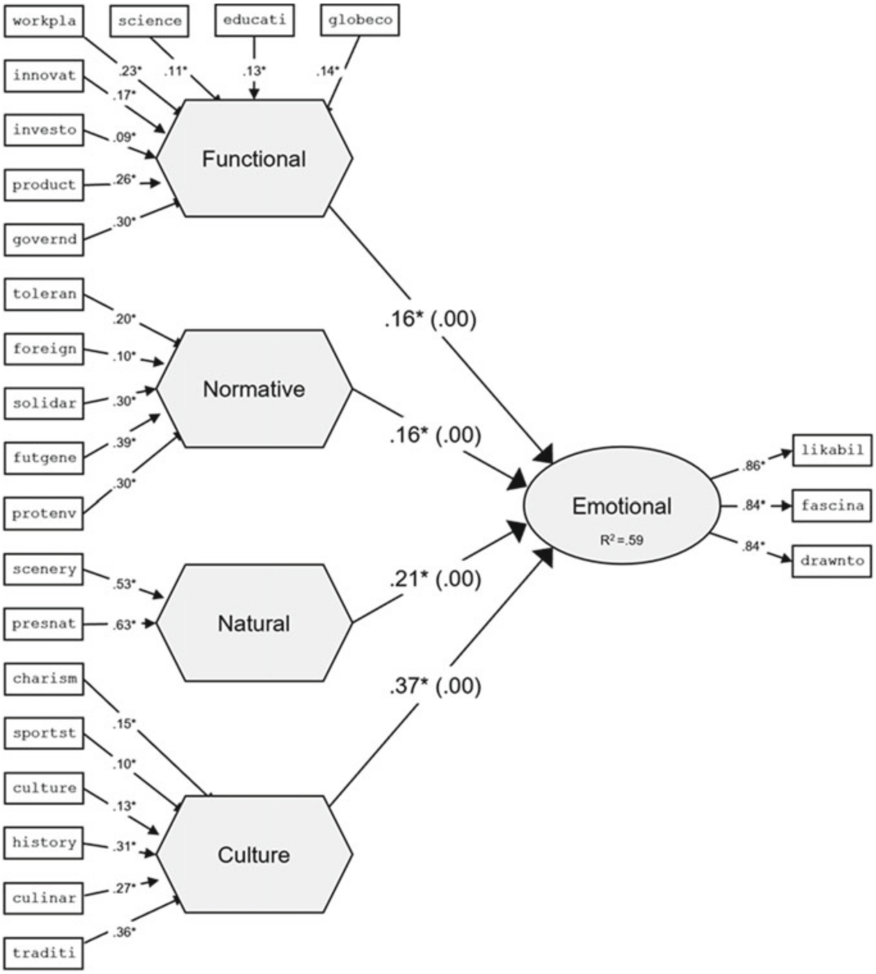

Fig. 11.5 PLS-SEM results (BRICS)

(4062) = −24.4, $p < 0.001$], as well as in their knowledge about Switzerland [t (4062) = −1.8, $p < 0.001$]. People from Western European countries have visited Switzerland more often and, thus, have more knowledge about Switzerland. Therefore, they can draw their opinions from their own experiences. Concerning viewing oneself as cosmopolitan, the BRICS and Western European countries again show significant differences [t (4060) = −6.2, $p < 0.001$], with people from Western Europe seeing themselves as cosmopolitan more often than people from BRICS countries. However, this is the respondents' own subjective opinion, and it correlates significantly with the visits. People who see themselves as cosmopolitan are more open to learning about a country and travel more, thus they are more likely to have visited Switzerland.

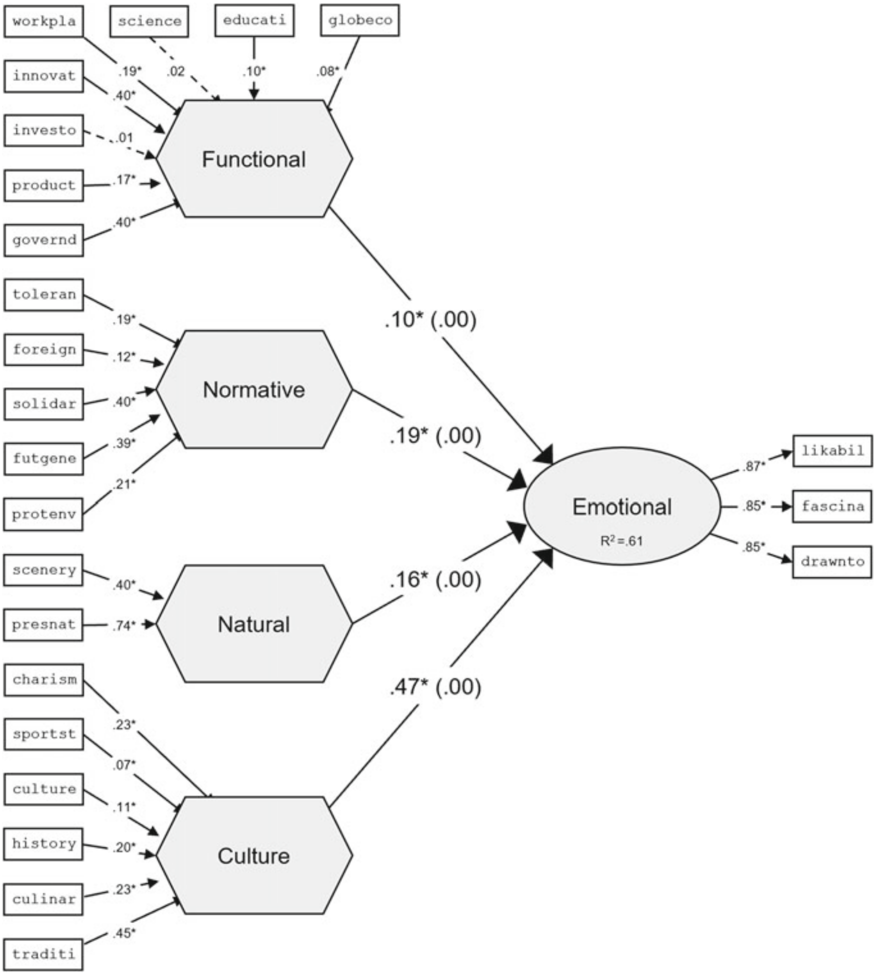

Fig. 11.6 PLS-SEM results (Western Europe)

Table 11.11 *t*-test differences between the BRICS and Western Europe in whether they visited Switzerland, their knowledge about Switzerland, and their number of cosmopolitans

	BRICS		Western Europe		*t* (4062)	*p*	Cohen's *d*
	M	*SD*	*M*	*SD*			
Visited CH	0.23	0.42	0.58	0.49	−24.338	0.001	−0.814
Knowledge CH	0.71	0.45	0.74	0.44	−1.775	0.001	−0.067
Cosmopolitan	0.24	0.42	0.33	0.47	−6.160	0.001	−0.202

Note the respondents answered the questions about the knowledge and the feeling of being cosmopolitan subjectively.

11.5 Discussion

Our results show that a country image can be measured as an attitudinal construct. All cognitive components have a positive effect on the affective dimension, with the functional dimension having the smallest and the cultural dimension having the largest impact, thus fully confirming hypothesis 2 and partially confirming hypothesis 3. Furthermore, the PLS-SEM allows the identification of the key value drivers in composing the country image of Switzerland.

The results of the cluster analysis show that the countries can be distinguished into the two groups of BRICS and Western European countries. It is noticeable that the countries in these clusters are not only differentiated in their image of Switzerland but also in their geographical, cultural, and political distance from Switzerland. In particular, the countries that share a common border, such as Germany, Italy, and France, have smaller average means in rating the different dimensions of Switzerland, i.e., they are more critical of Switzerland. The UK, on the contrary, rates the five dimensions of the image of Switzerland much higher. Being a little further away seems to have a small impact on the evaluation of a country's image. Since people's attitudes toward a country are built on their direct and indirect experiences of the country (Jain & Winner, 2013), it is understandable that proximity not only has an impact on the possibility of direct experiences with a foreign country (Wang & Shoemaker, 2011) but also on the number of indirect information sources. As the news values theory suggests, proximity is a factor that determines what news will be published (Eilders, 2006; Galtung & Ruge, 1965). Thus, countries that are nearer to each other (geographically, culturally, and politically) might learn more information about each other than about distant countries, as the variety and intensity of news will deliver more information. The results confirm that countries that are (geographically, culturally, and politically) close to Switzerland are more critical. This might be a consequence of greater knowledge based on the availability of foreign news (Eilders, 2006; Galtung & Ruge, 1965; Staab, 1990), as foreign news coverage tends to concentrate on countries in the immediate geographic region (Sreberny-Mohammadi, 1984).

Analyzing the image dimensions of the two clustered groups, we can see differences in how they form their image of Switzerland. The natural dimension, in particular, has a high effect on the affective dimension, and the evaluation of the land's history and scenery has a high influence on BRICS countries. These results underline the suggestion that the more geographically distant a country is, the more exotic the nature and culture might be perceived to be and the more the image is built on surface-level information, such as the landscape of a country, thus resulting in higher ratings. The results show that the BRICS countries base their image of Switzerland mostly on stereotypical attributes, with landscapes and some cultural attributes being the most important (Bender et al., 2013; Chen et al., 2016; Cuddy et al., 2009; Dovidio et al., 2010; Kym, 2010). The Western European countries, on the other hand, receive more information about Switzerland and are, therefore, also able to construct an image with respect to the functional dimension, taking the government and the innovativeness of Switzerland into consideration.

Finally, the *t*-test confirms these findings further, as it shows that the groups differ significantly regarding how frequently they travel to Switzerland. Respondents from Western European countries have visited Switzerland significantly more often, which improves their knowledge about Switzerland and gives them the ability to form an image based on their own experience (Roth & Diamantopoulos, 2009). In addition, the propensity for individuals to view themselves as cosmopolitan differs significantly between the two groups of countries, which might have an influence on how they rate other countries and how much knowledge they try to gather about them. It can be assumed that cosmopolitan individuals are more open and interested in other countries and, therefore, more willing to learn more detailed information about them.

11.6 Conclusion

The findings show that PLS-SEM can be applied to measure the value drivers of the country image dimensions and to compare country clusters. This could help public diplomacy practitioners to develop communication activities and campaigns with similar aims and measures that may work in all countries belonging to the same cluster. In all models, the cultural dimension has the strongest explanatory power contributing to the formation of a country image. However, the single value drivers differ between the clusters, not only with respect to the cultural dimension but also to all country image dimensions.

Interestingly, the effect of the functional dimension of a country image is rather low. Here, public diplomacy might consider the scope for raising the knowledge and awareness about the country's politics and markets, even if that is much more difficult than advertising using the beauty of the countryside.

Finally, the presented results are obtained based on a representative study surveying the country image of Switzerland and might, therefore, be limited to small, successful countries only. To further explore this topic, another sample would be necessary to investigate the differences in countries with different political systems, reputations, and sizes.

It is important to point out that we called one group of countries BRICS due to their constellation. However, this is only to give the group a distinct name that is clear to the reader; it is not based on their common economical state.

To sum up, with this research, we propose a measurement instrument that is capable of analyzing the polyphony of voices in public diplomacy, be it in different countries or even in different stakeholder groups and channels. It could support public diplomacy in developing aligned and concerted communication activities in different target countries, taking into consideration the value drivers of each dimension that might differ from country to country but also benefiting from similarities that appear in country clusters.

Appendix

See Table 11.12.

Table 11.12 Indicator list with wordings

Indicator	Item wording
Functional	
Feducati	Switzerland provides great opportunities for education
Finnovat	Switzerland stands for creative ideas and innovative solutions
Fscience	Switzerland is recognized internationally as a significant location for science and research
Fproduct	Switzerland produces very high-quality goods and services
Fglobeco	Switzerland holds a strong position in the global economy
Fworkpla	Switzerland is a highly attractive country to work in
Finvesto	Switzerland is an investor-friendly country
Fgovernd	Switzerland is competently governed
Normative	
Nfutgene	Switzerland takes responsibility for future generations
Nprotenv	Switzerland is very active in protecting the environment
Nsolidar	Switzerland shows solidarity and responsibility in tackling global challenges
Ntoleran	Switzerland is a tolerant and open-minded country
Nforeign	Foreigners are (generally) welcome in Switzerland
Cultural	
Aeculture	Switzerland has unique and internationally recognized cultural assets (e.g., literature, music, arts, film, design, architecture, etc.)
Aeculinar	Switzerland is known for its delicious food and cuisine
Aehistory	Switzerland has a rich history
Aetraditi	Switzerland has appealing traditions
Aecharism	Switzerland has charismatic people (e.g., in politics, sports, culture, media, etc.)
Fsports	Athletes and sports teams from Switzerland are internationally successful
Nature	
Aescenery	Switzerland has a very beautiful scenery
Aepresnat	Switzerland has a lot of preserved nature
Emotional	
Elikabil	I like Switzerland
Efascina	Switzerland is fascinating
Edrawnto	I am drawn to Switzerland

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Chapter 12
To Survive or not to Survive: Findings from PLS-SEM on the Relationship Between Organizational Resources and Startups' Survival

Jubalt Alvarez-Salazar and Jean Pierre Seclen-Luna

Abstract This study explores the phenomenon of startup survival in an incipient entrepreneurship ecosystem. For this purpose, multiple and simultaneous relationships between organizational resources, incubation, and startup survival are validated empirically. The analysis used PLS-SEM on a sample of 119 startups operating in different markets in Peru. The results show that survival is explained directly by a combination of entrepreneurial and organizational capital but indirectly by a chain of causal links. In this way, social capital determines human capital, and human capital also determines entrepreneurial capital. Thus, this study contributes to the literature in management and entrepreneurship with one alternative way to measure a phenomenon of greater complexity to demonstrate the survival of Peruvian startups.

12.1 Introduction

A startup is a new venture designed to develop its value proposition under extreme uncertainty (Ries, 2011; Tanev, 2012), basing its operation on its high innovative capacity (Aulet & Murray, 2013). Thus, they experiment to reduce uncertainty by designing and implementing a replicable, scalable, and profitable business model (Blank & Dorf, 2012) and overgrow as an effect of solving emerging problems that affect many people (OECD, 2016). Thus, the phenomenon of startups has drawn the attention of policymakers and researchers.

The existence of startups is beneficial for countries where entrepreneurs create or develop them. When these ventures are consolidated, they can create wealth, renew the business structure, or create new markets (Acs, 2010; Fritsch, 2011; OCDE,

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2016). Simultaneously, they improve people's quality of life, offering innovative solutions to social and environmental problems that are common globally (Amit & Zott, 2001; World Economic Forum, 2019). However, boosting the creation of these ventures is not a sufficient condition to generate benefits for their founders and society. So, it is necessary to know startups' survival and consolidation (Isenberg, 2016).

In this respect, the empirical evidence shows that startups must be able to cover their operating costs with sales revenues, overcoming the "valley of death" (Murphy & Edwards, 2003; Tanriserver et al., 2012), but that is a big challenge. In fact, between 70 and 90% of startups globally do not survive, and those that manage to do so have experienced close failure (Ejermo & Xiao, 2014; Hyder & Lussier, 2016; Ghosh 2011, as cited in Nobel, 2011).

It is recognized that the low survival rate of startups (Statista, 2020) has become more critical in Latin American countries, mainly for two reasons. First, there are high venture creation rates but limited innovative capacity (Lederman et al., 2014). Second, the conditions for venture consolidation are unfavorable (Seclen-Luna & Barrutia, 2019).

The development of startups is affected by the entrepreneurship ecosystem (Stam, 2015). Compared to mature ecosystems, the conditions for startup development are underdeveloped in emerging countries. A sample of this is the reduced Index of Dynamic Entrepreneurship Score for Peru at 26.23% (Kantis et al., 2019). According to this report, the indicators with the lowest levels in Peru are STI platform development, weak business structure, and low human capital. Thus, we can appreciate the limited conditions offered by the Peruvian entrepreneurship ecosystem compared to other mature ecosystems. However, even considering the restrictions on creating startups in incipient ecosystems, there are some cases where different actors in the ecosystem are driving their creation and consolidation. In Peru, the capacity to develop startups is just beginning, and specialists expect more of these ventures in the short term (MIT REAP Team Lima, 2018).

In addition, the evaluation of the government program Startup Peru results showed that 79% of the startups financed with monetary transfers from the State have survived, and that 9.5% more startups that benefited achieved the breakeven point than those that were not (Goñi Paccioni & Reyes, 2019). This implies that, even without receiving public resources, some startups manage to survive in the Peruvian context. Therefore, previous arguments raise the following question: what factors affect startup survival in Peru?

Usually, research conducted in entrepreneurship is on mature ecosystems (Block et al., 2017). However, the performance of variables may differ between developed and emerging countries (Capelleras & Rabetino, 2008). In addition, they commonly do not consider the effect of multiple and simultaneous relationships between variables that explain startup survival (Santisteban & Mauricio, 2017). Therefore, considering all those mentioned above, the previous studies consulted in the literature may provide a partial approximation to startup survival, which may not apply to the Peruvian context.

Furthermore, the literature reviewed reveals that, like in Latin America, the research on the survival of startups in Peru still is scarce and limited (Lopez & Álvarez, 2018). Thus, this research addresses this phenomenon using PLS-SEM[1] to identify the complexity of the multiple and simultaneous relationships that determine it. It is crucial because startups are a source of economic, social, and environmental value generation when they manage to survive, which is rare (Ejermo & Xiao, 2014; Hyder & Lussier, 2016; Ghosh 2011, as cited in Nobel, 2011). Thus, in the face of a more significant push for startup creation in nascent ecosystems, understanding how startups use their scarce resources (Aulet, 2013; Ries, 2011) to survive in unfavorable conditions (Kantis, 2005) could help future entrepreneurs and policymakers make improved decisions.

Moreover, not focusing on the factors determining survival could generate a contradictory effect, as the survival rate could be reduced even more and may increase resource losses for founders. It will also imply lower returns for private investors and a reduction in the effect of public policies associated with the corresponding loss of efficiency in public spending. Therefore, the entrepreneurial ecosystem may become unattractive (Fuentelsaz et al., 2018), reducing the momentum for innovative entrepreneurship.

12.2 Theoretical Framework

According to the resource-based theory (Barney, 1991; Conner, 1991; Wernerfelt, 1984) and the theory of dynamic capabilities (Teece et al., 1997), organizational resources, such as human capital, social capital, entrepreneurial capital, and organizational capital, as well as the incubation process interact to enable survival startups. From this perspective, startups possess or quickly generate organizational resources that interact with each other to achieve survival. The dynamic capabilities of these ventures allow transforming these newly acquired resources to sustain their experimentation process. In this way, startups survive in their early stages and initiate their growth process (Alvarez-Salazar, 2021). In addition, the contingency theory is considered to explain that the context also determines the way the startup configures its resources. Thus, the theoretical framework of this research is based on the three theories mentioned.[2] The previous elements (organizational resources, incubation, and startup survival) are studied, and the study's hypotheses are generated.

[1] PLS-SEM was selected as the technique for the study because it is suitable for composite models and formative indicators. More details are provided in the methodological section.

[2] Appendix 12.1 shows the summary of theoretical frameworks.

12.3 The Human Capital and Startup Survival

Human capital comprises the founders' and teams' characteristics, attitudes, knowledge, and experience that add value to the startup (e.g., Acs, 2010; Coleman, 2000; Okamuro & Ikeuchi, 2018; Wang et al., 2019). These resources are essential to achieve survival and drive venture performance (e.g., Acs et al., 2007; Baptista et al., 2014; Cooper et al., 1994; Gimmon & Levie, 2010; Jiang et al., 2016; Linder et al., 2020; Nielsen, 2014). The broad literature recognizes, on the one hand, the relevance of education or the level of academic studies achieved by the founders to achieve survival (e.g., Colombo & Grilli, 2005; Plehn-Dujowich, 2010). On the other hand, some studies highlight that experience in management and technological application is more important than academic knowledge to achieve survival (Gimmon & Levie, 2010). In particular, the specific professional expertise of the founder in the industry in which the startup operates (Colombo & Grilli, 2005; Fontana et al., 2016). In addition, international exposure could also be relevant depending on whether the founder has studied or worked abroad (Alvarez-Salazar, 2021). In addition to this controversy, other studies highlight experience as an entrepreneur because it predisposes to better outcomes when the founder has created other startups (Baptista et al., 2014; Colombo & Grilli, 2005; Plehn-Dujowich, 2010). The motivation to develop the business is also essential, and the entrepreneur may be motivated by opportunity or necessity (Cancino et al., 2012; Oe & Mitsuhashi, 2013), maybe a serial entrepreneur, or, on the contrary, perhaps a novice entrepreneur (Baptista et al., 2014; Colombo & Grilli, 2005; Plehn-Dujowich, 2010). On the other hand, the complementarity of the founding team concerning technical and management skills (Baptista et al., 2014; Miloud et al., 2012) is also related to startup survival. Furthermore, the global vision has also recognized that effect on their survival (e.g., Cannone & Ughetto, 2014).

In short, it is possible to observe that multiple studies have shown that the presence of different components of human capital in a venture has a direct relationship with survival.

12.4 The Social Capital and Startup Survival

Social capital is an intangible asset that results from existing and potential resources derived from the social structure in which an organization participates, which can be individual or collective. Thus, the direct influence of social capital on the survival of new ventures has been demonstrated in multiple studies (Bosma et al., 2004; Davidsson & Honig, 2003; Linder et al., 2020). Therefore, social capital is the value generated in the startup from the generation and participation in contact networks by obtaining resources that otherwise could not be acquired by the venture (Raz & Gloor, 2007). For example, the more basic way to take in contact is access to family or friendship networks, referring to the ability of ventures to obtain critical resources such as access to customers, services, knowledge, or investment of entrepreneurial capital (Alvarez-Salazar, 2021). Despite this, other networks are generated by professional experience (Bastié et al., 2013) and specialized networks (e.g., when the startup is moving to higher technological sophistication) that can affect the probability of survival, especially when the founder's network of contacts is denser (Song et al., 2019). Therefore, the number of networks in which the startup participates and the alliances it manages to establish with other consolidated companies are essential for survival (Baum & Silverman, 2004). In any case, the creation or access to contact and exchange networks requires planning that the founder performs considering the stage of the life cycle, the industry, and the country where the startup operates (Stam et al., 2014).

12.5 The Entrepreneurial Capital and Startup Survival

Entrepreneurial capital is the money invested in creating, operating, and scaling a startup (Robb & Robinson, 2014). The literature indicates that the accumulation of entrepreneurial capital positively impacts survival (Lee & Zhang, 2011a, 2011b). Thus, the founder's contribution, which multiple researchers in more developed ecosystems have studied, is a determinant of the survival of startups (Cooper et al., 1994; Cressy, 2006; Frid, 2014; Korunka et al., 2010; Plehn-Dujowich, 2010; Robb & Robinson, 2014). However, in a developing ecosystem, a contribution can be from three sources: personal savings, money loans by other persons, and the entrepreneur's opportunity cost; personal savings are the most important for survival (Alvarez-Salazar, 2021). Another source could be private venture capital since, in mature ecosystems, it is a necessary condition for a venture to survive (Gonzalo et al., 2013; Hechavarría et al., 2016). Without the participation of angel investors, it is impossible to maintain the experimentation process, let alone think about growth.

Nevertheless, private equity investment is still underdeveloped in emerging countries such as Peru (Hernández & González, 2016). On the other hand, public funds could be understood as a complementary source. Moreover, for many startups, it has been decisive to continue with the experimentation process in the initial stages (Auerswald, 2015). Finally, all these sources could be affected by the investor's risk profile concerning the ability to attract entrepreneurial capital from startups. For example, investors in the Peruvian ecosystem are highly risk-averse because they are engaging in a learning process to invest in highly uncertain ventures (Alvarez-Salazar, 2021).

12.6 The Organizational Capital and Startup Survival

The literature recognizes that organizational capital is the knowledge incorporated into the venture through experimentation (Blank, 2016; Moberg, 2001). This is because, in the birth and transition stages, the startup changes dynamically until the stage of accelerated growth. Thus, the generation of the minimum viable product

(MVP) in short periods is necessary; this allows the entrepreneurship and their innovative products to be evaluated and adapted to the expectations of the target market, generating knowledge in uncertain fields of action (Isaac et al., 2010; Kerr et al., 2014). An MVP is the basic version of the innovative product made available to a group of target customers to obtain feedback, allowing the startup to generate knowledge (Ries, 2011). Hence, the learning cycle involves prototyping very quickly to make a group of target customers use it, measure the responses to its use, and learn what the market expects (Coviello & Joseph, 2012). This is how the MVP becomes the vehicle for potential customers to give feedback to the startup, thus reducing uncertainty. In this context, the number of iterations conducted in the experimentation process may affect the startup's survival since the startups generate knowledge and make decisions methodically (Ries, 2011). Moreover, the intensity of using analytical knowledge to create an innovative product (product definition) is related to solving market needs through a process that requires more time for experimentation and, consequently, more significant amounts of funding (Alvarez-Salazar, 2021). The business model's maturity level may also affect the startup's survival (Osterwalder & Pigneur, 2010).

12.7 The Role of Incubation in the Startup Survival

Incubators have the fundamental role of contributing to the survival of startups (Stayton & Mangematin, 2019). The incubation process seeks to fill gaps in the resources and capabilities that the venture has through a direct transfer from the incubator to the startup. For example, incubators' two most frequent service resources are access to investor networks and mentors (Del Sarto et al., 2020). On the other hand, legal and fiscal support, access to potential customers, access to suppliers, availability of workspace, access to laboratories, and links between entrepreneurs are less critical. Given the increased number of incubators nowadays, they tend to compete with each other and other incubation industry organizations to attract startups (Aernoudt, 2004; Vanderstraeten & Matthyssens, 2012). Thus, the level of service provided by the incubator and, at the same time, the participation of the entrepreneurs in the incubation process could be different (Rice, 2002). In that sense, it is also possible that the incubator provides management capabilities, which can cover the traditional management of a business, or the direction of the experimentation process based on agile methodologies (Ries, 2011).

12.8 The Startup's Survival

Survival analysis of firms is a topic of interest in divergent literature, especially when many new firms fail early (Strotmann, 2007). It may be fueled by a lack of resources, such as skill sets, financing, adequate infrastructure in the pre-commercialization phase, and others (Markham, 2002). Thus, several factors have been studied to explain the survival or failure of startups. However, there is still no consensus on measuring the survival concept in the startup survival literature. For instance, on the one hand, one way to measure survival is when new businesses cannot break even (Murphy & Edwards, 2003).

Conversely, when sales growth is considered (Picken, 2017), achieving accelerated growth without breakeven implies that the venture has high sales revenue but no ability to demonstrate profits. In that sense, some studies highlight the relevance of the availability of a cash stock at the end of the transition stage (Alvarez-Salazar, 2021) because when the startup achieves breakeven, it is an organization that is still weak to respond to a liquidity crisis. Thus, initiating accelerated growth requires a stock of cash to support the operation. On the other hand, other indicators of survival may be some operational actions, such as increasing staff, changing locations, increasing transactions, expanding commercial reach, and connecting to international networks (Alvarez-Salazar, 2021). Thus, growth in operations indicates the survival of startups overcoming the transition stage. However, multiple previous studies (Ejermo & Xiao, 2014; Massey, 2016; Rank, 2014; Ritter et al., 2018) have also shown that the period of continuous operation can be considered a startup's survival indicator. In any case, considering simultaneously all these indicators could be an adequate assessment. Therefore, more explorations must understand the startup's survival, particularly in the context of developing countries.

12.9 Hypothesis and Startup Survival Structural Model

This study considers the general hypothesis that there are multiple and simultaneous relationships between organizational resources, the role of incubation, and the survival of startups. Thus, the measurement and structural models are proposed as an abstraction of the startup survival phenomenon.

Firstly, the literature acknowledges that human capital coexists with social and entrepreneurial capital (Alvarez-Salazar, 2021; Linder et al., 2020). Moreover, human capital also coexists with organizational capital, which suggests these capitals are linked. In addition, it is important to mention that the personal knowledge of the founders is integrated into the knowledge of the venture collectively, so human capital determines organizational capital (Politis, 2005). Thus, based on these arguments, we arise the following propositions:

Hypothesis 1. Human capital has a direct effect on survival.

Hypothesis 2. Human capital has a direct effect on entrepreneurial capital.

Hypothesis 3. Human capital has a direct effect on organizational capital.

Secondly, some authors stated that social capital is linked to human capital. For example, Coleman (2000) proposes that the former will determine the latter. In addition, social capital also coexists with entrepreneurial capital to a lesser extent, mainly because, in the Peruvian ecosystem, access to finance in the initial stages requires contacts (Alvarez-Salazar, 2021). Thus, social capital determines entrepreneurial capital (e.g., Linder et al., 2020). This suggests that

Hypothesis 4. Social capital has a direct effect on survival.

Hypothesis 5. Social capital has a direct effect on human capital.

Hypothesis 6. Social capital has a direct effect on entrepreneurial capital.

Thirdly, regarding the relationships in which organizational capital is involved, Alvarez-Salazar (2021) highlights that startups could not exist without the knowledge that allows them to create an innovative product that generates the market fit and subsequent accelerated growth. Moreover, organizational capital could not develop without the capabilities of the founders and their teams. Thus, organizational capital coexists with human capital. In addition, it is possible to identify relationships between organizational capital and entrepreneurial capital. Therefore, this would suggest that

Hypothesis 7. Organizational capital has a direct effect on survival.

Hypothesis 8. Organizational capital has a direct effect on entrepreneurial capital.

Fourthly, turning to the relationships that involve entrepreneurial capital, some authors mention that it is a resource obtained from others, necessary for survival (Miloud et al., 2012). There are relationships between social capital and entrepreneurial capital because networks provide access to private investors, and human capital is the main asset that attracts investment in a startup firm. However, since the possession of entrepreneurial capital does not increase human capital or social capital, according to Linder et al. (2020), social capital and human capital would not indicate an effect of entrepreneurial capital. This suggests that

Hypothesis 9. Entrepreneurial capital has a direct effect on survival.

Fifthly, as proposed by several authors, incubators directly affect the survival of startups (Hackett & Dilts, 2004; Stayton & Mangematin, 2019). In the Peruvian context, this seems true for ventures founded by novice entrepreneurs (Alvarez-Salazar, 2021). Although incubators may coexist with human capital, social capital, organizational capital, and entrepreneurial capital, in the Peruvian context, incubators usually focus on facilitating access to agents and not on the direct transfer of resources. Consequently, the incubation process only increases the social capital of the startup. This is because, until now, incubators cannot transfer monetary resources or human capital directly in the Peruvian context. Instead, they accumulate social capital by linking to networks of private investors and mentoring networks, which they then transfer to the startups. Thus, this suggests that

Hypothesis 10. The incubation process has a direct effect on survival.

Hypothesis 11. The incubation process has a direct effect on social capital.

Finally, the factors beyond the entrepreneur's control that affect survival cannot be ignored, for example, the ecosystem development, the industry where the startups operate, the type of markets, and the COVID context. First, if we focus on ecosystem development, several authors argue that a strong ecosystem facilitates the development of innovative entrepreneurship (e.g., Isenberg & Dillon, 2013; Malecki, 2009; Spigel, 2015). Since there is no classification of the level of development of regional ecosystems in the Peruvian context, this study uses the location of the venture as a proxy variable, with a marked difference between the development of the Lima ecosystem and those located in provincial cities.

Second, the literature shows that in more developed ecosystems, the life cycle in which the industry is located affects the venture's survival (Startup Genome, 2018). However, in Latin American ecosystems, startups operate mainly in mature vertical industries such as cross-cutting service industries, specialized industries, and industries focused on online sales (Alvarez-Salazar, 2020). Moreover, the vertical industries in which startups operate have fuzzy boundaries (Libert et al., 2016), which is proven by the fact that most startups operate in more than one industry type. For example, an online retail startup may develop capabilities to work in a specialized vertical industry such as Fintech (by developing its own payments platform) simultaneously, so both contexts affect the startup.

Third, the market type targeted by the venture highlights that, in most cases, these are business-to-business (B2B) and business-to-consumer (B2C) markets, being not exclusive. For example, some startups begin by targeting B2C markets, but later iterations migrate to B2B or even serve multiplatform markets. In addition, innovative ventures can venture into other types of markets that are also attractive and represent an opportunity for their growth such as Business to Government (B2G) and Consumer to Consumer (C2C), as Meira et al. (2014) stated.

Fourth, it is impossible to avoid the effects of the COVID-19 pandemic on these relationships, as this has a bearing on changing market risks and appropriate policy and regulatory responses. Figure 12.1 shows the nomogram of the startup survival structural model proposed.

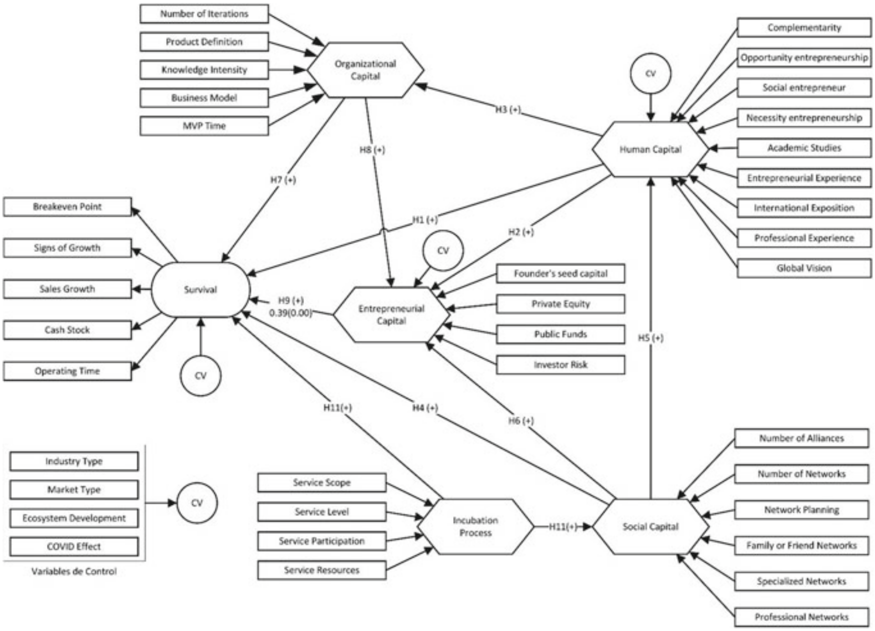

Fig. 12.1 Nomogram of the startup survival structural model proposed

12.10 Method

12.10.1 Sample and Data Collection

Although Peru does not have a registry to define the size of the startup population, there are around 500 startups (OECD, 2016), which have grown in the last 4 years. The collection of public information from several sources[3] identified 613 startups in Peru by 2020.

First, the venture's location was considered a selection criterion to obtain a probability sample of startups through a stratified random sampling process (Williamson, 2018). In this way, the sample was sought to be composed of 80% startups founded in Lima and 20% startups founded in provinces to collect the differences between entrepreneurship ecosystems with different levels of development; however, the response rate was low. Thus, this study opted for quota sampling for three reasons: first, this type of sampling has a closer approximation to stratified random sampling (Lohr, 2019). Second, it does not require a detailed sampling frame in which everyone

[3] Startup Peru Program, from the incubators Jaku and Kaman in Arequipa; Emprende UNACH in Cajamarca; Wichay UC in Junín; UTEC Ventures, Incubadora 1551, Start UPC, USIL Ventures, ACM Ventures, Emprende UP and Bio Incuba in Lima; Negocios S360 and Tufelis in Trujillo; reports generated with Crunch Base.

Table 12.1 Parameters for the selection of sample elements

Parameter	Value	RR
Expected response rate	30%	
Sample frame size	613	
Required sample size	114	
Invitations required	380	
Proportion Lima	80%	
Proportion Provinces	20%	
First round		
Lima invitations	304	
Provinces invitations	76	
Answers Lima	78	26%
Answers provinces	26	34%
Second round		
Lima invitations	52	
Answers Lima	15	29%

Note RR refers to the response rate obtained

in the population is identified (Rukmana, 2014). Third, it has been shown that inference is possible in quota sampling if the arbitrary selection of participants is reduced and the representativeness of critical population characteristics in the study sample is endured (Smith, 1983). In addition, to determine the sample size, an a priori statistical power analysis was performed (Cohen, 1988) through the G*Power 3.1.9.7[4] software (Faul et al., 2007). In that way, a sample size of 119 startups was determined.

Table 12.1 summarizes the rounds of data collection and Table 12.2 summarizes the sample controls to ensure that the quota sample is representative and to avoid bias (Yang & Banamah, 2014). This assured that the primary criteria were met to make inferences about the population using quota sampling. Thus, participants in the study were not chosen in a discretionary manner, and participation quotas were ensured by considering some representative conditions of the sampling frame.

For the collection of information, a questionnaire was prepared according to the theoretical framework considered, especially following the study by Álvarez-Salazar (2021) for the Peruvian context. It is important to highlight that there was no need to test the instrument's validity using correlational criteria (Hayduk, 1987)—criterion and construct validity—before applying PLS-SEM since this is empirically contrasted when the measurement models are tested. However, it is necessary to establish the correspondence between the observable and latent variables for the

[4] The application of G*Power for the A priori statistical power analysis used a test with the *F*-statistic for multiple linear regression, considering a statistical power of 0.8 and a probability of error of 0.05 for nine predictors included in the theoretical model, assuming that the minimum effect of being obtained is 0.15. Considering the results of the contrasted model, the post hoc statistical power analysis results in actual statistical power of 0.99.

Table 12.2 Sample quota controls

Quota control	Attribute	Target	Achieved	Justification
Type of location	Lima	80%	78%	Characteristics of the population
	Province	20%	22%	
Balance point	Achieved	50%	49%	Avoid bias
	Unsuccessful	50%	51%	
Sales growth	Achieved	50%	48%	Avoid bias
	Unsuccessful	50%	52%	
Use of high technology	Yes	50%	49%	Avoid bias
	No	50%	51%	

different constructs included in the theoretical model (Martínez & Martínez, 2009). Although initially, this correspondence was covered in the Alvarez-Salazar study, the content validity of the questionnaire was determined by expert judgment (Escobar-Peréz and Cuervo-Martinez, 2008). To this end, the fieldwork was conducted between April and July 2020 and began with a pilot study with a convenience sample of three founders. The recommendations of the pilot study were also collected online and incorporated into the final questionnaire.

Briefly, the questionnaire comprises closed single-choice and multiple-choice questions (in both cases of dichotomous or polytomous type) that consider nominal and ordinal variables. It also considers open questions for numerical and nominal variables. Appendix 12.2 provides a more detailed characterization of the composition of the questionnaire.

12.10.2 Procedure

The methodological decision to apply PLS-SEM in this research is based on three reasons. First, the size of the startup population in Peru is small, which implies a limitation in the use of procedures that require large sample sizes to achieve statistical power, as is the case of CB-SEM (Kline, 2016). On the contrary, PLS-SEM emerges as a methodological alternative to perform analyses when observations are scarce, i.e., with a reduced sample size (Wold, 1980). Consequently, it can be used when there are limitations specific to the population (Rigdon, 2016), as in the case of this research. Finally, applying the PLS-SEM has led to the recognition that sample sizes with a more significant number of observations provide more excellent reliability in the results (Goodhue et al., 2012).

Second, the theoretical model of startup survival to be tested is multi-block. A reflective model (survival) is a form of several composite models (organizational resources) that simultaneously have relationships. PLS-SEM is suitable for testing the proposed hypotheses since it combines the scores generated for each latent variable, allowing to test models with the complexity presented in this research (Chin, 1998a). This criterion has been tested in previous studies on the Peruvian innovation ecosystem (e.g., Seclen-Luna & Alvarez-Salazar, 2021) and published in relevant journals. Third, PLS-SEM is also adequate for evaluating the proposed model's predictive capability (Henseler, 2021; Shmueli et al., 2019).

A critical aspect of applying the technique is the choice of the measurement models that characterize the constructs; a wrong choice could affect content validity generate confusion or non-existent relationships between latent variables, and inadequately apply existing theories (Coltman et al., 2008). As pointed out in the theoretical framework, the constructs of human capital, social capital, entrepreneurial capital, organizational capital, and incubation process have causal relationships between indicator variables and those latent variables. Therefore, we consider them composite measurement models (e.g., Henseler, 2021).

Of course, it is possible to think that these measurement models could also be formative. Nevertheless, it cannot be ignored that "PLS-SEM is primarily used to develop theories in exploratory research" (Hair et al., 2014, p. 20). Therefore, the variables that determine the survival of Peruvian startups may differ from those identified in theory consulted. On the other hand, survival is proposed as a reflective model because its achievement can only be determined when five correlated variables are present in the startup: breakeven point, accelerated sales growth, cash availability, indications of growth in operations, and the period of continuous operation.

The sequence of steps applied followed the guidelines proposed by Hair et al. (2017), and its implementation was performed in the statistical software environment R (R Core Team, 2020), using the package "cSEM: Composite-Based Structural Equation Modeling" (Rademaker & Schuberth, 2020). However, it is necessary to highlight that although PLS-SEM is robust for the analysis of non-normal data, some indicator variables presented excessive asymmetry (greater than 1 or less than −1), requiring caution with the results obtained (Hair et al., 2014). That is why the use of Ordinal PLS (Ord-PLS) could be the most appropriate alternative considering the characteristics of the indicator variables. However, PLS-SEM was made because it is the most highly developed variance-based structural equation modeling technique (Schuberth et al., 2018, p. 12). Thus, the cSEM package was resorted to (Rademaker & Schuberth, 2020).

Nevertheless, since several technique-specific procedures have not yet been implemented, PLS-SEM was used for model evaluation. The results were subsequently validated using Ord-PLS to determine structural coefficients, weights, and loads. Thus, if the results obtained by applying PLS-SEM meet the criteria of validity and reliability, then, when validated with the results of the Ord-PLS application, our findings are confirmed, identifying slight differences when estimating the model with ordinal variables (Cantaluppi, 2012).

Table 12.3 Analysis of variance of VIF of out-of-range measurement models[5]

Construct	Excluded variable	Collinearity (VIF)			
		Ser_Sco	Ser_Lev	Ser_Par	Ser_Res
INNPRO	-	7.573	13.385	10.676	8.937
	Ser_Sco		12.536	9.625	8.524
	Ser_Lev	7.076		8.164	7.051
	Ser_Par	6.810	10.271		8.636
	Ser_Res	7.219	10.622	10.320	
	Ser_Lev ^ Ser_Par	5.196			5.196
	Ser_Par ^ Ser_Res	6.227	6.227		
	Ser_Lev ^ Ser_Res	6.040		6.040	
Construct	Excluded variable	Fun_Cap	Pri_Equ	Pub_Fun	Inv_Ris
ENTCAP	–	1.225	5.392	2.584	3.751
	Pri_Equ	1.104		1.601	1.620
	Rie_Inv	1.219	2.598	2.536	

12.11 Results

12.11.1 Evaluation of Measurement Models

The evaluation of composite and reflective measurement models has different criteria (Sarstedt et al., 2016). In the first case, the procedure began with evaluating the non-existence of multicollinearity through the variance inflation factor (VIF), maintaining constructs whose values were less than 3.3 (Becker et al., 2015). As seen in Table 12.3, in the Incubation Process construct, the estimated VIF for all the indicator variables of the measurement model has values above acceptable. The same is true for the indicator variable private equity and investor risk profile as part of the entrepreneurial capital measurement model. Table 12.3 also shows the results of the exploration of collinearity behavior as a function of the exclusion of each indicator variable to assess whether, as a result, convergent validity improves. We conclude that the composite measurement model for the incubation process construct cannot be measured by the proposed indicator variables, becoming a limitation of this research. However, as shown below, it is presented as a control variable. In addition, the variable Investor Risk, collinearly with the private capital variable in the Entrepreneurial Capital construct, was eliminated.

[5] In all tables presented in this section, the variables have been coded to facilitate the reading of the results as follows: HUMCAP = Human Capital; ENTCAP = Entrepreneurial Capital; SURVIV = Survival; SOCCAP = Social Capital; COVID = COVID impact; ECODEV = Ecosystem Development; TRASER = Transversal Service Industry; B2CMAR = B2B Market; ORGCAP = Organizational Capital; INNPRO = Incubation Process; Opo_Ent = Opportunity entrepreneurship; Ent_Exp = Entrepreneurial Experience; Int_Exp = International Exposition; Glo_Vis = Global Vision; Pri_

Afterward, the significance of the weights and loadings was evaluated, retaining the indicator variables that had weights with statistical significance and loadings greater than 0.5 (Hair et al., 2014). It is important to highlight that some indicators were retained to maintain the consistency of the construct, even when the criteria specified above are not met (Benitez et al., 2020). In addition, bootstrapping was used as a resampling method following Streukens and Leroi-Werelds (2016). Furthermore, the relevance and significance analysis of the weights and loadings of the indicator variables means that some of them must be excluded (Sarstedt et al., 2017). Although measurement models could lose conceptual unity when indicator variables are excluded (Hair, Sarstedt, et al., 2019a, 2019b, 2019c), it should be kept in mind that concepts are artifacts of human creation and that they can have different configurations (Benitez et al., 2020). Table 12.4 shows that 12 indicator variables were retained out of 28 evaluated (Appendix 12.2).

As for the assessment of survival, as a reflective construct, the assumptions of internal consistency are met (Hair, Risher, et al., 2019a, 2019b, 2019c). Convergent validity has also been evaluated, identifying that the indicator variable operating time does not correlate with the other four variables, so it was excluded from the

Table 12.4 Evaluation of composite measurement models

Construct	Indicator	Collinearity (VIF)	Weight		Loadings	
			score	*p*-value	Score	*p*-value
ORGCAP	Num_Ite	1.850	0.360	0.050	0.720	0.000
	Pro_Def	1.390	0.220	0.160	0.470	0.000
	Bus_Mod	2.000	0.690	0.000	0.920	0.000
SOCCAP	Net_Pla	1.650	0.400	0.030	0.690	0.000
	Spe_Net	1.670	0.530	0.000	0.780	0.000
	Pro_Net	1.310	0.480	0.000	0.660	0.000
HUMCAP	Opo_Ent	1.260	0.390	0.020	0.490	0.000
	Ent_Exp	1.400	0.400	0.010	0.550	0.000
	Int_Exp	1.510	0.350	0.030	0.610	0.000
	Glo_Vis	1.440	0.520	0.000	0.730	0.000
ENTCAP	Pri_Equ	2.490	0.520	0.000	0.880	0.000
	Pub_Fun	2.490	0.600	0.000	0.910	0.000

Notes (1) The last five rows of the table are the control variables that generate significant variation in R^2

Equ = Private Equity; Pub_Fun = Public Funds; Inv_Ris = Investor Risk; Bre_Poi = Breakeven Point; Sig_Gro = Signs of Growth; Sal_Gro = Sales Growth; Cas_Sto = Cash Stock; Num_Ite = Number of Iterations; Pro_Def = Product Definition; Bus_Mod = Business Model; Net_Pla = Network Planning; Spe_Net = Specialized Networks; Pro_Net = Professional Networks; Ser_Sco = Service Scope; Ser_Lev = Service Level; Ser_Par = Service Participation; Ser_Res = Service Resources.

Table 12.5 Evaluation of the reflective measurement model

Construct	Indicator	Internal consistency			AVE	Weight		Loading	
		α_C	ρ_A	ρ_C		score	*p*-value	score	*p*-value
SURVIV	Bre_Poi	0.766	0.774	0.851	0.589	0.288	0.000	0.720	0.000
	Sig_Gro					0.323	0.000	0.787	0.000
	Sal_Gro					0.369	0.000	0.835	0.000
	Cas_Sto					0.319	0.000	0.722	0.000

measurement model (Hair, Risher, et al., 2019a, 2019b, 2019c). Regarding discriminant validity, survival is the only reflective model, as there are no others of the same type; assessing the existence of similarities between latent variables becomes meaningless (Henseler et al., 2015). Finally, the loadings presented by the indicators were evaluated. These are greater than 0.708 (Hair et al., 2019a, 2019b, 2019c). The result of the evaluation of the reflective model can be found in Table 12.5.

12.11.2 Evaluation of the Structural Model

Following a quality check of the measurement models, we determined the absence of collinearity between the latent predictor variables. Since the technique is based on linear regressions, collinearity generates biases in the path coefficients, so the model evaluation results lose reliability (Hair et al., 2019a, 2019b, 2019c). From the evaluation of the structural model, the assumptions of non-collinearity are met (Becker et al., 2015). Moreover, in the structural model, all path coefficients have statistical significance after bootstrapping with 5000 resamples (Hair et al., 2019a, 2019b, 2019c). Considering that the magnitude of the coefficient should be at least 0.20 and ideally above 0.30 to be relevant (Chin, 1998b, p. xiii), there is strong support in the empirical data for the hypotheses proposed in the model. In all cases, the path coefficients are relevant, as they are above 0.3 and have high levels of significance (p-value < 0.001).

In addition to determining the significance and relevance of the path coefficients, the structural model's evaluation involves determining the predictive accuracy and relevance of the model (Hair et al., 2017), whose evaluation parameters are found in Table 12.6. It is important to emphasize that the predictive accuracy evaluation parameters define the explanatory power of the model (Shmueli et al., 2019). The primary parameter that demonstrates predictive accuracy is the level of variance explained (R^2), considering that levels of 0.67 can be described as important, 0.33 moderate, and 0.19 weak (Chin, 1998a, p. 323). Complementarily, the effect size f^2 is evaluated following the criteria determined by Cohen (1988, p. 413), considering that effect sizes of 0.02 are small, 0.15 are moderate, and 0.35 are large.

Therefore, it is possible to identify which variables contribute the most to variance explanation (Hair et al., 2017). We find that the R^2 coefficients of determination

Table 12.6 Evaluation of structural model

Endogenous variable	Exogenous variable	VIF	Score	Std-err	t	p-value	95% CI		R^2	f^2
ENTCAP	HUMCAP	1.380	0.240	0.102	2.343	0.019	0.046	0.447	0.316	0.061
	INNPRO	1.079	−0.139	0.084	1.649	0.099	−0.291	0.037		0.026
	ORGCAP	1.056	0.440	0.074	5.954	0.000	0.293	0.578		0.268
	SOCCAP	1.407	0.147	0.103	1.423	0.155	−0.067	0.336		0.304
HUMCAP	COVID	1.122	−0.204	0.106	1.933	0.053	−0.393	0.016	0.390	0.061
	ECODEV	1.022	−0.105	0.079	1.330	0.184	−0.270	0.046		0.018
	TRASER	1.150	−0.189	0.087	2.183	0.029	−0.364	−0.029		0.051
	B2CMAR	1.120	−0.169	0.089	1.906	0.057	−0.346	0.000		0.042
	SOCCAP	1.080	0.448	0.084	5.331	0.000	0.283	0.610		0.022
ORGCAP	HUMCAP	1.000	0.028	0.113	0.247	0.805	−0.171	0.272	0.001	0.001
SURVIV	COVID	1.187	−0.187	0.081	2.303	0.021	−0.340	−0.022	0.442	0.053
	ENTCAP	1.450	0.387	0.090	4.281	0.000	0.191	0.546		0.185
	HUMCAP	1.556	−0.038	0.101	0.376	0.707	−0.212	0.183		0.002
	ORGCAP	1.238	0.338	0.073	4.614	0.000	0.195	0.484		0.166
	SOCCAP	1.420	0.006	0.117	0.053	0.957	−0.230	0.231		0.000

of survival, entrepreneurial capital, and organizational capital are moderate. These levels are acceptable for exploratory research (Benitez et al., 2020). Also, we find that organizational capital and social capital have a moderate effect on the R^2 of entrepreneurial capital. On the other hand, in the R^2 of human capital, all the effects are small, while in the R^2 of survival, entrepreneurial capital and organizational capital have moderate effects. All this only proves that the explanatory power of the model is moderate.

Both the values of precision and predictive relevance prove that the model is helpful as a first approximation to the explanation of survival in emerging ecosystems such as the Peruvian one, finding support so that hypotheses H2, H5, H7, H8, and H9 are accepted. However, it is necessary to test whether these relationships endure when the control variables are included: the level of development of the ecosystem in which the startup was created; the type of industry in which the venture operates; and the type of market.

In addition, the model was tested considering one additional control variable to those initially proposed. The preliminary evaluation excluded the incubation process because the measurement model did not meet the convergent validity assumptions. However, this decision is because of the difference that could exist in the incubation processes when startups have experienced founders concerning when they are novices (Alvarez-Salazar, 2021). Therefore, the incubation service could generate significant changes in the strength of relationships and consequently in the R^2 of the constructs. The rest are nominal variables, whose inclusion requires them to be dichotomous and treated as a single indicator variable of an exogenous construct (simple measurement model), which influence each endogenous construct that configures the structural model (Henseler et al., 2016). Thus, the following nominal variables are considered: transversal services industries, online sales industries, specialized industries, business-to-business market, business-to-consumer market, ecosystem development, and incubation process.

It should be noted that the industry variable has been expressed in three dichotomous variables, while the market variable has been described in two. Nevertheless, this does not imply that this is a process of creating dummy variables, in which one of the categories becomes the references for the others (Falk & Miller, 1992, p. 71), as this requires that the possible values in the variables are mutually exclusive. However, a startup can simultaneously target both the B2B and B2C markets or operate in an integrated manner in the cross-service industry and online sales service industries. Furthermore, considering the variables as part of the model requires determining whether the endogenous variables' explanatory power (R^2) should have significant variation by their inclusion (Atinc et al., 2012). For this purpose, an ANOVA analysis was performed on the three endogenous variables included in the structural model. Table 12.6 shows the evaluation of the structural model.

The model's predictive ability results were validated using $\text{PLS}_{\text{predict}}$, a procedure that works best for identifying variables with high predictive power (Chin et al., 2020). Table 12.7 shows the results of the application of $\text{PLS}_{\text{predict}}$, considering a grouping of 10 sections (folds), 40 repetitions of cross validation between the sections applying the algorithm, and a multiple linear regression model (MLR). The evaluation guidelines postulated by Shmueli et al. (2019) were followed. Thus, we found that the prediction errors are not symmetric in either PLS (skewness range −0.96 to 0.23) or MLR (skewness range −0.79 to 0.12). Consequently, using the mean absolute error (MAE) provides a better guide for comparison than the root mean square error (RMSE). Given that most of the indicators have a lower MAE in the case of PLS than in MLR, it is validated that the model, including control variables, has moderate predictive power.

Changing the focus of the analysis, we will now turn to determine the existence of mediation effects. As shown in Table 12.6, some of our hypotheses were not supported by the empirical data. Therefore, based on the advantages of applying PLS-SEM, we explored the indirect effects. In the nomogram (see Fig. 12.2), human capital mediates between social and entrepreneurial capital. Simultaneously, entrepreneurial capital exerts the same effect between survival and organizational capital, as well as between survival and human capital. It is now necessary to systematically assess the type of mediation and its existence in terms of the statistical significance of direct and indirect effects (Nitzl et al. 2016). Mediation is complete when only the indirect effect is statistically significant; partial when both the direct and indirect effects are statistically significant; complementary when the coefficients have the same direction; competitive when they are opposite; and unmediated when the direct effect and the indirect effect are not statistically significant (Zhao et al., 2010).

Considering this, as seen in Table 12.8, the existence of a complete mediation of human capital between social capital and entrepreneurial capital is verified. The same occurs between human capital and survival, where mediation is exercised by entrepreneurial capital. In addition, a complementary mediation between organizational capital and survival is identified, which is exercised by entrepreneurial capital.

Table 12.7 Predictive performance assessment (PLS-Predict)

Construct	Indicator	MAE PLS	MAE MLR	RMSE PLS	RMSE MLR	Q^2_{predict}
HUMCAP	Opo_Ent	0.738	0.692	0.962	0.943	0.065
	Ent_Exp	1.126	1.144	1.355	1.427	0.086
	Int_Exp	1.135	1.183	1.378	1.449	0.081
	Glo_Vis	0.474	0.566	0.603	0.695	0.166
ENTCAP	Pri_Equ	1.667	1.665	1.920	1.950	0.185
	Pub_Fun	1.381	1.478	1.619	1.723	0.210
SURVIV	Bre_Poi	1.168	1.155	1.409	1.449	0.184
	Sig_Gro	1.325	1.434	1.614	1.714	0.169
	Sal_Gro	1.032	1.030	1.235	1.273	0.256
	Cas_Sto	1.253	1.296	1.454	1.519	0.186

Notes (1) the path between human capital and organizational capital is excluded because the results indicate that this relationship is not statistically significant

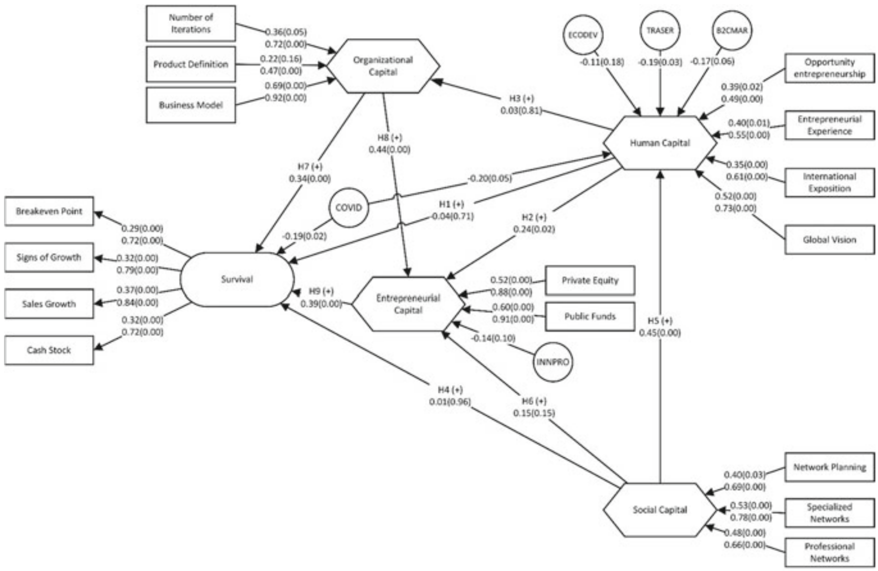

Fig. 12.2 Startup survival model evaluation summary

Table 12.8 Direct and indirect effects between constructs

Exogenous variable	Endogenous variable	Direct		Indirect	
		Score	*p*-value	Score	*p*-value
ENTCAP	HUMCAP	0.240	0.019	0.012	0.809
	SOCCAP	0.147	0.155	0.113	0.045
SURVIV	HUMCAP	-0.038	0.707	0.107	0.148
	ORGCAP	0.338	0.000	0.170	0.000
	SOCCAP	0.006	0.957	0.088	0.169

Consequently, verifying the existence of direct and indirect relationships provides support to the general hypothesis that guided this research: the survival of startups in the Peruvian context is the effect of multiple and simultaneous relationships between various types of organizational resources. Whether directly or indirectly, they all have an influence, with organizational capital being the most important type of resource but requiring the complementation of entrepreneurial capital, which in turn is determined by a chain of resources that involves structural relationships with human capital and social capital.

12.11.3 Validation of Results with Ord-PLS

One characteristic of the data used is that some of the variables presented asymmetry outside the range of −1 to 1, mainly because they are ordinal variables of five levels. For this reason, the decision was made to validate the results obtained with PLS-SEM by applying Ord-PLS, a computationally more demanding algorithm, since the calculation of the estimates resorts to the use of polychoric correlations, but which has the property of adjusting better to the use of indicator variables with ordinal data, correcting the negative biases that occur when PLS-SEM is applied. The result of the evaluation in all cases complied with the assumptions of the application of the technique, except for the predictive relevance tests (Q^2, q^2, and $PLS_{predict}$) that are not yet implemented in any commercial packages to apply PLS or in the statistical software environment R. Due to this limitation, this technique has been used only as a validation method. It is concluded that the model configuration remains stable since none of the indicator variables was excluded from its constructs by loss of significance, and the relevance of the weights and loadings has minimal variations. The same occurs with the structural model for direct and indirect effects. Table 12.9 compares the results obtained for the two algorithms' path coefficients. It is concluded that the model is stable and can be used to explain the survival of Peruvian startups in an exploratory way.

Table 12.9 Comparison of structural model with PLS-SEM and Ord-PLS

Endogenous variable	Exogenous variable	PLS-SEM		Ord-PLS	
		Score	*p*-value	Score	*p*-value
Direct effects					
HUMCAP	SOCCAP	0.448	0.000	0.466	0.000
HUMCAP	ORGCAP	0.028	0.805	0.012	0.938
ENTCAP	ORGCAP	0.440	0.000	0.514	0.000
ENTCAP	HUMCAP	0.240	0.019	0.381	0.001
ENTCAP	SOCCAP	0.147	0.155	0.094	0.509
SURVIV	ORGCAP	0.338	0.000	0.357	0.002
SURVIV	ENTCAP	0.387	0.000	0.377	0.000
SURVIV	HUMCAP	−0.038	0.707	0.020	0.910
SURVIV	SOCCAP	0.006	0.957	−0.042	0.798
Indirect effects					
ENTCAP	SOCCAP	0.113	0.045	0.187	0.010
SURVIV	ORGCAP	0.170	0.000	0.169	0.004
SURVIV	SOCCAP	0.088	0.169	0.061	0.038
SURVIV	HUMCAP	0.107	0.148	0.124	0.012

12.11.4 Evaluation of the Importance and Performance of the Variables (IPMA)

We have found that the theoretical model, even subject to the effects of the control variables and considering the excessive asymmetry of some of the variables, has a moderate capacity to explain the survival of startups in the Peruvian context. Thus, the importance of indicator variables and latent variables in determining survival has been noted. In this section, we complement our analysis with the importance and performance analysis (IPMA) results to identify which variables in the model Peruvian startups should focus on to improve their chances of survival. Through this algorithm, we consider the path coefficients of the latent variables and the weights of the indicator variables to assess their importance and relate it to the average of these estimates as a performance measure (Ringle & Sarstedt, 2016).

So, following the procedure Hair et al. (2018) described, the IPMA matrix shown in Table 12.10 has been developed. The evaluation parameters are established concerning the importance and performance averages as ordered pairs for the constructs and their indicators, taking an endogenous construct explicitly as a reference (Hair et al., 2018). This way, constructs and variables below average have the most significant opportunities for improvement (Hair et al., 2018, p. 118).

Table 12.10 Importance-performance matrix

Predictors		Endogenous constructs [2]							
		SURVIV		ENTCAP		HUMCAP		ORGCAP	
		I	D	I	D	I	D	I	D
Exogenous constructs	ENTCAP	0.387	44.799						
	HUMCAP	0.069	75.598	0.252	75.598			0.028	75.598
	ORGCAP	0.508	46.839	0.440	46.839				
	SOCCAP	0.094	58.366	0.260	58.366	0.448	58.366	0.012	58.366
Indicators	Pub_Fun	0.228	46.555	−0.048	59.664				
	Pri_Equ	0.205	42.521	0.093	54.202				
	Ent_Exp	0.029	55.252	0.106	55.252			0.012	55.252
	Glo_Vis	0.039	85.714	0.141	85.714			0.016	85.714
	Int_Exp	0.023	63.445	0.083	63.445			0.009	63.445
	Opo_Ent	0.023	76.261	0.082	76.261			0.009	76.261
	Bus_Mod	0.352	52.941	0.305	52.941				
	Pro_Def	0.107	54.202	0.103	58.824				
	Num_Ite	0.187	24.79	0.162	24.79				
	Net_Pla	0.030	69.538	0.082	69.538	0.142	69.538	0.004	69.538
	Pro_Net	0.037	58.824	0.171	50.42	0.178	58.824	0.005	58.824
	Spe_Net	0.062	50.42			0.294	50.42	0.008	50.42

Notes (1) Data are standardized. (2) I = Importance, and D = Performance

In the case of survival, the two exogenous constructs that determine it are in improvement. Peruvian startups have low performance in generating organizational and entrepreneurial capital. This means that they have more significant opportunities to increase their chances of survival if they work on the variables of these constructs. Thus, if startups grow their estimates of organizational capital by one point (from 47 to 48), they will improve their probability of survival by 0.50. While, if they do so in entrepreneurial capital (45 to 46), the estimate of survival achievement would increase by 0.39 points.

As for the variables, the most significant effect on survival achievement is the business model's consolidation level. This is followed by the financing obtained from public funds and private investors. The lowest performance is seen in the number of iterations. While it may be thought that the venture would increase its chances of survival by simply carrying out more iterations, it should be considered that more iterations imply the consumption of more resources. Perhaps, for this reason, the number of iterations is reduced.

Besides being an exogenous construct that explains survival, entrepreneurial capital is also an endogenous construct defined by organizational capital, human capital, and social capital. As can be seen, organizational capital is the latent variable with the most significant opportunities to improve its performance. Thus, when the startup manages to increase the estimate of this resource by one point, the entrepreneurial capital increases by 0.44 points. As for the indicator variables, the impact on improving the performance of the consolidation of the business model and the number of iterations should be the focus of attention to increase the probability of attracting funding.

In the case of social capital, the only exogenous construct is human capital. The criterion for assessing the impact of improved performance on the endogenous variable is the same. Thus, when the venture improves its social capital estimates by one point, human capital increases by 0.45, and ventures should consider focusing primarily on working with and obtaining resources from specialized and professional networks.

Finally, in the case of organizational capital, an endogenous variable concerning its relationship with human capital, the total effects (significance) estimates are minimal. As can be seen in Table 12.6, this relationship is not statistically significant.

From the above, it is confirmed that organizational capital is the primary determinant of survival, and it may be the most significant opportunity for improvement in Peruvian startups. Focusing on improving the estimates of this resource implies that, at the first level, they should consolidate the business model early and iterate more frequently to get feedback from the market. At a second level, the focus is on product designs that involve greater complexity, such as that derived from using analytical knowledge for commercial purposes.

12.12 Discussion

The application of PLS-SEM has allowed us to identify how multiple and simultaneous relationships between organizational resources determine the survival of Peruvian startups. In this section, we discuss the main findings of this research.

Firstly, organizational capital is the main exogenous variable that determines the survival of Peruvian startups. Not only because the relationship between this organizational resource and survival has a relevant path coefficient (0.34) but also because it partly determines entrepreneurial capital, the proposed model could be an acceptable alternative way to measure the organizational capital of startups that goes beyond what Sveiby (1997) called the organization's internal structure. For startups in the birth and transition stages, survival is achieved when the organizational capital is embodied through systems, processes, and procedures (Lev & Radhakrishnan, 2003; Subramaniam & Youndt, 2005; Sveiby, 1997). Building up the above requires more extended periods than startups have available to experiment and achieve customer attraction. However, the appropriate measures for these organizational resources are the ability to constantly iterate to adapt the product to market expectations, which is part of the dynamic capacity to detect opportunities (Teece, 2007). This, with the caveat, is not based on the constant observation of the market in search of new technologies or competitors but a more intensive prospecting action in pursuit of customer feedback on the novelties introduced in the product. The proposed model also considers the business model's level of consolidation, which implies a clear understanding of how the startup generates value (Osterwalder & Pigneur, 2010). The results show that as the business model matures, organizational capital increases. Furthermore, this could suggest that the business model is a first tangible approximation of an early-stage startup to a systematically designed internal structure, with the difference that it is not intended to be something that lasts over time. Entrepreneurs know that this design is subject to constant change if customer attraction is not achieved, which relates to three dynamic capabilities: the ability to learn, the ability to integrate, and the ability to coordinate (Pavlou & El Sawy, 2011). Finally, how the innovative product is designed is highlighted, as those based on analytical knowledge have more value than those that copy existing products in other realities. As Velu (2015) states, knowledge allows product design to be more sophisticated, influencing a proposal for an innovative business model. Our model shows that when these three variables come together, it generates higher estimates of organizational capital, and therefore the startup increases its chances of survival.

Secondly, it is important to mention that the model proposed did not corroborate the causal relationship between social capital and the achievement of survival that was evidenced by several types of research conducted in mature ecosystems (Bosma et al., 2004; Davidsson & Honig, 2003; Linder et al., 2020; Vila et al., 2013). Nevertheless, the construct remains relevant as part of a system of multiple and simultaneous relationships as social capital is a determinant of human capital, which partly determines entrepreneurial capital, the organizational resource that influences survival. In this way, social capital is proposed as the beginning of a chain of interlinked resources, indirectly affecting the achievement of the startup survivals. Consequently, in the Peruvian context, the relationship between social capital and human capital is better adjusted to the sociological reasoning of Coleman (2000). He points out that social capital determines human capital. Also, these relationships are approximated in the business field by Spender (2009), who states that it is the relationship between the generation of community benefits through social capital that drives the generation of unique benefits that are caused by human capital.

The findings confirm the conformation of the measurement model of social capital by some researchers. Thus, social capital increases when startups participate in specialized networks, as Rank (2014) found in analytical knowledge-intensive startups. However, given the low sophistication of entrepreneurship in Peru, this is a transversal condition for any venture. Moreover, the results show that professional networks are an indicator of the social capital measurement model, which is consistent with Bastié et al. (2013), who, among others, identified networks generated by professional experience and inherited networks from family businesses as sources of better performance. In addition, networking planning is relevant as well. When startup founders identify the networks in which they will participate and establish what resources they will obtain from them, social capital increases, which is consistent with the results of previous studies in different contexts (Dashti & Schwartz, 2017; Stam et al., 2014).

Thirdly, the model proposed includes the effects of human capital, highlighting that this resource is related to social capital and even has a direct effect on entrepreneurial capital, thus confirming the conclusions of previous studies (e.g., Cooper et al., 1994; Fairlie & Robb, 2009; Linder et al., 2020). However, it could not be established that it determines survival directly (e.g., Ejermo & Xiao, 2014). Instead, it has an indirect effect. So, for human capital to contribute to the achievement of survival, it requires entrepreneurial capital as a mediating variable. Concerning the measurement model of human capital, the founder's global vision of the scope of his startup is the most relevant variable. However, no references to a variable of this type related to survival were found in the literature. This could be linked to the fact that startups are created to be global business initiatives (Alvarez-Salazar, 2021) since the market size that allows the business scaling requires internationalization (Rasmussen & Tanev, 2015).

The entrepreneurial experience is important (Colombo & Grilli, 2005; Fontana et al., 2016). Although few Peruvian entrepreneurs could be examples of successful founders, there are already several who are trying entrepreneurship more than once. In this way, they are learning from their failures in a process like the reasoning of Triebel et al. (2018). Thus, it is predicted that in the medium term, there will be startups that consolidate and generate more excellent value. In addition, there is the motivation of entrepreneurship by opportunity, which is consistent with the study by Cowling (2006).

Fourthly, the results confirm the link between entrepreneurial capital and startup survival (Coleman et al., 2013; Gimmon & Levie, 2010; Lee et al. 2011; Robb & Robinson, 2014; Soto-Simeone et al., 2020; Vinturella & Erickson, 2013). However, the model proposed takes entrepreneurial capital as a configuration of resources that could be intermediate between the reasoning of Linder et al. (2020) and Spender (2009), being shaped directly by human capital and organizational capital and indirectly by social capital through the mediating effect generated by human capital. This confers a singular and important characteristic to the entrepreneurial capital; it confers a mediating effect between these three resources and survival. In other words, generating entrepreneurial capital is the mandatory intermediate milestone to achieving startup survival. Additionally, the results highlight another exciting finding. While in mature ecosystems funding from private investors is the main factor that determines the survival of early-stage startups (Gonzalo et al., 2013; Hechavarría et al., 2016), in Peru, its influence on the generation of entrepreneurial capital (0.53) is slightly below the influence of public funding (0.59). The latter is also important in mature ecosystems but much lower than private capital investment (Sohn et al., 2012).

Fifthly, the findings highlight relevant information concerning survival. Although there is extensive literature that has pointed to several criteria for assessing startup survival: operational continuity (e.g., Soto-Simeone et al., 2020), achieving breakeven (e.g., Murphy & Edwards, 2003), robust accelerated growth (e.g., Picken, 2017), and possessing a stock of cash to respond to shocks (Alvarez-Salazar, 2021). This study proposes that survival may not be evidenced by these conditions alone but requires all of them. Thus, when the proposed model is evaluated, the results show that operational continuity is the only variable that does not share a common factor with breakeven, accelerated growth, signs of growth, and cash stock. Although, of course, it is evident that when a startup has stopped operating, it has not managed to survive, this result shows that maintaining operational continuity in a startup is not a sufficient condition to affirm that survival has been achieved.

12.13 Conclusion

The startups that survive in the incipient Peruvian entrepreneurial ecosystem do so because they fundamentally develop organizational capital and possess entrepreneurial capital. The latter is generated by organizational and human capital, formed by social capital. In this way, the general hypothesis that guides this research has been proven: startup survival is the effect of multiple and simultaneous direct relationships between organizational resources. However, we also found that human and social capital have indirect effects.

The study has some theoretical implications because it contributes to filling four gaps identified in the literature on the startup's survival. First, findings show that startup survival is a complex phenomenon, the contrasted structural model evidence that survival is achieved with the presence of multiple organizational resources. This supports one of the conclusions of Linder et al. (2020), who states that isolated organizational resources are insufficient to achieve startup survival. Nevertheless, it is important to highlight that these relationships may vary depending on the context (e.g., Benitez et al., 2020). This is why the configuration of the constructs is unique to the Peruvian case. Thus, the survival model could have some variations in its measurement models if it is evaluated in other realities with similar ecosystems. However, the behavior of the structural model is expected to be stable in the relationships that have been demonstrated.

Second, an alternative approach to understanding how startups generate organizational capital is presented. Our findings suggest that startups follow the theoretical underpinnings that claim that organizational capital is generated when firms appropriate the knowledge generated in their organizational assets (Hansen et al. 1999; Hormiga et al., 2011; Spender, 2009). Nevertheless, they do not do so by developing structures, systems, processes, procedures, patents, and other instruments as it occurs in consolidated firms (Lev & Radhakrishnan, 2003; Subramaniam & Youndt, 2005; Sveiby, 1997). In the case of Peruvian startups, this cannot be the case in the initial stages since the generation of these instruments requires time that the startup does not have in a context of constant change. Therefore, a contribution of this study is a more appropriate way of measuring the creation of intellectual capital in startups, which takes as indicators processes that require the presence of dynamic capabilities, learning, integration, and coordination (Pavlou & El Sawy, 2011).

Third, a measurement model is proposed to establish whether a startup has survived. In this way, it is shown that the frequently used criterion of continuity of operations to consider that a venture has survived (Soto-Simeone et al., 2020) loses meaning when evaluating the survival of startups, owing to their operating conditions and the life cycle itself are different from those of a traditional venture (e.g., Aulet, 2013). Thus, survival should be identified as a reflection of four conditions: breakeven, accelerated growth, signs of growth, and cash stock.

The fourth contribution is to understand better how early-stage startups achieve survival in incipient ecosystems such as the Peruvian one from multiple and simultaneous relationships. That is, how founders manage to generate attractive business models in conditions of various shortages. Evidencing that, although the entrepreneurial bricolage (Baker & Nelson, 2005; Yu et al. 2019)makes multiple attributes that characterize the founders of startups that achieve survival stand out, 12 of these attributes are the ones that find support in the empirical data as a component of the organizational resources.

On the other hand, as in any scientific study, this work has certain limitations. The first is inherent to using self-reported information (Podsakoff & Organ, 1986). The phenomenon of entrepreneurship in Peru has been driven since 2012, so the data provided by the participants could be subject to recall bias, given that the data collection was between 2019 and 2020. The second recognized limitation is that the sample has been taken from a sampling frame constructed from different sources of information. Public agencies, private associations, companies, and incubators have qualified these ventures as such. However, at the time of data collection, it was not possible to distinguish whether the startup selected in the sample would remain a startup soon or would stop overgrowing and become a traditional venture.

Finally, three research opportunities are identified from the results obtained. The first relates to the incubation process that determines the survival of startups. This is a relationship that the literature picked up in multiple studies (e.g., Hackett & Dilts, 2004; Stayton & Mangematin, 2019). However, multicollinearity in the measurement model did not allow us to test this hypothesis. Further research is required to understand how the incubation service influences the survival of any startup. Perhaps this would help design a service appropriate for the Peruvian context, considering the differences between startups. The second opportunity obeys the need to understand what makes a startup become a traditional venture. The model has failed to identify whether a startup in accelerated growth will become a traditional venture, as Aulet and Murray (2013) state. The third research opportunity is that an incipient ecosystem such as the Peruvian one has been taken as a context to contrast a proposed survival model. However, the conceptualization could be applied to any ecosystem. The organizational resources included in the proposed model will be present in every startup, and the variables that make them up may change according to the operating contexts (Benitez et al., 2020). Ultimately, these are composite measurement models, and, depending on the environment, they could take other indicator variables to measure the same construct, but the structural model tested should remain stable.

Appendix 12.1: Summary of Theoretical Frameworks

Theories			
	Resource-based theory	Theory of dynamic capabilities	Contingency theory
Theoretical foundations	Companies achieve success by possessing VRIO organizational resources that generate competitive advantages (Barney, 1991; Conner, 1991; Wernerfelt, 1984)	Dynamic capabilities enable an organization to adapt, integrate, and reconfigure its skills, resources, and competencies to the needs imposed by an uncertain environment (Teece et al., 1997)	Companies align their structure, processes, and decision-making with responding to the characteristics of the environment to achieve their objectives (Burns & Stalker, 1961; Kast & Rosenzweig, 1973; Lawrence & Lorsch, 1967)
Relationship to survival	Startups possess or rapidly generate VRIO resources that interact with each other to achieve survival	The dynamic capabilities of startups are the basis for ordinary resources and capabilities to be rapidly transformed to support the changes involved in the experimentation process	The context determines the way startups configure some of their resources
Factors			
Human capital	The founder has a high knowledge and experience level (Wing-Fai, 2019) The founder and his team as valuable early-stage resources (Coleman et al., 2016) The founder seeks opportunities and organizes resources (Alvarez & Busenitz, 2001) The founder's mindset, culture, and leadership The founder's psychological capital (Bockorny & Youssef-Morgan, 2019; Hsu et al., 2014)		

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Theories			
	Resource-based theory	Theory of dynamic capabilities	Contingency theory
Social capital	Exchange of resources through links established within social structures (Davidsson & Honig, 2003; Spender, 2009) The ability to link and maintain formal or informal networks (Bandera & Thomas, 2019) Access to information and other resources (Raz & Gloor, 2007)	• The creation and managing of contact networks (Ramachandran & Ray, 2006) • The nonlinear relationship of dynamic capabilities with survival (Ritter et al., 2018) • Seizing opportunities and consolidation and growth (Teece, 2018)	• Networking as a resource for responding to environmental changes (Zhang et al., 2013)
Organizational capital	The knowledge the startup manages is appropriate (Hormiga et al., 2011) Scientific discoveries and technological inventions to create value in the startup (Seclen-Luna & Barrutia, 2019) Shared knowledge at the organizational level drives cooperation (Carmona-Lavado et al., 2010)	• Market modeling, product, process, and business model development (Giardino et al., 2014; Teece, 2007) • The evaluation and adaptation of ventures and their technologies in uncertain fields of action (Kerr et al., 2014) • Experimentation as a mechanism for knowledge creation (Schoemaker et al., 2018; Zahra, 2006)	• Operational processes to respond to contingencies that emerge from the context (McDermott et al., 2003; Sahi et al., 2019)
Entrepreneurial capital	• The money invested in creating or scaling a startup (Robb & Robinson, 2014; Hansen et al., 1999) The various sources of monetary resources are accessed sequentially (Frid, 2014)		• Entrepreneurial capital is the main contingent factor in the startup (Rompho, 2018; Guo et al., 2017)

Appendix 12.2: Variables Linked to the Model

Latent variables	Indicator variable	Type	Values
Survival	Break-even point	Ordinal	1. Operating cost covered by the founder's contribution 2. Operating cost covered by venture capital 3. Operating cost covered by sales and investment income from own- or third-party sources 4. Operating cost covered by sales revenues until the start of growth 5. Cost of operations covered by sales revenue
Survival	Signs of growth[a]	Ordinal	1. 01 growth indicator 2. 02 signs of growth 3. 03 signs of growth 4. 04 signs of growth 5. 05 signs of growth 6. 06 signs of growth
Survival	Annual sales growth (maximum in 3 years)	Ordinal	1. Less than 5% of 2. From 5 to 20% 3. From 21 to 70% 4. From 71% to 150 5. More than 150%
Survival	Months of operation	Numeric	Number of months operating as of December 2019
Survival	Cash *stock*	ordinal	1. No cash in *stock* 2. The cash *stock* allows the company to operate for a few days while other income is being earned 3. The cash *stock* allows to operate for 1 month without sales revenues 4. Cash *stock* allows operating for more than 1 month without sales revenues 5. Cash *stock* sustains accelerated *startup* growth

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Latent variables	Indicator variable	Type	Values
Human capital	Academic studies of the founders	Ordinal	Founders with university studies 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Professional experience of the founders	Ordinal	Founders with professional experience in the *startup* sector 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Entrepreneurial experience of the founders	Ordinal	Founders created or collaborated in the creation of *startups* 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	International Founders Exhibition	Ordinal	Founders with studies or work abroad 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Complementarity of founders	Ordinal	Founders with complementary technical and managerial skills 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Entrepreneur by opportunity	Ordinal	*Startup* founded as an investment opportunity 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree

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Latent variables	Indicator variable	Type	Values
Human capital	Social entrepreneur	Ordinal	*Startup* founded to contribute to solving social problems 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Entrepreneur by necessity	Ordinal	*The startup was* founded to obtain a family source of income 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Human capital	Global vision	Ordinal	*The startup was* founded to be a multi-Latin or international company 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Social capital	Network planning	Ordinal	Founders planned the networks from which they draw resources: 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Social capital	Professional networks	Ordinal	Founders obtained resources from their networks generated in previous works 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Social capital	Family or friendship networks	Ordinal	Founders obtained resources from their family or friends' networks 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree

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Latent variables	Indicator variable	Type	Values
Social capital	Specialized networks	Ordinal	Founders obtained resources from networks formed by affinity with other *startups* 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Social capital	Number of networks	Ordinal	Founders have been involved in as many networks as possible 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Social capital	Number of alliances	Ordinal	Founders have obtained resources through alliances with consolidated companies 1. Strongly disagree 2. Disagree 3. Neutral 4. Agreed 5. Totally agree
Entrepreneurial Capital	Founder's contribution	Ordinal	1. No own investment 2. Less than S/. 1000 3. S/. 1001 to S/. 20 000 4. S/. 20 001 to S/. 50 000 5. S/. 50 001 to S/. 100 000 6. More than S/. 100 000
Entrepreneurial capital	Private Equity	Ordinal	1. No private investment 2. Less than S/. 10 000 3. S/. 10 001 to S/. 50 000 4. S/. 50 001 to S/. 100 000 5. S/. 100 001 to S/. 250 000 6. More than 250,000
Entrepreneurial capital	Public funds	Ordinal	1. No public funds 2. Less than S/. 10 000 3. S/. 10 001 to S/. 50 000 4. S/. 50 001 to S/. 100 000 5. S/. 100 001 to S/. 250 000 6. More than 250,000
Entrepreneurial capital	Investor risk	Ordinal	No investment Low risk tolerance Average risk tolerance High risk is tolerance

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Latent variables	Indicator variable	Type	Values
Organizational capital	Product definition[a]	Ordinal	1. *Copycats* 2. Emerging 3. Research
Organizational capital	Knowledge intensity[a]	Ordinal	1. Low-level A 2. Low-level B 3. Low-level C 4. Intermediate level A 5. Medium level B 6. Medium level C 7. High-level A 8. High-level B 9. High-level C
Organizational capital	Number of iterations	Ordinal	1. Less than 10 2. From 10 to 20 3. From 21 to 30 4. From 31 to 40 5. More than 40
Organizational capital	MVP time	Ordinal	1. Less than 10 days 2. 10 to 20 days 3. From 21 to 50 days 4. From 51 to 100 days 5. More than 100 days
Organizational capital	Business model	Ordinal	1. To be tested 2. Being validated in the initial context 3. Validated in the initial context 4. Being modified by the growth 5. Consolidated
Incubation process	Incubation process	Nominal	(a) Yes (b) No
Incubation process	Scope of service	Ordinal	1. No incubation process 2. One of the defined scopes 3. Two of the defined scopes 4. Three of the defined scopes 5. Four of the defined scopes 6. The five defined scopes
Incubation process	Level of service	Ordinal	1. No incubation process 2. Malo 3. Regular 4. Good 5. Very good 6. Excellent

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Latent variables	Indicator variable	Type	Values
Incubation process	Participation in the service	Ordinal	1. No incubation process 2. Never 3. From time to time 4. Approximately half of the time 5. Most of the time 6. Always
Incubation process	Service resources[a]	Ordinal	1. No incubation process 2. Weighting level 1 3. Weighting level 2 4. Weighting level 3 5. Weighting level 4 6. Weighting level 5
Control variable	Ecosystem development[a]	Nominal	(a) Lima (b) Provinces
Control variable	Industry type[a]	Nominal	(a) Cross-cutting services (b) Online sales (c) Specialized
Control variable	Market type	Nominal	(a) *Business to Business* (B2B) (b) *Business to Consumer* (B2C) (c) *Consumer to Consumer* (C2C) (d) *Business to Government* (B2G)
Control variable	COVID effect[a]	Ordinal	1. Momentary or total paralysis 2. Risk to business continuity 3. Opportunity to boost business

Note (1) The values of the variables accompanied by "a" were obtained by weighting the answers to the questions asked (these are multiple answers with conditions that can co-occur). (1) In the case of ordinal variables, the values assumed are numbered from lowest to highest

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Chapter 13
Influence of Earnings Quality Dimensions on the Perception of Earnings Quality: An Empirical Application of Composite PLS Using Archival Data

Manuel Cano-Rodríguez and Ana Licerán-Gutiérrez

Abstract Despite the fact that empirical research on earnings quality (EQ) has used a wide range of earnings properties that are expected to be related to EQ, research on how these properties affect investors' perception of earnings quality is scarce, as most of the papers on EQ focus on a single EQ dimension. Moreover, extant research presents some limitations, as most studies rely on first-generation statistical methods (mainly OLS), without empirically testing the validity of the indicators used for capturing the underlying EQ dimension. This paper aims to explore how the different EQ properties described by previous literature map onto stockholders' perceptions of EQ. Using partial least squares path modeling (PLS-PM), our results show that some of the properties more widely studied by accounting research (such as accruals quality) have little influence on stockholders' perceptions of earnings quality, whereas other, less studied properties (such as persistence and smoothing) exhibit a stronger relationship with stockholders' perceptions of EQ. Our results also show that the most usual indicators previously used in empirical research to represent accounting conservatism do not converge in a single construct, possibly indicating that those indicators may represent different underlying concepts.

13.1 Introduction

Earnings quality (EQ) is arguably the most common topic in accounting research. Given that EQ is not directly observable, prior literature has defined several desirable properties of reported earnings that can be expected to be related to it (Dechow et al., 2010). This multidimensional nature of EQ is present in previous research,

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as researchers have used several different proxies that represent the diverse desirable properties of EQ. Notwithstanding the general theoretical agreement on the variety of facets that are representative of EQ, empirical research on EQ presents some problems. Thus, most empirical papers on EQ deal with just one of those desirable properties, without considering the other related properties. Moreover, although some papers have tried to develop multidimensional measures of EQ, those measures are simply additions to the proxies of the different properties, without considering their possible interactions or each one's relative importance. Moreover, empirical researchers have developed a multitude of empirical proxies for each of the different EQ properties, though there is no clear consensus on which ones best represent the associated properties (Ewert & Wagenhofer, 2011; Licerán-Gutiérrez & Cano-Rodríguez, 2019).

In this chapter, we aim to overcome the abovementioned empirical problems in the measurement of EQ by using a second-generation regression method, specifically, the PLS-PM method. This method allows us to measure unobservable variables, like the EQ dimensions, testing the validity of the resulting constructs. In our structural model, we analyze how the four EQ properties most commonly used in EQ literature (accruals quality, earnings smoothing, earnings persistence, and accounting conservatism) affect stockholders' perception of earnings quality. Each of the structural latent variables is measured using the most common empirical indicators previously used in empirical EQ research. In summary, we present the results of a two-step validation of PLS both for each latent variable, as measured by its indicator (measurement model), and between latent variables (structural model). Next, we compare the estimation power of the PLS method to that of the single-indicator approach in both in-sample and out-of-sample measurements.

Our study contributes to prior literature on earnings quality in several ways. First, we offer an empirical validation of earnings quality proxies. This fact is important given the existence of multiple proxies to represent heterogeneous characteristics of reported earnings and their perceived usefulness by the users of such information. Second, our results highlight which earnings properties have a greater influence on perceived EQ, which can be useful for both researchers and practitioners. Thus, by showing the earnings properties that are more relevant for investors, our results can guide researchers to focus their investigations on the more relevant facets of earnings quality; on the other hand, our results can help practitioners design their disclosure.

This chapter is structured as follows. Section 13.2 presents a theoretical framework to define EQ and the relationship among all its facets. Section 13.3 presents the research design of the model for measuring earnings quality using the PLS method. Section 13.4 presents the results (measurement and structural model analysis) and discussion. Section 13.4 presents additional analyses and robustness checks (time-series invariance, endogeneity, and unobserved heterogeneity). Section 13.5 concludes the chapter.

13.2 Theoretical Framework

13.2.1 Definition of Earnings Quality

Empirical studies in social sciences seek to assess whether theoretical models fit well with the real world at two levels: conceptual and operational (Bisbe et al., 2007). The conceptual level specifies the relationships among conceptual variables that, together, result in a theory (Bollen, 2002). The operational level determines the procedures to empirically represent those conceptual variables, defining both the proxies (empirical measures) and the way in which these proxies relate to the concept they measure (Babbie, 2017).

Focusing on earnings quality research, at the conceptual level, there is no generally accepted definition of EQ (Chaney et al., 2008; Hermanns, 2006), but previous research has identified a series of earnings properties that are expected to enhance EQ (see, among others: Dechow et al., 2010; Perotti & Wagenhofer, 2014; Schipper & Vincent, 2003). Given that an in-depth approach of the conceptualization of EQ and its characteristics is beyond the scope of this study, we use as a reference the conceptualization of Dechow et al. (2010), who group these characteristics into several properties that represent EQ: earnings and accruals persistence, accruals quality, earnings smoothness, and accounting conservatism. These four measures represent earnings characteristics that, theoretically, are expected to affect earnings quality. Besides, a relevant feature of these four characteristics is that they are constructed entirely from the accounting information revealed by companies, but not on the reaction of the users of that accounting information. These four earnings characteristics are the exogenous variables of our model. As the endogenous variable, we use perceived earnings quality. This measure aims to capture how investors (specifically, stockholders) react to the reported earnings. Next, we describe each of these properties.

13.2.1.1 Perceived Earnings Quality

Whenever information on earnings makes a difference in decision-making, information users perceive earnings as quality. There are multiple users of financial information disclosed by companies, each of whom uses it for different purposes (e.g., equity investors, debt investors, clients, suppliers, employees, public authorities, etc.). Precisely because they have different goals, the perception of disclosed information will differ according to their decision-making process. In this study, we focus on equity investors, who analyze financial information to make decisions about their investments in companies listed on the stock market, either with the aim of controlling the company, or just to speculate with financial investments (looking for under- or overpriced companies and seeking to benefit from the differences between price and value). Information on earnings is used by equity investors to infer the true situation of the company and confirm or update their beliefs on it (Li, 2014). In any case, the better the information used to evaluate the company, the more efficient the decision is expected to be (Biddle & Hilary, 2006; Biddle et al., 2009). Considering this from investors' perspective, higher-quality information on earnings is reflected in a better company valuation, which, in the case of listed firms, is observed in higher prices and returns (Perotti & Wagenhofer, 2014). This is what, in other words, we can refer to as relevance, in the sense of greater perceived usefulness of information for users to make better decisions. This study, as explained in the next section, considers perceived usefulness by equity investors linking accounting information that is used for valuation purposes by investors with their reaction in the market, hence using market variables for its measurement.

13.2.1.2 Earnings Persistence

Earnings persistence is associated with the stability of earnings (or cash flows) over time (Dechow et al., 2010). Persistence is associated with the extent to which earnings in a given year are able to predict future earnings (Freeman et al., 1982). Hence, persistence is expected to be closely related to earnings predictability.

Prior literature supports the idea that persistence increases EQ (Ewert & Wagenhofer, 2015), because of its relationship with earnings predictability, as more persistent earnings allow for more accurate forecasts (Karuna, 2019; Kwon et al., 2019) and for the enhanced ability of earnings to reflect underlying firm value (Bradshaw & Sloan, 2002). Consequently, information on more persistent earnings leads to stronger reactions in the market, with greater returns and overpricing (Bradshaw & Sloan, 2002; Dhole et al., 2021; Fu, 2019; Karuna, 2019; Nichols & Wahlen, 2004; Sobrinho et al., 2014).

Given the agreement in prior literature that relevance is perceived by investors as a property that enhances EQ and makes information more useful, we propose the following Hypothesis 1:

H1: Higher levels of persistence are positively related to a better perceived EQ by investors.

13.2.1.3 Accruals Quality

Accruals quality is associated with the reliability of disclosed information on earnings, as managers can manipulate earnings using accruals in a less costly way. Accruals quality is usually assessed by analyzing the difference between the total and the expected levels of accruals. The higher this difference (known as abnormal or discretionary accruals), the lower the quality of accruals.

As investors make their decisions based on accounting information, if such information is not sufficiently reliable, they will get an incorrect idea about the real economic situation of the company; hence, the efficiency of their investment will decrease (Biddle et al., 2009; Biddle & Hilary, 2006; F. Chen et al., 2011). Previous literature shows that earnings of the companies with a higher level of discretionary accruals (thereby lower accruals quality) are perceived as less relevant by investors (Barton et al., 2010; Kwon et al., 2019; Marquardt & Wiedman, 2004), who react adversely in the stock market, as reflected in mispricing (Chan et al., 2009; Fu, 2019; Ogneva, 2012; Perotti & Wagenhofer, 2014), and lower earnings response coefficient and returns (DeFond & Park, 2001; Dimitropoulos & Asteriou, 2009; Fu, 2019; Kumar & Saini, 2019; Mashruwala and Mashruwala, 2011). Considering this, we state Hypothesis 2 as follows:

H2: Higher levels of accruals quality are positively related to a better perceived EQ by investors.

13.2.1.4 Earnings Smoothing

Earnings smoothing occurs when managers try to reduce abnormal variations in earnings (Beidleman, 1973). It is considered that earnings smoothing can enhance earnings quality because smoothed earnings are more persistent (Francis et al., 2004; Tucker & Zarowin, 2006), thereby improving earnings predictability and information about future earnings and cash flows. Investors would perceive this increase in the information content of earnings positively, increasing their valuation of earnings and increasing the market returns (Cussatt et al., 2019; Sun, 2011; Tucker & Zarowin, 2006). Other studies also show that smoothed earnings allow for better forecasts by analysts (Biddle & Hilary, 2006; Burgstahler et al., 2006; Lang et al., 2003), thereby increasing investment efficiency (Biddle & Hilary, 2006). Apart from that, smoothing has been also used by managers for conveying useful information (signaling role) to investors (Ewert & Wagenhofer, 2015). We, hence, formulate Hypothesis 3 as follows:

H3: Higher levels of smoothing are positively related to a better perceived EQ by investors.

13.2.1.5 Accounting Conservatism

The Financial Accounting Standards Board (1980) defines conservatism as a prudent reaction to uncertainty that is reflected in accounting for the risk and uncertainty in companies' performance.

Conservatism is considered a desirable property of earnings because of its ability to reduce information asymmetry (Ball & Shivakumar, 2008; Chen et al., 2014; García Lara et al., 2014; Jain et al., 2020; LaFond & Watts, 2008), limiting managers' opportunistic behavior when disclosing information (Bangmek et al., 2016; Brown Jr. et al. 2006; L. H. Chen et al., 2014; Cheng et al., 2011; Ciftci, 2010; Gao, 2013), thereby avoiding manipulating earnings upwards (Chen et al., 2014; Gao, 2013), mainly via accruals (Brown Jr. et al. 2006; Cheng et al., 2011). Additionally, conservatism is claimed to improve contracting efficiency (Brown Jr. et al. 2006; Chen et al., 2014; Jain et al., 2020; Qiang, 2007). Moreover, another group of authors identify positive effects of conservatism to improve equity valuation by investors, in the sense that it improves the information environment for financial analysts, allowing for more precise forecasts (Bangmek et al., 2016; García Lara et al., 2014; Kim & Pevzner, 2010). This is perceived by investors as high-quality information (more relevant) and, consequently, companies opting for conservative reporting have a better market reaction (Bangmek et al., 2016; Ciftci, 2010), pricing conservative earnings more favorably than non-conservative ones (Bandyopadhyay et al., 2017; Chen et al., 2014). Overall, there is a common agreement that the key to understanding conservatism as positive for EQ perception (and, hence, improved market reaction) is that it helps to increase the reliability of reported conservative earnings (Bandyopadhyay et al., 2010; García Lara et al., 2008, 2018). That is why accounting standards impose conservative valuation principles, prioritizing the stewardship protection role of accounting versus its valuation role (Ribeiro et al., 2019), with greater efficacy in common-law countries with higher investor protection (García Lara et al., 2008).

All these things considered, we define the hypotheses for the effect of conservatism on perceived EQ in the following way.

H4: Higher levels of conservatism are positively related to a better perceived EQ by investors.

A graphical representation of the hypotheses is shown in Fig. 13.1.

13.3 Research Design

To empirically validate the measurement of earnings quality, we design a PLS model. Such a model will be applied to archival data on accounting information. In this section, we first describe the sample selection process to collect the archival data. Later, we explain in detail the earnings quality model that will be estimated with the PLS method and define all variables.

13.3.1 Sample Selection

For the analysis of the validity of earnings quality proxies, we collected archival accounting data from listed firms between 1970 and 2020. Data were collected from Standard and Poor's Compustat, whereas market data (i.e., returns) were collected from the Center for Research in Security Prices (CRSP). The sample was restricted to nonfinancial firms because the differentiation between financial and operating activities is unclear for financial firms (Richardson et al., 2005), thereby hindering

Fig. 13.1 Relationships between facets of earnings quality and perceived earnings quality. *Note: This figure shows the relationships between the structural variables and the indicators to estimate such structural variables. The explanation and details for the indicators of each variable can be found in* Sect. 3.2 *"Measure and scale"*

the estimation of some indicators, such as those of accruals quality. We thus deleted from our database firms with SIC Codes from 6000 to 6999.

Following previous literature, we dropped observations with share prices lower than one dollar or with negative book values (Basu, 1997; Beaver & Ryan, 2000; Khan & Watts, 2009). We also deleted firm observations with missing data for any of the variables used to calculate the different proxies (Dechow & Dichev, 2002; Francis et al., 2004; Richardson et al., 2005). In addition, it is advisable to require a minimum number of firm-year observations for any two-digit SIC (Standard Industrial Classification) code in any given year of database items that are necessary to calculate the proxies that will be indicators of the different latent variables in the model to make the results more robust (Kothari et al., 2005). In this sense, although some of the referent studies consider up to ten observations to be sufficient (see, among others: Dechow & Dichev, 2002; Francis et al., 2004; Kothari et al., 2005; McNichols, 2002), we want to enhance robustness and thus require at least twenty observations.

Finally, regarding the treatment of outliers in our sample, we winsorize all variables at 1% and 99%. This allows us to control outliers without trimming the sample and deleting more observations. After the sample selection process, the final number of observations after estimation is 72,212.

13.3.2 Measure and Scale

13.3.2.1 Model Design

According to the framework for measuring earnings quality discussed in the Theoretical Framework section, we describe the structural and measurement parts of the model.

13.3.2.2 Structural Model

The structural model estimates the influence of the constructs representing all properties of reported earnings that are indicative of earnings quality on the *Earnings Quality Perceived by Equity Investors (PERCEIVED_EQ)* construct. That is, we analyze how the combination of different earnings properties that are expected to increase the usefulness of the earnings figure for decision-making influences the earnings quality perceived by equity investors. Next, we review the measurement models of these variables.

13.3.2.3 Measurement Model

In the case of earnings quality, its different facets (both earnings properties and perceived earnings quality) have been empirically observed in prior literature through several proxies that are representative of those concepts. All these proxies have a reflective relationship with the facets that they measure because they are manifestations of such facets, and changes in the facets cause changes in those proxies. Moreover, all proxies of each facet share a common theme and are closely related to each other because they all measure the same concept; hence, the proxies are perfectly interchangeable. There are multiple proxies for each facet in prior literature (Ewert & Wagenhofer, 2011) but no common agreement on which proxy best empirically represents the facet (Licerán-Gutiérrez & Cano-Rodríguez, 2019). We next describe, in general, the literature on which we have based our proxy selection for both the dependent and independent variables, and Appendix 1 provides details on all proxies.

13.3.2.4 Dependent Variable

The dependent variable is the *Earnings Quality Perceived by Equity Investors* (*PERCEIVED_EQ*) construct. This variable is intended to measure the reactions of equity investors to the earnings quality level. It is thus not a directly observable concept, and it is measured using several empirical proxies that prior literature has considered to represent equity investors' reactions to earnings quality: the coefficient and the R^2 from two models: the value relevance model (which relates the price of shares with book value per share and earnings per share), and the earnings response coefficient (ERC) model (which relates returns obtained in the stock market with earnings disclosed by companies).

13.3.2.5 Independent Variables

We include as independent variables the different properties of accounting information that determine the overall extent of earnings quality (Dechow et al., 2010): accruals quality *(ACCRUALS_QUALITY)*, earnings smoothing *(SMOOTH)*, persistence *(PERSISTENCE)*, and conservatism *(CONSERVATISM).* To represent these earnings properties, we use the most common empirical proxies used in previous research to measure them in a reflective way.

Prior literature has typically observed a difference between the actual level of accruals and the estimated level of accruals in the absence of earnings manipulation, called discretionary accruals (Dechow et al., 2010; Ewert & Wagenhofer, 2011). Then, the lower this difference is, the higher the accruals quality is, as most of the observed accruals in a company come from the normal recognition of accounting earnings and not from the manipulation of earnings. Hence, *accruals quality* is the inverse of discretionary accruals and is adopted for estimation in several models (see, among others: Ball & Shivakumar, 2006; Dechow et al., 1995; Dechow & Dichev, 2002; Jones, 1991; Kothari et al., 2005; McNichols, 2002).

Regarding the *earnings smoothing* measurement, we find two proxies in prior literature: the ratio of deviation of earnings to deviation of cash flows (Leuz et al., 2003) and the correlation of total or discretionary accruals changes and cash flows changes (Leuz et al., 2003; Tucker & Zarowin, 2006).

There are several proxies to measure *earnings persistence*. The most common approaches are the autoregression coefficient of earnings on lagged earnings and the R^2 of such a regression. This basement model has been adapted in other models that regress cash flows on lagged earnings or that disaggregate earnings into accruals and cash flows, and both models take either the coefficient or the R^2 of later regressions as proxies for persistence.

For *conservatism*, there is a wide variety of proxies; the most popular measure is differential timeliness in the recognition of losses versus gains, with a timelier recognition of losses. This model, proposed by Basu (1997), has been modified to improve its estimation and consider other aspects, as happens with the absolute earnings reversal model, also by Basu, and other, more recent models (see, among others: Ball & Shivakumar, 2005; Barth et al., 2014; Callen et al., 2010; Cano-Rodríguez & Nunez-Nickel, 2015; Dutta & Patatoukas, 2017; Khan & Watts, 2009). Based on different approaches, other models analyze the greater or lesser extent of conservatism according to the amount of large, negative accruals (Givoly & Hayn, 2000), skewness of earnings (Gassen et al., 2006; Givoly & Hayn, 2000), or market-to-book (MTB) ratio (Beaver & Ryan, 2000).

13.3.3 Data Analysis

To estimate our model, we run a PLS path modeling using Smart-PLS 3 software (Ringle et al., 2015). The selection of the statistical technique of PLS is based on the following reasons. First, given the large amount of proxies that consider different and heterogeneous aspects that make earnings more useful for decision making, with non-zero correlations between them (see, for example, Beaver et al., 2012; L. H. Chen et al., 2014; Dechow et al., 2010; Dechow & Dichev, 2002; García Lara et al., 2005; Pae, 2007), traditional OLS techniques may not be sufficient. In this sense, Ewert and Wagenhofer (2015), point out that a limitation of previous studies of EQ is the fact that although some of them use more than one measure, they consider neither the relationships between the facets of EQ (some are negatively related to each other), nor whether what they measure is aligned what with they represent. More modern methods (second-generation methods), such as partial least squares (PLS), have been proven to overcome traditional methods in such situations, allowing empirical testing of assumptions about conceptual (latent) variable measurement. In particular, PLS has the advantage of analyzing multiple relationships simultaneously in a single, systematic, and comprehensive way (Hair & Sarstedt, 2019; Nitzl, 2016; Ramli et al., 2018, 2019), and the model analyzes the relationships between those latent variables only after proving that latent variables are appropriately represented in reality by the proxies that they measure (Fornell, 1982; Fornell & Larcker, 1981). Second, the measurement of EQ, as previously exposed, shows a proxy selection problem, given the existence of multiple proxies with no clear superiority of any of them. PLS is especially indicated for models with a large number of indicators, because of its ability to deal with multicollinearity (Hair et al. 2017). Finally, recent research on PLS highlights its advantages when analyzing secondary (archival) data, because PLS allows for good integration and treatment of archival data (Hair & Sarstedt, 2019; Nitzl, 2018), such as, specifically, data from financial statements (Nitzl, 2018).

13.4 Results

13.4.1 Descriptive Statistics

Table 13.1 shows a detailed summary of the descriptive statistics (Panel A) as well as the correlation matrix (Panel B) of all the indicators. The mean values of the different indicators are in line with those reported in previous research considering a time-series approach.

Regarding the correlation matrix (Panel B), among the indicators that proxy for earnings quality perceived by investors, the correlation is not very high compared to that of indicators obtained from the two different models used for the estimation (earnings response coefficient, on the one hand, and value relevance of book value and earnings, on the other hand). In this sense, the only indicators that show a slightly higher correlation (0.1874) are those that refer to the coefficient for earnings (*PERC_EQ1_ERC_coeff* and *PERC_EQ4_RELEV_Earn_coeff*). For the indicators measuring persistence, the correlations between the proxies are positive, with values ranging from 0.1062 to 0.6811; the indicators estimated with the earnings persistence model (*PERS1_earn_coeff* and *PERS2_earn_R2*) have better correlations with the rest of the indicators. However, it is noteworthy that there is a low correlation between the variance of earnings (*PERS7_var_earn*) and the rest of the proxies for persistence, even with negative values, ranging from −0.0111 to 0.0416. The correlations among the indicators of accruals quality are mostly high, with values ranging between approximately 0.4 and 0.9, except for the indicators AQ5_Dechow_Dichev and AQ6_Mc_Nichols. These two indicators show a different behavior from the others. This can be explained by the fact that, by definition, these two models use a different approach in the sense that the dependent variable is not total accruals but working capital, and they consider the effect of past, current, and future cash flows on working capital instead of the proportion of total accruals that are not explained by the expected level of accruals absent earnings manipulation. In addition, as can be observed in detail in Appendix 1, these two indicators are calculated with the standard deviation of the error term in a rolling window of five years, while the rest of the indicators consider the error term only on an annual basis. Finally, the correlations among the different conservatism metrics are near zero, and even negative for some cases. These low correlations are, however, in line with concerns in prior literature that the different proxies for conservatism do not measure a single and clear theoretical concept (Wang et al., 2009), with empirical papers demonstrating low or even negative correlations between some of the proxies (Givoly et al., 2007; Ryan, 2006; Wang et al., 2009).

Next, we analyze the results from the model estimation of PLS.

Table 13.1 Descriptive statistics

Panel A: Descriptive statistics								
Variable	*n*	Mean	St. Dev	p25	p50	p75	Min	Max
PERC_EQ1_ERC_coeff	72,212	3.180	8.010	−0.283	1.901	5.812	−21.825	34.892
PERC_EQ2_ERC_R2	72,212	0.331	0.285	0.070	0.263	0.548	0.000	0.971
PERC_EQ3_RELEV_Book_v_coeff	72,212	0.934	4.883	−0.873	0.738	2.643	−17.267	20.101
PERC_EQ4_RELEV_Earn_coeff	72,212	3.244	13.733	−1.193	1.419	6.312	−45.777	63.011
PERC_EQ5_RELEV_R2	72,212	0.670	0.274	0.479	0.744	0.905	0.028	0.998
PERS1_earn_coeff	72,212	0.193	0.571	−0.162	0.157	0.498	−1.317	2.243
PERS2_earn_R2	72,212	0.235	0.257	0.029	0.126	0.378	0.000	0.936
PERS3_disagg_coeff	72,212	0.229	0.855	−0.233	0.204	0.663	−2.536	3.300
PERS4_disagg_R2	72,212	0.499	0.298	0.232	0.498	0.763	0.009	0.992
PERS5_CFO_coeff	72,212	−0.064	1.444	−0.592	0.001	0.560	−5.571	4.740
PERS6_CFO_R2	72,212	0.252	0.254	0.039	0.160	0.409	0.000	0.930
PERS7_var_earn	72,212	−0.011	0.058	−0.005	-0.001	0.000	−1.116	0.000
AQ1_DAngelo	72,212	0.938	0.079	0.926	0.962	0.983	0.443	1.000
AQ2_Industry	72,212	0.946	0.062	0.931	0.965	0.985	0.473	1.000
AQ3_Jones	72,212	0.943	0.071	0.929	0.965	0.985	0.501	1.000
AQ4_Dechow_95	72,212	0.941	0.074	0.927	0.964	0.984	0.490	1.000
AQ5_Dechow_Dichev	72,212	0.967	0.066	0.976	0.994	0.998	0.411	1.000

(continued)

Table 13.1 (continued)

Panel A: Descriptive statistics

Variable	*n*	Mean	St. Dev	p25	p50	p75	Min	Max
AQ6_Mc_Nichols	72,212	0.966	0.071	0.976	0.994	0.998	0.364	1.000
AQ7_Kothari	72,212	0.945	0.064	0.930	0.965	0.985	0.587	1.000
AQ8_Ball_Shivakumar_year	72,212	0.938	0.077	0.927	0.962	0.983	0.484	1.000
AQ9_Ball_Shivakumar_industry	72,212	0.947	0.063	0.934	0.967	0.985	0.532	1.000
SMOOTH1_dev_earn_cfo	72,212	0.746	0.485	0.383	0.668	0.994	0.076	2.771
SMOOTH2_corr_accr_cfo	72,212	−0.696	0.409	−0.963	−0.877	−0.608	−0.998	0.844
CONS1_Skewness	72,212	−0.145	0.694	−0.643	−0.163	0.337	−1.462	1.410
CONS2_Givoly_Hayn	72,212	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CONS3_MTB	72,212	2.312	3.393	0.948	1.597	2.706	−9.734	28.130
CONS4_Basu	72,212	0.028	1.716	−0.062	0.000	0.120	−8.953	9.041
CONS5_abs_earn_rev	72,212	4.222	9.962	0.000	1.600	3.838	0.000	75.428
CONS6_Cano_Nunez	72,212	0.022	0.515	−0.137	−0.003	0.142	−1.937	2.394

Panel B: Correlation matrix

Correlations for perceived earnings quality indicators

	PERC_EQ1_ERC_coeff	*PERC_EQ2_ERC_R2*	*PERC_EQ3_RELEV_Book_v_coeff*	*PERC_EQ4_RELEV_Earn_coeff*	*PERC_EQ5_RELEV_R2*
PERC_EQ1_ERC_coeff	1.0000				
PERC_EQ2_ERC_R2	0.3041*	1.0000			
PERC_EQ3_RELEV_Book_v_coeff	0.0140*	0.0271*	1.0000		

(continued)

Table 13.1 (continued)

Panel B: Correlation matrix

Correlations for perceived earnings quality indicators

	PERC_EQ1_ERC_coeff	*PERC_EQ2_ERC_R2*	*PERC_EQ3_RELEV_ Book_v_coeff*	*PERC_EQ4_RELEV_ Earn_coeff*	*PERC_EQ5_RELEV_R2*
PERC_EQ4_RELEV_ Earn_coeff	0.1874*	0.0648*	−0.4753*	1.0000	
PERC_EQ5_RELEV_ R2	0.0621*	0.0736*	0.1102*	0.0889*	1.0000

Correlations for persistence indicators

	PERS1_earn_ coeff	*PERS2_earn_R2*	*PERS3_disagg_ coeff*	*PERS4_disagg_ R2*	*PERS5_CFO_ coeff*	*PERS6_CFO_R2*	*PERS7_var_earn*
PERS1_earn_ coeff	1.0000						
PERS2_earn_R2	0.4349*	1.0000					
PERS3_disagg_ coeff	0.6811*	0.2735*	1.0000				
PERS4_disagg_ R2	0.2553*	0.5701*	0.2006*	1.0000			

(continued)

Table 13.1 (continued)

Correlations for persistence indicators

	PERS1_earn_coeff	*PERS2_earn_R2*	*PERS3_disagg_coeff*	*PERS4_disagg_R2*	*PERS5_CFO_coeff*	*PERS6_CFO_R2*	*PERS7_var_earn*
PERS5_CFO_coeff	0.3020*	0.1404*	0.1860*	0.0472*	1.0000		
PERS6_CFO_R2	0.1062*	0.2638*	0.0615*	0.1525*	−0.0167*	1.0000	
PERS7_var_earn	0.0416*	0.0383*	0.0191*	0.0233*	−0.0111*	0.0325*	1.0000

Correlations for accruals quality indicators

	AQ1_DAngelo	*AQ2_Industry*	*AQ3_Jones*	*AQ4_Dechow_95*	*AQ5_Dechow_Dichev*	*AQ6_Mc_Nichols*	*AQ7_Kothari*	*AQ8_Ball_Shivakumar_year*	*AQ9_Ball_Shivakumar_industry*
AQ1_DAngelo	1.0000								
AQ2_Industry	0.4921*	1.0000							
AQ3_Jones	0.3557*	0.6465*	1.0000						
AQ4_Dechow_95	0.3553*	0.6669*	0.9560*	1.0000					

(continued)

Table 13.1 (continued)

Correlations for accruals quality indicators

	AQ1_DAngelo	*AQ2_Industry*	*AQ3_Jones*	*AQ4_Dechow_95*	*AQ5_Dechow_Dichev*	*AQ6_Mc_Nichols*	*AQ7_Kothari*	*AQ8_Ball_Shivakumar_year*	*AQ9_Ball_Shivakumar_industry*
AQ5_Dechow_Dichev	0.1313*	0.1089*	0.1969*	0.1964*	1.0000				
AQ6_Mc_Nichols	0.1242*	0.0970*	0.2161*	0.2123*	0.8737*	1.0000			
AQ7_Kothari	0.3847*	0.7348*	0.8387*	0.8697*	0.1769*	0.1851*	1.0000		
AQ8_Ball_Shivakumar_year	0.3887*	0.4564*	0.3853*	0.3867*	0.1367*	0.1277*	0.4205*	1.0000	
AQ9_Ball_Shivakumar_industry	0.4069*	0.5752*	0.5144*	0.5069*	0.2061*	0.2078*	0.5480*	0.4131*	1.0000

Correlations for smoothing indicators

	SMOOTH1_dev_earn_cfo	*SMOOTH2_corr_accr_cfo*
SMOOTH1_dev_earn_cfo	1.0000	
SMOOTH2_corr_accr_cfo	0.5829*	1.0000

Correlations for conservatism indicators

	CONS1_Skewness	*CONS2_Givoly_Hayn*	*CONS3_MTB*	*CONS4_Basu*	*CONS5_abs_earn_rev*	*CONS6_Cano_Nunez*
CONS1_Skewness	1.0000					

(continued)

Table 13.1 (continued)

Correlations for conservatism indicators						
CONS2_Givoly_Hayn	0.0136*	1.0000				
CONS3_MTB	0.0118*	0.0093*	1.0000			
CONS4_Basu	−0.0176*	0.0039	−0.0056	1.0000		
CONS5_abs_earn_rev	−0.0287*	−0.0037	−0.0204*	0.0003	1.0000	
CONS6_Cano_Nunez	−0.0646*	0.0104*	−0.0139*	0.0556*	0.0215*	1.0000

Note St. Dev is standard deviation; p25, p50, and p75 are, respectively, the percentiles 25, 50 (median value), and 75 of the distribution; min is the minimum value of the distribution; and max is the maximum value of the distribution.

* means statistical significance at 5% level.

13.4.2 Measurement Validity Assessment

In this section, we analyze the validity of the measurement models. We consider each proxy as individually- and the different proxies as aggregately explaining the same theoretical facets of earnings quality. To this end, we follow recent advances in measurement validity assessment suggested by Hair et al. (2020), who propose a step-by-step procedure including, at the indicator level, the analysis of individual indicator reliability and statistical significance with a bootstrapping procedure, and at the construct level the assessment of composite reliability, convergent validity, and discriminant validity.

This analysis is presented for each latent variable individually. However, to facilitate comparison between variables, as well as the changes from the initial to the final situation, we display all of the results regarding measurement validity assessment in Table 13.2. For each of these latent variables, we display three blocks of results. First, we report the outer loadings for each individual indicator. Second, the values of the composite reliability index for each construct are presented. Finally, we report the average variance extracted (AVE) for the convergent validity assessment.

To ensure that we are using valid constructs of the different earnings quality proxies, the three former measures have to be evaluated (Hair et al., 2016, 2017a, 2017b), considering the usual thresholds (see, for example: Hair et al., 2016, 2017a, 2017b; Henseler, 2021): indicator loadings above 0.7, composite reliability above 0.7, and AVE above 0.5. About indicator loadings, however, a researcher can consider retaining loadings between 0.4 and 0.7 if the construct reliability and validity of the concept they measure are not affected (Chin, 1998; Henseler, 2021; Mehmetoglu & Venturini, 2021). Values for loadings below 0.4 indicate that the indicator is not able to empirically represent the concept (Henseler, 2021; Mehmetoglu & Venturini, 2021) and thus must be deleted from the model. Additionally, although not tabulated in Table 13.2, we run a bootstrapping test with 5,000 subsamples to check the statistical significance of each individual indicator, and the results show *p*-values of 0.000 for all indicators. Hence, we can affirm that every indicator that is selected in the final model after the depuration not only shows an adequate extent of reliability but also that it is statistically significant.

According to the aforementioned rules, we applied the following process for depurating our constructs. We first estimated the model using all the indicators listed in Appendix 1. This model, including all the indicators, was our original model. After estimating the model, we removed indicators that did not accurately represent their associated latent variable. To decide which indicator should be removed from the model, we ordered the loadings of all the indicators and removed the indicator with the smallest value. After dropping that indicator, the model was estimated again. This process was repeated until the aforementioned thresholds for measurement reliability and validity were met: For the sake of brevity, we do not report the results of the intermediate steps.

Next, we discuss the results of the validity tests for the different latent variables. We start with the analysis of the validity of the dependent variable

Table 13.2 Results from the measurement validity assessment

	Original situation			*Final situation*		
	Indicator loadings	Composite reliability	AVE	Indicator loadings	Composite reliability	AVE
Perceived earnings quality (PERCEIVED_EQ) construct:		0.641	0.288		0.737	0.588
PERC_EQ1_ERC_coeff	0.786			0.872		
PERC_EQ2_ERC_R2	0.423					
PERC_EQ3_RELEV_Book_v_coeff	0.300					
PERC_EQ4_RELEV_Earn_coeff	0.653			0.644		
PERC_EQ5_RELEV_R2	0.357					
Persistence (PERSISTENCE) construct		0.735	0.325		0.821	0.544
PERS1_earn_coeff	0.862			0.896		
PERS2_earn_R2	0.690			0.680		
PERS3_disagg_coeff	0.761			0.805		
PERS4_disagg_R2	0.517			0.514		
PERS5_CFO_coeff	0.266					
PERS6_CFO_R2	0.266					
PERS7_var_earn	0.258					
Accruals quality (ACCRUALS_QUALITY) construct		0.875	0.483		0.915	0.614
AQ1_DAngelo	0.546			0.558		
AQ2_Industry	0.842			0.843		
AQ3_Jones	0.893			0.887		
AQ4_Dechow_95	0.902			0.896		
AQ5_Dechow_Dichev	0.158					
AQ6_Mc_Nichols	0.164					
AQ7_Kothari	0.906			0.902		
AQ8_Ball_Shivakumar_year	0.559			0.559		
AQ9_Ball_Shivakumar_industry	0.734			0.748		
Earnings smoothing (SMOOTH) construct		0.879	0.785		0.881	0.788
SMOOTH1_dev_earn_cfo	0.836			0.849		

(continued)

Table 13.2 (continued)

	Original situation			*Final situation*		
	Indicator loadings	Composite reliability	AVE	Indicator loadings	Composite reliability	AVE
SMOOTH2_corr_accr_cfo	0.933			0.924		
Conservatism (CONSERVATISM) construct		0.260	0.178		1.000	1.000
CONS1_Skewness	0.842			1.000		
CONS2_Givoly_Hayn	0.077					
CONS3_MTB	0.283					
CONS4_Basu	−0.024					
CONS5_abs_earn_rev	0.431					
CONS6_Cano_Nunez	−0.292					

(*PERCEIVED_EQ*); next, we discuss the validity of four earnings properties: persistence (*PERSISTENCE*), accruals quality (*ACCRUALS_QUALITY*), earnings smoothing (*SMOOTH*), and conservatism (*CONSERVATISM*).

13.4.2.1 Validity of the Dependent Variable

First, the indicator *V_RELEV1_Book_v_coeff* exhibits a high, negative loading for the original model. This value indicates a strong relationship between the latent variable and the indicator, but its sign is the opposite of what we expected. For the indicators to be positively related to earnings quality, we changed the computation of *V_RELEV1_Book_v_coeff*, calculating it as the coefficient for book value in the value relevance model multiplied by -1. Hence, all the further results from the PLS estimation, for both the measurement and the structural model, are derived from taking this additive inverse for *V_RELEV1_Book_v_coeff*.

In the original model, there are three indicators with values below 0.4: *PERC_EQ3_RELEV_Book_v_coeff* and *PERC_EQ5_RELEV_R2*. Additionally, the proxy of the R^2 for the earnings response coefficient (*PERC_EQ2_ERC_R2*) yields a value that only slightly exceeds 0.4. After the depurative process, we delete these three indicators because their inclusion affects the construct's reliability and validity. In other words, neither the R^2 from the two models nor the coefficient for the book value of value relevance of accounting information is sufficiently correlated with the common, aggregated representation of the extent of earnings quality as perceived by investors. In fact, in this original situation, the low correlation of these indicators with the construct means that the aggregated measure is not representative of all of its indicators (composite reliability index = 0.641) and that those indicators are not able to explain a sufficient amount of the behavior of perceived earnings quality (AVE = 0.288).

The former three indicators were therefore removed from the model, leaving only two indicators in the final model: *PERC_EQ1_ERC_coeff* and *PERC_EQ4_RELEV_Earn_coeff*, both considering the earnings coefficient for the estimation models. In the final situation, the coefficient for the ERC model exceeds the minimum value for loadings of 0.7. With respect to the coefficient for the value relevance model, this indicator is slightly below 0.7. However, we decided to maintain this indicator given that the metrics for the reliability of the construct reach the minimum values (composite reliability = 0.737; AVE = 0.588).

13.4.2.2 Persistence Measurement Validity

The results shown in Table 13.2 (original situation) indicate no evidence of problems in most of the persistence indicators. There are two indicators with loadings above 0.7: *PERS1_earn_coeff* (loading = 0.862) and *PERS3_disagg_coeff* (loading = 0.761). Additionally, two of the indicators show loadings between 0.4 and 0.7 (*PERS2_earn_R2* (loading = 0.690) and *PERS4_disagg_R2* (loading = 0.517)). We must evaluate whether these indicators affect construct reliability and validity to decide whether they should be retained in or removed from the model.

After the iterative depurative process, the three indicators with loadings below 0.4 in the original model (*PRED7_var_earn*, *PERS5_CFO_coeff*, and *PERS6_CFO_R2*) were deleted. With respect to *PERS2_earn_R2* and *PERS4_disagg_R2*, although the loadings remained below 0.7 after the depuration, we kept them because both construct reliability (composite reliability index = 0.821) and validity (AVE = 0.544) met the thresholds.

13.4.2.3 Accruals Quality Measurement Validity

In broad terms, we can observe in the original situation in Table 13.2 for the construct of *ACCRUALS_QUALITY* that most of the indicators represent the same theoretical concept, as evidenced by the high magnitudes of the indicator loadings. Two of the indicators, however (*AQ5_Dechow_Dichev* and *AQ6_Mc_Nichols*), do not meet the threshold to be individually considered good representations of the concept they measure, as they have loadings below 0.4 (0.158 and 0.164, respectively). This result is in line with previous comments regarding the different approaches of the models by Dechow and Dichev (2002) and McNichols (2002). In this sense, we want to highlight that these concepts have been traditionally considered as measuring the same concept of accruals quality in prior literature, being used as alternative proxies of any of the other models. According to the results from the PLS validation process, these two measures do not represent the same concept of accruals quality, and one should be cautious when using them as alternatives to the other proxies because they do not actually measure the same concept. Regarding the aggregate representation of *ACCRUALS_QUALITY*, even after these two indicators are deleted, the results support the validity of the latent variable, as shown by a high composite reliability index (0.875). However, the fact that these two indicators do not measure the same concept means that, aggregately, the indicators (if all are kept) are not able to explain half of the variance of accruals quality (AVE = 03,483).

After the depuration of the model, *AQ5_Dechow_Dichev* and *AQ6_Mc_Nichols* were deleted, slightly increasing the construct reliability (0.915) and yielding acceptable levels for the AVE (0.614).

13.4.2.4 Earnings Smoothing Measurement Validity

We continue with the analysis of measurement validity for the accounting properties of earnings with the latent variable representing earnings smoothing (*SMOOTH*). The results show that the two proxies used in prior literature do represent the same theoretical concept. This is evidenced by the high indicator loadings (even exceeding 0.8), as well as the values for composite reliability (0.879) and average variance extracted (0.785). After the model depuration, both indicators remained, with no significant changes in the construct reliability or validity.

13.4.2.5 Conservatism Measurement Validity

We conclude the analysis of measurement validity for the accounting properties of earnings with the latent variable representing the extent of conservatism (*CONSERVATISM*). The results for the measurement validity of *CONSERVATISM* demonstrate the existence of problems in empirically representing this theoretical concept. First, the results reported in the original situation for the *CONSERVATISM* construct in Table 13.2 indicate that the different proxies used in prior literature to measure conservatism do not truly represent a single, common concept. In fact, even at the individual indicator level, we can observe how most of the proxies have loadings that are low, even negative in some cases. The only exception is *CONS3_Skew*, with an acceptable loading magnitude (0.842). These results provide empirical evidence that the proxies of conservatism do not measure the same concept. We have to indicate, however, that our *CONS1_Basu* measure is estimated on a time-series basis, which can affect the validity of these indicators, as prior literature documents problems with the time-series estimation of these metrics (Artiach & Clarkson, 2011; Cano-Rodríguez & Nunez-Nickel, 2015; Givoly et al., 2007; Ryan, 2006; Wang et al., 2009).

Our results, then, empirically confirm the theoretical concerns that the research on conservatism has not been able to find a proper way of measuring it. In fact, prior literature highlights the low correlations between the different empirical measures of conservatism (Givoly et al., 2007; Ryan, 2006; Wang et al., 2009). Proxies in conservatism research have focused only on single aspects of conservatism, and this focus does not provide an accurate assessment of the overall extent of conservatism, especially when such aspects are not independent of each other (Givoly et al., 2007).

Apart from the problem of the different theoretical views of conservatism, the literature also points out that the lack of positive associations between the proxies of conservatism is due to the existence of measurement errors in the estimation of the variables, such as the omission of variables or the difficulties in setting a correct time window (Roychowdhury & Watts, 2007; Wang et al., 2009). In summary, the results for indicator loadings indicate that there is no group of proxies that can measure the concept individually considered. Our results are in line with those of several empirical works that evidence contradictions between the different aspects reflected by conservatism measures (Ball et al., 2000; Beaver & Ryan, 2005; Giner & Rees, 2001; Givoly et al., 2007; Roychowdhury & Watts, 2007; Wang et al., 2009).

Such heterogeneity observed in the low magnitudes of the loadings reflects that each proxy measures a different concept. These concerns are confirmed by the unacceptable values for aggregated concept valuation (composite reliability index = 0.260 and AVE = 0.178).

After we delete indicators with loadings that are too low, only one final indicator remains: *CONS3_Skew*. Throughout the iterative process, construct reliability and validity did not meet the thresholds, and we subsequently eliminated the different indicators for *CONSERVATISM*. Given that this measure is represented by a single indicator, we must be cautious about the true nature of this construct, as we cannot properly speak of “conservatism”; we can only speak of a reflection of a specific aspect of conservative accounting practices (in this case, for *CONS3_Skew*, the observation of greater skewness in the distribution of earnings). Then, from this point on in our study, when we talk about conservatism, we consider this specific aspect.

In summary, the results of the validation of individual proxies demonstrate the claimed lack of validity of the measures to reflect the extent of conservatism. Each proxy measures different concepts. Consequently, the main conclusion we can extract from empirical evidence is that conservatism cannot be considered a single theoretical concept measured with several proxies; rather, it is represented by different aspects denoting conservative practices in accounting recognition.

13.4.2.6 Analysis of Discriminant Validity

Discriminant validity analysis empirically tests whether different latent variables actually represent different or the same theoretical concept; that is, if concepts that are empirically represented are distinguishable.

To test discriminant validity, we estimate Heterotrait-Monotrait (HTMT, hereafter) and HTMT2 (Roemer et al., 2021). To be considered acceptable, the value of HTMT should not exceed 0.9 (less restrictive) or 0.85 (more conservative) (Roemer et al., 2021). The classical HTMT criterion considers arithmetic mean values (Henseler et al., 2015), whereas new versions of this criterion (MTMT2) improve its calculation by considering geometric mean values (Roemer et al., 2021). We present in Table 13.3 each pair of variables (presented in matrix form): The first one (at the top) refers to the results for HTMT in its classical version, whereas the second one (below, written into square brackets []) presents the HTMT2.

Table 13.3 Discriminant validity. HTMT and HTMT2 criterion

	ACCRUALS_ QUALITY	*CONSERVATISM*	*PERCEIVED_EQ*	*PERSISTENCE*
CONSERVATISM	0.0221			
	[0.0221]			
PERCEIVED_EQ	0.0752	0.1260		
	[0.0684]	[0.1245]		
PERSISTENCE	0.0339	0.0445	0.2246	
	[0.0301]	[0.0446]	[0.2175]	
SMOOTH	0.0667	0.1107	0.2029	0.1159
	[0.0670	[0.1104]	[0.1734]	[0.0602]

These results are presented only for the final model, with depurated indicators in the construct measurement validity assessment.

After the iterative process, the results for all the properties yield acceptable values for both HTMT and HTMT2, which are, by and large, far from even 0.85. In conclusion, the results for discriminant validity indicate that the facets of earnings quality are different from each other because they represent different concepts.

13.4.3 Structural Model Valuation

After assessing the validity of the measurement model, we present the results for the evaluation of the structural model. This assessment indicates whether the properties of earnings quality explain the expected outcomes for earnings quality in terms of investor responsiveness to accounting information. To do so, we analyze the in-sample and out-of-sample power of the model, also following the step-by-step procedure suggested by Hair et al. (2020).

The first step is to check the absence of collinearity concerns. In this regard, we obtain the VIF values for the explanatory variables *ACCRUALS_QUALITY* (VIF = 1.002), *PERSISTENCE* (VIF = 1.011), *CONSERVATISM* (VIF = 1.01), and *SMOOTH* (VIF = 1.019). Given that all of them have VIF values below the threshold of 5, we can confirm the absence of collinearity.

Next, PLS offers tests of R^2, f^2, and Q^2. R^2 and f^2 analyze the in-sample predictive power of the model, whereas Q^2 indicates the out-of-sample predictive power. The results for these tests are shown in Table 13.4.

In Table 13.5, we can observe how the consideration of a single facet of earnings quality in the model has an in-sample power of approximately 0.2%—0.5%, as indicated by the adjusted R^2. The only exceptions are *PERSISTENCE* and *SMOOTH*, which show similar, higher levels of estimation power (1.40% and 1.20%, respectively). For the model with all latent variables, the estimation power is 2.80%. Henceforth, the reported values for the estimation power are not very high. In line with these

Table 13.4 Structural model valuation. R-Square and Q-Square

	Adjusted R^2	f^2 *(effect size)*	Q^2
Complete	0.028		0.016
PERSISTENCE	0.014	0.011	0.008
ACCRUALS_QUALITY	0.002	0.001	0.001
SMOOTHING	0.012	0.008	0.007
CONSERVATISM	0.005	0.004	0.003

Table 13.5 Magnitude and significance of the relationships

	Coefficient	St Dev	*t*-statistics	*p*-value	C.I. 5%	C.I. 95%	Hypothesis confirmation
PERSISTENCE	0.106	0.004	27.101	0.000	0.099	0.112	Supported
ACCRUALS_ QUALITY	0.036	0.003	10.416	0.000	0.031	0.042	Supported
SMOOTHING	−0.091	0.004	25.919	0.000	−0.097	-0.085	Rejected
CONSERVATISM	0.059	0.004	16.766	0.000	0.053	0.065	Supported

Note St Dev is the standard deviation; and C.I. is the Confidence Interval for hypotheses testing

low values of R^2, for effect size, f^2 values show a low value, ranging from 0.001 (*ACCRUALS_QUALITY*) to 0.011 (*PERSISTENCE*). Considering that the exogenous variables are determinants of earnings quality, and the endogenous variable is the response of earnings quality information perceived by users (equity investors), a future debate is needed regarding whether the consideration of the outcomes of earnings quality reflects an appropriate empirical representation of the earnings quality concept. Actually, other previous studies have already called the attention on the loose of informativeness of earnings (Dechow, 1994; Dechow et al., 2014; Ewert & Wagenhofer, 2015; Karuna, 2019; Sloan, 1996; Thinggaard & Damkier, 2008). Some of the alleged reasons are that earnings are usually available for investors untimely, making it less relevant for them (Caylor et al., 2007; Dechow et al., 2014; Karuna, 2019; Thinggaard & Damkier, 2008), as well as the bias introduced in earnings information (Dechow et al., 2014; Ewert & Wagenhofer, 2015). Other authors also justify it because of the inability of reported earnings to incorporate certain issues such as the intangibles, research and development, and special items (Ciftci, 2010; Karuna, 2019). This theoretical reasoning is also reflected in the empirical studies analyzing the value relevance of earnings, where the explanatory power (adjusted R^2) also shows very low values, even below 10% (to cite some examples, see: Bandyopadhyay et al., 2010; Caylor et al., 2007; Ciftci, 2010; Dechow, 1994; DeFond & Park, 2001; Tucker & Zarowin, 2006). Thus, despite our analysis showing a low explanatory power, it is not unusual when considering the perceived relevance of earnings information.

The out-of-sample estimation power in earnings quality measurement can be observed by analyzing the values for Q^2. These values, calculated as one minus the sum of the squared errors divided into the sum of squared residuals, consider the estimation error in the PLS Path Modeling. The closer this value is to one, the lower the error generated in the estimation. In Table 13.5, it is noteworthy how properties have low values for Q^2 (in a range of 0.001 to 0.003), except for *PERSISTENCE* and *SMOOTH*, which exhibit considerably higher out-of-sample predictive power than the rest of the properties. When we include all the properties, Q^2 is 0.016, which keeps on showing a low value.

In the second step, we check the sign, magnitude, and statistical significance of each coefficient from the latent variables of the accounting properties to explain the perception of earnings quality in Table 13.5.

Table 13.5 shows that all the properties are statistically significant in explaining the perception of earnings quality. Regarding the hypotheses, results confirm, as expected, the positive relationship between both persistence (H1) and accruals quality (H2) with perceived EQ. These results are in line with the wide agreement in prior literature that these two properties are valuable for investors, who can make better investment decisions if accounting information is persistent and reliable (good accruals quality).

About earnings smoothing, our results do not confirm that smoothing enhances perceived EQ, but that it is negatively associated with earnings quality. This can be explained because the possible increase in the predictive ability of earnings which is attributed to earnings smoothing (potentially increasing perceived usefulness for investors) happens at the expense of the reliability of earnings. The reason is that earnings smoothing may be due to earnings manipulation strategies, rather than a real signal of the usual activity of the company (Chua et al., 2012; Dechow et al., 2010; Ewert & Wagenhofer, 2015; Schipper & Vincent, 2003), thereby introducing biased information for investors (Ewert & Wagenhofer, 2015). Actually, stockholders' reaction to a stable growth in performance creates an incentive for managers to smooth earnings (Myers et al., 2007): companies that exhibit a stable history of improvements in their performance are usually rewarded with abnormally high returns, whereas companies that report too volatile earnings get usually abnormally low returns. Apart from that, managers also have incentives to show smoothed earnings when they are paid with stock options based on the performance of the company, preventing them from earning less when performance is weak (Grant et al., 2009). In short, when earnings smoothing is linked to manipulation, the link between accounting and true economic performance is weaker, increasing earnings opacity and, hence, having adverse effects on the market (Bhattacharya et al., 2003) and eliminating or reducing the information content of earnings (Mayberry et al., 2015). For smoothed earnings to be actually useful for investors, they should arise from usual activity (Ben-Hsien & De-Hsien, 2004; Kothari et al., 2005; Schipper & Vincent, 2003), so that investors perceive that smoothed earnings imply higher EQ (Barton et al., 2010). Otherwise, smoothing is not associated with long-term higher market returns (Lilien et al., 2020) or even lower valuation weight in the market (Lapointe-Antunes et al., 2006). Hence, that negative sign has a theoretical justification.

Lastly, about conservatism, results show that conservatism improves the utility of reported earnings, thus confirming H4. Hence, despite the open debate in prior literature about the pros and cons of conservatism as a property that represents EQ, there is empirical evidence that conservatism is generally used as a protective mechanism for investors, and they perceive it as a desirable property for reported earnings.

However, it is surprising that, although accruals quality is the most commonly analyzed property of EQ (Licerán-Gutiérrez & Cano-Rodríguez, 2019), its coefficient is smaller than that of the rest of the properties of accounting information (thereby explaining a lower proportion of the level of earnings quality perceived by equity investors) that have been less adopted in earnings quality models, such as smoothing or persistence.

Finally, we also run a PLS-predict procedure to reinforce the conclusions of the out-of-sample predictive power of the model. The results yield a value for Q^2_predict of 0.028; hence, because a positive value implies that the prediction error of the PLS-SEM results is smaller than the prediction error of simply using the mean values (Evermann & Tate, 2016; Shmueli et al., 2016, 2019), then our model estimated with PLS offers better predictive performance. In any case, to analyze the strength of the prediction, we compare the results of the errors from PLS-PM with the ones of LM (Evermann & Tate, 2016; Shmueli et al., 2016, 2019) for the two indicators of the dependent variable, *PERCEIVED_EQ*, and check that the error is lower in PLS-PM for *PERC_EQ4_RELEV_Earn_coeff*, but it is higher for *PERC_EQ1_ERC_coeff*. Then, the condition that errors in PLS-PM are lower than in LM is true for half of the indicators, concluding that the model has a medium out-of-sample predictive power.

In conclusion, taking together the results for R^2, f^2, and Q^2, we can conclude that both in-sample and out-of-sample power are low when analyzing how determinants of *EQ* explain *PERCEIVED_EQ*, even if we include all of the properties that define *EQ*. However, despite this low predictive power, there is a property that shows considerably better power to explain the extent of earnings quality perceived by equity investors; this property is *PERSISTENCE*. This result is in line with prior literature on users of financial information that has obtained empirical evidence of a perception of the persistence of earnings as the most relevant property of accounting information (Tucker & Zarowin, 2006). Notwithstanding its higher predictive value, persistence is surprisingly not usually considered a representative property for earnings quality. Other properties are more widely adopted in prior literature as appropriate representations of earnings quality, such as accruals quality or conservatism (Licerán-Gutiérrez & Cano-Rodríguez, 2019).

13.4.4 Additional Analyses

To ensure that our results are robust, we present in this subsection a brief comment on several robustness tests.

First, given that our model has estimated the indicators on a time-series basis, it is advisable to check time-series invariance; that is, the absence of autocorrelation effects. To this end, we have run the Lagrange-Multiplier test, in which, through a chi-square distribution, the null hypothesis of the absence of autocorrelation effects is tested, both for first and second order. The results yield p-values above 0.1 both for the first order (p-value = 0.802) and the second order (p-value = 0.798). Because we cannot reject the null hypothesis, we can confirm the absence of autocorrelation effects.

Second, we check whether the model presents endogeneity problems. In cases of endogeneity, the explanatory variable is correlated with the residuals in the estimated model, thereby violating conditions for OLS estimators to be unbiased and compromising the generalizability of research findings (Ullah et al., 2021). Then, according to the definition, we check whether there exists any statistically significant correlation between the residuals of *PERCEIVED_EQ* and the four explanatory variables in our model. Results show that the magnitude of the correlation is 0 in all cases, and, in any case, none of them are statistically significant, as evidenced by p-values clearly above even 0.1 for the correlation of the residuals with *ACCRUALS_QUALITY* (0.9999), *PERCEIVED_EQ* (0.9995), *CONSERVATISM* (0.9998), and *SMOOTH* (0.9996). Additionally, we test for potential dynamic endogeneity, observing whether past values of the dependent variable (L.*PERCEIVED_EQ*, where the time set is 1 month) affect current values, including it as a control variable (Ullah et al., 2021). Results show that this lagged variable is not statistically significant (p-value = 0.200), thereby indicating that past values do not affect current outcomes. Finally, we also check whether the explanatory variables significantly define the current perception of earnings quality but not such perception in the following period (F.*PERCEIVED_EQ*, where the time set is 1 month). The results show, as expected, that whereas the coefficients for the four properties significantly explain the current perception of earnings quality, they are not statistically significant to explain perceived earnings quality one month later (p-values for *ACCRUALS_QUALITY*, *PERSISTENCE*, *CONSERVATISM*, and *SMOOTH* are, respectively: 0.556, 0.367, 0.781, and 0.156). Thus, we can conclude that there is no evidence of endogeneity, neither general nor dynamic, in the definition of the model.

Finally, as suggested by Sarstedt et al. (2020), we also consider it interesting observing the potential unobserved heterogeneity in our data. To this end, we run the Finite-Mixture PLS (FIMIX-PLS) procedure, which can detect heterogeneity. Our results are inconclusive because fit indices are better whenever the number of segments is increased, but the segment sizes are not sufficient. Furthermore, if we continue increasing the number of segments, the fit indices always point to the highest number of segments. This leads us to conclude that our sample does not suffer from unobserved heterogeneity, and it is not necessary to cluster the sample in segments to get a better explanatory power of the proposed model.

13.4.5 Discussion of the Results

In this subsection, we briefly summarize a discussion of the results. To begin with, a validation of the proxies used in prior literature to measure each of these properties can be performed to select only the properties that correctly and empirically represent the theoretical facet of earnings quality they aim to measure. This way, the application of a PLS model can help solve the traditional proxy selection problem about earnings quality that is so widely discussed in prior literature (Dechow et al., 2010; Ewert & Wagenhofer, 2011; Leuz & Wysocki, 2016; Licerán-Gutiérrez & Cano-Rodríguez, 2019).

Second, while we find no surprising results about the appropriateness of accruals quality measurement, the most traditional and widely used property associated with earnings quality, despite this appropriate measurement, the fact is that it is the property with a lesser incidence on perceived earnings quality by investors. On the other hand, other properties that are less considered in the literature, such as persistence or earnings smoothing, are proven to correctly measure earnings quality, yet they show the highest incidence of the perception of earnings quality.

Third, in line with the discussions and criticisms of the different proxies used in prior literature for conservatism, there is evidence of scant connections between them (Givoly et al., 2007; Ryan, 2006; Wang et al., 2009), as shown by the fact that the proxies are not measuring the same, common concept (if kept together, composite reliability and AVE yield inacceptable values). In any case, we want to highlight that this does not mean that the measures are incorrect, but that they are not representative, aggregately, of the same concept, but rather of different aspects that are indicative of a conservative attitude by managers when disclosing accounting information. This opinion of conservatism proxies capturing different aspects is in line with Givoly et al. (2007), and with a group of authors whose studies show contradictions between conservatism proxies (Ball et al., 2000; Beaver & Ryan, 2005; Giner & Rees, 2001; Givoly et al., 2007; Roychowdhury & Watts, 2007; Wang et al., 2009).

Finally, there is a need to connect the theoretical understanding that earnings quality is explained by different aspects with the empirical research design, given that, as shown by our results, the explanatory power when considering the simultaneous effect of the different properties of earnings increases both the in-sample and out-of-sample predictive ability of the model. This fact, which is improved by the use of methods such as PLS, confirms the intuition of Leuz and Wysocki (2016) that structural equation modeling is suitable for measuring earnings quality.

13.5 Conclusions, Limitations, and Future Research Lines

Earnings quality is a pervasive topic in empirical accounting finance, but researchers have used many different proxies for representing EQ. Those proxies present several statistical estimation problems (Leuz & Wysocki, 2016) and they capture different aspects of earnings quality, making it difficult to assess which EQ characteristics are more relevant for investors. In addition, the extant literature reveals the existence of weak or negative correlations among proxies measuring the same concept, which raises doubts about whether those proxies all really capture the desired EQ characteristic. In this paper, we use PLS to assess whether each proxy appropriately measures its associated EQ characteristic. The results show that the empirical proxies of accruals quality, smoothing, and persistence all represent the same underlying concept, whereas the proxies for conservatism fail to represent a single common theoretical concept. Given the extended use of these two proxies in prior literature as alternative measures of accruals quality, researchers should be cautious when concluding that the concept to which these two proxies refer is equivalent to the concept to which other proxies refer.

Apart from the validity assessment for the measurement, PLS also analyzes the predictive power of the model. In our model, we relate EQ properties with the EQ perceived by equity investors. Our results show that, although EQ properties explain only a small portion of the variance of perceived EQ, some properties exhibit greater explanatory power than others: Persistence of earnings shows the strongest explanatory power in terms of both in-sample (adjusted R^2) and out-of-sample (Q^2) predictive power. Given that prior literature has focused less on this property as representative of earnings quality than on other properties, such as accruals quality or conservatism, our study offers new insights for earnings quality measurement in future research. Considering the higher predictive power and appropriate validity measurement of persistence, we suggest that this property be considered more frequently in earnings quality studies. On the other hand, although accruals quality results show that this property is best measured by its indicators, it is less important to explain the level of earnings quality perceived by equity investors. We consider that future studies of earnings quality should continue to consider accruals quality but correct the weight given to this property to explain the outcomes of earnings quality.

Our study must be interpreted considering that it presents several limitations. To apply the PLS method, we required that all the indicators were measured at the firm level. Despite many of them usually being estimated in a firm-specific way in prior literature, there are various indicators whose typical estimation is not made at this level. One example would be Basu's model coefficients (Basu 1997), for which we have used a time-series estimation, despite previous literature warning about the potential problems associated with this type of estimation for this measure. Thus, we cannot determine if the low validity observed for this measure is produced by a real lack of validity or by the estimation method. Additionally, we were unable to use some additional indicators, such as the C-Score (Khan & Watts, 2009) or the Ball and Shivakumar (2005) measure for conservatism, because their inclusion in our study would produce serious attrition problems because of the loss of observations.

A second set of limitations related to our empirical model is produced by the fact that this is a first and exploratory study. Because of the exploratory nature of our study, we included only those earnings properties that are commonly used in previous literature (namely, persistence, accruals quality, smoothness, and conservatism), as well as the empirical proxies most commonly used to represent them. There are, however, other earnings properties that would arguably affect earnings quality, such as comparability, timeliness, understandability, etc., which were not included in our model, mainly because of the lack of research and empirical indicators for representing them. Another limitation is the lack of control variables in our study. Given that our aim was to focus on the validity of the measure of the different earnings properties, we did not include other variables that may influence equity investors' perception of earnings quality. This lack of additional control variables can be the cause of the low explanatory power of the model.

In future research, we aim to use the PLS technique in further research to obtain more accurate conclusions about earnings quality, with higher predictive power and a lower reduction of the bias in estimated parameters. In particular, further research can be oriented towards the application of PLS to estimate the effects of earnings quality on other dependent variables, such as tax effect, investment efficiency, firm performance, cost of equity, or cost of debt. This research can be used to provide more robust evidence of the advantages of PLS in terms of higher predictive power and lower estimation bias, as well as to revise the validity of the conclusions from previous empirical studies that focus on a single facet of earnings quality. Additionally, this study contributes to a validation of the main proxies used in prior literature to measure earnings quality using a systematic process that has been widely employed in other fields of research, such as management accounting, marketing, or organizational behavior, and can also be applied in financial accounting issues such as earnings quality measurement. Thus, we could apply the validation scale process in other fields of finance and accounting. Furthermore, there is a chance for earnings quality research to work towards the improvement of conservatism measurement. First, it is necessary to make clear what to understand as conservatism. In this sense, it would be interesting to join the efforts of researchers and accounting standards regulators, towards a common agreement. Second, once the concept is clear, future research lines could be orientated to the development of new measures of conservatism that correctly reflect the theoretical concept from an empirical point of view. Finally, this quantitative analysis could be enriched by a complementary qualitative analysis considering the opinions of experts and practitioners such as auditors, managers, investors, or regulators. This would help to deepen the importance given by the different users of accounting information, comparing it with what quantitative analysis indicates.

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Appendix 1: Estimation Models

In this Appendix, we present a detailed description of the process of calculating the proxies (empirical indicators) that are more commonly used in the earnings quality literature to measure the different facets of earnings quality that are not directly observable (latent variable, construct). The indicators are sorted according to the latent variable to which they are related. All estimated indicators will be winsorized at 1%.

Construct 1: Earnings quality perceived by equity investors (*PERCEIVED_EQ*)

All of the following indicators are calculated for each firm following a longitudinal approach using a 5-year rolling window:

1. ***ERC1_coeff*** and ***ERC2_R2:*** Coefficient (β_1) and adjusted R^2 (respectively) from the earnings response coefficient (ERC) model:

$$Returns_t = \beta_0 + \beta_1 \frac{EPS_t}{P_{t-1}} + \varepsilon_t$$

2. ***V_RELEV1_Book_v_coeff, V_RELEV2_Earn_coeff*** and ***V_RELEV3_R2:*** Coefficients (β_1 and β_2) and adjusted R^2 (respectively) from the value relevance of the earnings model (proportion of price explained by earnings):

$$Price_t = \beta_0 + \beta_1 BookValueperShare_t + \beta_2 EPS_t + \varepsilon_t$$

For all of the aforementioned equations, the variables are defined as follows:
$Returns_t$ = Returns from CRSP (Ret).
EPS_t = Earnings Per Share (Basic) including Extraordinary Items (#53).
$Price_t$ = Price from CRSP (Prc).
P_{t-1} = Price from CRSP (Prc).
Book Value per Share$_t$ = Book Value Per Share from CRSP (Bkvlps).

Construct 2: Persistence *(PERSISTENCE)*

All of the following indicators are calculated for each firm following a longitudinal approach using a 5-year rolling window:

1. ***PERS1_earn_coeff*** and ***PERS2_earn_R2:*** Slope coefficient (β_1) and adjusted R^2 (respectively) from the regression of earnings persistence:

$$Earnings_{t+1} = \beta_0 + \beta_2 Earnings_t + \varepsilon_t$$

2. ***PERS3_disagg_coeff*** and ***PERS4_disagg_R2:*** Slope coefficient (β_1) and adjusted R^2 (respectively) from the regression of disaggregated earnings persistence:

$$Earnings_{t+1} = \beta_0 + \beta_2 CFO_t + \beta_2 TA_t + \varepsilon_t$$

3. ***PERS5_CFO_coeff*** and ***PERS6_CFO_R2:*** Slope coefficient (β_1) and adjusted R^2 (respectively) from the regression of cash flow persistence on earnings:

$$CFO_{t+1} = \beta_0 + \beta_2 Earnings_t + \varepsilon_t$$

4. ***PERS7_var_earn:*** Variance of Earnings Before Extraordinary Items (#18) multiplied by –1 ().

For all of the aforementioned equations, the variables are defined as follows:

$Earnings_{t+1}$ = Earnings Before Extraordinary Items (#18) in the following fiscal year.

$Earnings_t$ = Earnings Before Extraordinary Items (#18).

CFO_t = Net Operating Cash Flows (#308).

TA_t = Total accruals = $\Delta CA_t - \Delta CL_t - \Delta Cash_t + \Delta STD_t - Dep_t$.

- ΔCA_t = Change in current assets (#4) from the previous year to the current year.
- ΔCL_t = Change in current liabilities (#5) from the previous year to the current year.
- $\Delta Cash_t$ = Change in cash and cash equivalents (#1) from the previous year to the current year.
- ΔSTD_t = Change in debt included in current liabilities (#34) from the previous year to the current year.
- Dep_t = Depreciation and Amortization (Income Statement) (#14)

CFO_{t+1} = Net Operating Cash Flows (#308) in the following fiscal year.

Construct 3: Accruals Quality (*ACCRUALS_QUALITY*)

All of the following indicators are calculated as 1—absolute value of the residuals from the following regressions, estimated by year-sector. For the sectors, we considered the Fama and French classification of 45 sectors:

1. ***AQ1_Dangelo***: Residuals from DeAngelo (1986) model:

$$TA_t = TA_{t-1} + \varepsilon_t$$

2. ***AQ2_Industry:*** Residual from the Industry model by Dechow and Sloan (1991):

$$TA_t = \alpha_1 + \alpha_2 Median(TA_t) + \varepsilon_t$$

3. ***AQ3_Jones:*** Residual from Jones (1991) model:

$$TA_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2 \Delta REV_t + \beta_3 PPE_t + \varepsilon_t$$

4. ***AQ4_Dechow_95:*** Residual from the Dechow, Sloan and Sweeney (1995) model:

$$TA_t = \beta_0 + \beta_1(1/AT_{t-1}) + \beta_2(\Delta REV_t - \Delta REC_t) + \beta_3 PPE_t + \varepsilon_t$$

5. ***AQ5_Dechow_Dichev:*** Residual from the Dechow and Dichev (2002) model:

$$\Delta WC_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \varepsilon_t$$

6. ***AQ6_Mc_Nichols:*** Residual from the McNichols (2002) model:

$$\Delta WC_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \beta_5 PPE_t + \varepsilon_t$$

7. ***AQ7_Kothari:*** Residual from the Kothari, Leone and Wasley (2005) model:

$$TA_t = \alpha_0 + \beta_1(1/AT_{t-1}) + \beta_2(\Delta REV_t - \Delta REC_t) + \beta_3 PPE_t + \beta_4 \mathrm{ROA}_{t-1} + \varepsilon_t$$

8. ***AQ8_Ball_Shivakumar:*** Residual from the Ball and Shivakumar (2006) model, estimated by year:

$$\mathrm{TA}_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \beta_5 PPE_t + \varepsilon_t$$

9. ***AQ9_Ball_Shivakumar:*** Residual from the Ball and Shivakumar (2006) model, estimated by industry (sectors by Fama and French (1997)):

$$\mathrm{TA}_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \beta_5 PPE_t + \varepsilon_t$$

For all of the aforementioned equations, the variables are defined as follows:

TA_t = Total accruals (Previously calculated).

Median (TA_t) is the median value of total accruals (TA_t) for firms in with same 2-digit SIC Code.

TA_{t-1} is total accruals (TA_t) at the beginning of the fiscal year.

AT_{t-1} = Total assets (#6) at the beginning of the fiscal year.

ΔREV_t = Change in net sales (#12) from the previous year to the current year.

PPE_t = PPE total gross (#7).

ΔREC_t = Change in net accounts receivable (#2) from the previous year to the current year.

ΔCFO_t = Change in Net Operating Cash Flows (#308) from the previous year to the current year.

ΔWCt = Working Capital variation = $\Delta AR_t + \Delta Inventory_t + \Delta AP_t + \Delta TP_t + \Delta Other\ assets_t$.

- ΔAR_t = Change (increase) in accounts receivable (#302).
- $\Delta Inventory_t$ = Change (increase) in inventories (#303).

- ΔAP_t = Change (decrease) in accounts payable (#304).
- ΔTP_t = Change (decrease) in taxes payable (#305).
- $\Delta Other\ assets_t$ = Change (increase) in other assets net (#307).

CFO_{t-1} = Net Operating Cash Flows (#308) at the beginning of the fiscal year.
CFO_t = Net Operating Cash Flows (#308).
CFO_{t+1} = Net Operating Cash Flows (#308) in the following fiscal year.
BTM_t = Book-to-Market ratio = *BVt/MVt.*

- BV_t is book value of common equity (#60)
- MV_t is market value of common equity = Number of common shares outstanding (#25) x Price close of fiscal year (#199).

ROA_{t-1} = Change in the ratio of Income Before Extraordinary Items (#18) / total assets at the beginning of the fiscal year (#6).
$DCFO_t$ = Dummy variable = 1 if $\Delta CFO_t < 0$, = 0 otherwise.
NOTE: All variables except BTM and ROA are deflated by total assets at the beginning of the fiscal year, AT_{t-1} (#6).

Construct 4: Earnings Smoothing (*SMOOTH*)

All of the following indicators are calculated for each firm following a longitudinal approach using a 5-year rolling window:

1. ***SMOOTH1_dev_earn_cfo:*** Ratio of standard deviation of earnings before extraordinary items (#18) over standard deviation of net operating cash flows (#308).
2. ***SMOOTH2_corr_accr_cfo:*** Correlation between total accruals (TA_t) (calculated as previously indicated) and net operating cash flows (#308).

Construct 5: Conservatism (*CONSERVATISM*).[1]

All of the following indicators are calculated for each firm following a longitudinal approach using a 5-year rolling window:

1. ***CONS1_Skewness:*** Skewness of Earnings Before Extraordinary Items (#18) by Givoly and Hayn (2000).
2. ***CONS2_Neg_Accr:*** Large negative accruals by Givoly and Hayn (2000): Sum of total accruals (TA_t) (previously calculated).
3. ***CONS3_MTB:*** Market-to-Book ratio: Value of MTB_t, previously calculated.
4. ***CONS4_Basu:*** Slope coefficient (β_1) from the model of differential timeliness based on returns by Basu (1997):

$$\frac{EPS_t}{P_{t-1}} = \alpha_0 + \alpha_1 DR_t + \beta_0 R_t + \beta_1 DR_t \cdot R_t + \varepsilon_t$$

[1] There are two additional popular measures for conservatism in previous literature that are not included in our analysis: the metric from Ball and Shivakumar's (2005) model and the C-Score from Khan and Watts' (2009) model. The reason for excluding these metrics is their strong data requirements, which would cause an attrition bias problem in our sample.

5. ***CONS5_abs_ear_rev:*** Absolute value of the slope coefficient (β_1) from the model of mean earnings reversal by Basu (1997):

$$\frac{\Delta X_t}{P_{t-1}} = \alpha_0 + \alpha_1 D_t + \beta_0 \frac{\Delta X_{t-1}}{P_{t-2}} + \beta_1 D_t \frac{\Delta X_{t-1}}{P_{t-2}} + \varepsilon_t$$

6. ***CONS6_Cano_Nunez:*** The difference between the slope coefficient for negative and positive returns (β_2 - β_1) from the model of differential timeliness based on the differential effect of positive and negative returns by Cano-Rodríguez and Nunez-Nickel (2015).

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Chapter 14
Importance-Performance Map Analysis of Capital Structure Using PLS-SEM: Evidence from Non-financial Sector

Umme Habiba Rehman, Ambreen Rehman, Zeeshan Ahmed, Muhammad Maaz Sajid, and Fasih Ur Rehman

Abstract This study aims to identify the most important determinant that affects the capital structure decision of non-financial firms listed on the Pakistan Stock exchange (PSX) with balanced panel data of firm, industry, and macroeconomic-specific observations for the period of 14 years (2006–2019) and variance-based regression technique of partial least square structural equation modelling (PLS-SEM). Subsequently 'Importance-Performance Map Analysis' (IPMA) was performed to determine the most important determinant of capital structure decisions for Pakistan's non-financial firms. The study illustrates the ceteris paribus interpretation that asset structure is the most important determinant of long-term debt selection in the capital structure decision for non-financial firms as such that leverage performance is increased by the amount of total effect of asset structure and cited tangibility as the most important indicator of asset structure in modelling the trend of capital structure which needs managerial attention to achieve optimal capital structure. The chapter provides prospects to financial managers and policy-makers for implementing better capital structure strategies to improve firm performance considering the importance of individual factors for the enrichment of investments and boost the economy.

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14.1 Introduction

Capital structure decision is one of the crucial tasks undertaken by financial managers predominantly in developing countries (Olarewaju, 2019), as it depicts a blend of equity and debt financing that management uses to maximize the firm's worth and enhances contribution toward economic growth (Khan & Jain, 2014). Otherwise, firms may face consequences such as increased capital cost, firm value deterioration, risk of bankruptcy, and fiscal forfeiture (Tailab, 2014). The current study aims to identify the most important determinant of capital structure by extending PLS-SEM with the additional use of important performance techniques with an enormous panel data set to elucidate trend of important exogenous dynamic in different periods for capital structure decision, hence contributing to the contemporary frame of research by not only imparting methodological advancement with the PLS-SEM procedure for secondary panel data for non-financial firms but also providing an opportunity for robust results by offering effect size for each path relationship with prediction power PLS-predict capacity, which was limited in past research.

The determinants that may influence corporate capital structure (leverage) are firm, industry, and macroeconomic-specific factors (dynamics). Firm-specific factors are fundamental internal corporate features and are within the control of corporate management (Sheikh & Qureshi, 2014). In this context, earlier research has adequately investigated the impact of imperative firm-level determinants of capital structure such as profitability, growth opportunity, and firm size, but there is still uncertainty concerning the exclusive role of firms' specific factors which depict mixed significance (Lee et al., 2020; Legesse & Guo, 2020), and in Pakistan's context (Razal et al., 2022), determining capital structure decision for firms (Lee et al., 2020).

Diverse trends of capital structure are exhibited by firms functioning in different industries as each industry exhibits particular traits according to its nature such as product type, risk level, technical variances, market barriers and performance, contribution to the economy, level of competition, and investment opportunities, which account for the heterogeneity among different industrial sectors (Ahsan et al., 2016; Ramzan & Qureshi, 2022). Macroeconomic determinants included factors that are beyond the corporate control and may impact corporate capital structure strategy through transforming opportunities and threats in an external operational business environment of the firms as they influence business cycles, and fiscal market productivities (Vo, 2017; Lee et al., 2020), and cost of capital (Panousi & Papanikolaou, 2012). Such macroeconomic uncertainties are found to significantly impact leverage trends in firms.

Hence, finance managers should be cognizant of these intrinsic and extrinsic factors that may influence capital structure decisions (Lee et al., 2020). Nevertheless, earlier research in the context of both advanced and emerging countries still underprovided an appropriate tool for financial managers and analysts to pursue optimal debt level, which may be attributed to the disparity in nature, maturity of debt and dissimilarity in macroeconomic settings in different countries. The current chapter probes the most important determinant of capital structure for non-financial firms in Pakistan's context, as non-financial sector includes both manufacturing and non-manufacturing sectors that contribute to the economy by the production of goods and services that are binding for the effective operation of the economic cycles and financial structure of the economy (Alyousfi, 2020) and also exhibits comparatively more systemic constancy as compared to the financial segment. Moreover, dynamics such as inappropriate product market policies, taxation laws, lack of investment in the workforce capabilities, lack of high-tech export-oriented industry and other regulatory reforms are major hurdles in achieving market efficiency and competition in different sectors and demand further probing for an important determinant of capital structure. In the past, a multitude of research focused on a corporate capital structure to recommend an appropriate capital strategy for firms and found the mixed influence of different firms, industries, and macroeconomic factors (Lee et al., 2017; Karapavicius & Yu, 2019; Lee et al., 2020), but research is still stagnant concerning the performance of the most important determinant in modelling the comportment of capital structure decisions. Erstwhile studies used orthodox ordinary least square regression methods for studying the nexus of capital structure and its determinants but failed to identify the most imperative determinant in this context.

The majority of erstwhile research employed ordinary least square regression (OLS) for studying archival panel data relationship between determinants and capital structure. OLS regression is a parametric method and necessitates data to be normally distributed. The precision of estimates in OLS regression is linked with predetermined assumptions that need to be met to achieve the best linear unbiased estimates (BLUE). Thus, estimates are assumed to be suboptimal if assumptions are closely met. Moreover, this pooled OLS regression often leads to series of other regression techniques such as fixed and random effect models to fulfil such assumptions. The existence of such hard assumptions in OLS techniques greatly demands a more robust and convenient method to analyse relationships with secondary panel data.

Recent years have witnessed a preferred use of partial least square structural equation modelling (PLS-SEM), especially in management sciences (Hair et al. 2012; Richter et al., 2019, 2019), as PLS-SEM appraises causal elucidations for composite models with several latent constructs, observed indicators and path relationships without accounting for distribution assumption for the data employed (Sarstedt et al., 2018). PLS-SEM also deals with measurement and structural model concurrently.

PLS-SEM determines the significance of the coefficient through bootstrapping technique, which is a non-parametric approach without any prerequisite regarding data distribution (Noonan & Wold, 1982; Lohmöller, 1989). The absence of a distribution assumption in PLS-SEM disregards any such expectation of optimal estimates (Ronkko et al., 2015; Ramli et al., 2018). OLS regression also offers equivalent weight to all observations with the assumption of homoscedasticity, irrespective of the degree of variation exhibited by observations in the data set, thus giving skewed and biased results (Hayes & Cai, 2007).

On the contrary, PLS-SEM quantifies individual weights of all indicators without any homoscedasticity assumption. In contrast to OLS, it analyses path relationships for single and multiple indicator loadings with an evaluation of measurement and structural models concurrently (Ramli et al., 2018). Researchers (Iacobucci et al., 2007, p. 146; Ramli et al., 2018) considered this simultaneous estimation as a more robust and statistically significant technique in reducing standard error instead of individual regression.

The use of the latent construct in PLS-SEM allows the existence of measurement error which is lacking in OLS regression (Ramli et al., 2018). Furthermore, PLS-SEM analyses several observed variables or indicators for each latent construct and determines the impact of the individual indicator, unlike OLS regression. It also evaluates construct reliability (statistical significance) and validity to explain variation in the factors and mitigate the issues of multicollinearity with redundancy complications for exogenous latent constructs. PLS-SEM could also be employed for research based on secondary data with real factual figures (Hair et al., 2018, 2019) as it demands limited information. The results are also robust (Hair et al., 2014) and do not tend to mitigate discrepancy between estimated and observed metrics of covariance, thus the chi-square model fit measure is not pertinent (Hair et al., 2019). PLS-SEM acquired edge over traditional regression methods as it gives robust results for multi-construct models with a small sample size (Hair et al., 2017), as the algorithm processes OLS regression independently for the determination of partial regression association in measurement and structural models (Sarstedt et al., 2016). In PLS-SEM the standard sample size for any given study depends on the nature of the populace (Rigdon, 2016). If there is heterogeneity in the population, the sample size should be greater to attain significance for a sampling error that is within acceptable limits (Cochran, 1977).

The significance of other model fit measures such as SRMR, which enumerate the divergence between estimated and observed covariance, is also limited, as it mainly focuses on the relationship between extrapolation and testing of theory and therefore should be substantiated accordingly (Shmueli, 2010). In this context, PLS-predict determines the predictive nature of PLS-SEM (Shmueli, 2016).

IPMA is a useful methodology in PLS-SEM that provides deep insight for appropriate managerial decisions by mapping importance and performance at the construct and indicator level equating the latent exogenous construct's total effects (including both direct and indirect effects) from the structural model on a certain endogenous construct with an average latent variable score of these constructs (Henseler et al., 2016) . The main focus is to identify an exogenous latent construct, which is highly important in shaping the behaviour of an endogenous construct (exhibiting robust total effects) but showing less performance (measure with lower values of average latent variable scores. The current chapter used importance-performance matrix (importance-performance map or impact performance map) technique to determine comparative importance (unstandardized total effect) versus performance (average scores) of latent exogenous variables in influencing capital structure decisions in non-financial firms. Thus, offers a ceteris paribus explanation for the impact of an exogenous variable on the target variable.

14.2 Theoretical Context and Literature Review

In line with irrelevance theory (Modigliani & Miller, 1958), regarding the capital structure decision, other renowned theories also proposed possible determinants of leverage configuration, such as trade-off, market timing, pecking order, and agency cost theories (Altman, 1984, 2002). In this connection, trade-off (TOT) and pecking order theories (POT) offered contradictory concepts. According to TOT, firm-specific factors such as firm size, tangibility, and profitability are positive, while growth opportunity is negatively related to leverage. TOT also emphasized that the leverage trend is related to traits displayed by different industries and macroeconomic factors, e.g. economic development and inflation are assumed to be positively associated with leverage for highly profitable firms while lending interest rates are negatively related. On the contrary, POT advocates for a negative impact of firm age, size, tangibility, profitability, and other performance measures on leverage as profitable firms choose internal incomes for financing business over other financing sources. Agency theory (Jensen & Meckling, 1976) denotes debt as an effective funding tool to mitigate agency cost as debt prevents managers or agents from prioritizing their interest; hence firms with high growth opportunities avail less debt due to information asymmetry. The market timing theory (Baker & Wurgler, 2002) rejects the notion of ideal leverage configuration and denotes market valuation (market to book ratio) as the leading cause with long-run effects. The theory describes how companies finance their capital either through debt or equity and highlighted leverage decision as a reflection of a firm's previous endeavours to issue or repurchase equity according to market opportunities, thus firms prefer issuance of equity with a high market to book ratio.

14.2.1 Firm Dynamics

Earlier research has also greatly emphasized on the firm-specific determinants for leverage decisions, such as growth opportunity, tangibility, firm age, size, and profitability (Bandyopadhyay & Barua, 2016; Matemilola et al., 2018) and found both negative (Fama & French, 2012; Yang et al., 2010) as well as positive (Espinosa et al., 2013) affiliations. Firms may be larger or smaller in size and may exhibit diverse trends for leverage structure. The larger firm employs a diversification strategy to minimize default risk, which depicts a positive association of firm size with leverage (Anwar & Sun, 2014). The current study measures latent construct firm size with proxies such as the internal logarithm of total revenue and the logarithm of the total asset.

The asset structure is also one of the fundamental determinants for studying the capital structure decision for non-financial firms due to the operational dependency of tangible assets in such firms. According to Ramli et al., (2018, 2019), reduction of agency cost can occur for a firm that carries collateralizable highly tangible assets

(Rajan & Zingales, 1995) and may lead to an increased value of the firm (Ramli et al., 2018). Studies also observed that asset structure plays a vitally important role in capital structure decisions for firms with fiscal constraints due to meagre accessible external financial resources (Almeida & Campello, 2007).

According to POT, information asymmetry indicates an inverse liaison of firm age with debt financing. As substantial relevant information is accessible for older companies that mitigate the issue of information asymmetry which encourages investors, older companies prefer equity financing rather than debt as compared to new firms. Studies in Pakistan's context also found a positive relationship between firm age and tangibility (Ahsan et al., 2016).

Growth opportunities denote performance and investment opportunities for firms, TOT suggests a negative association between leverage and growth opportunity (Touil & Mamoghli, 2020) as the latter is intangible and cannot be collateralized for debt borrowing like tangible assets. Likewise, agency theory also proposed a negative association between leverage and growth opportunity as a higher level of growth opportunities leads to agency conflicts, and the firm tends to borrow less to avoid such conflicts. In contrast to TOT and agency cost theory, pecking order theory suggests a positive relationship for the association between leverage and growth opportunity, as growth opportunity is an indication of healthy business performance, and access to finance in a competitive market is easier.

According to TOT, leverage and profitability are positively associated as profitable firms could avail more debt due to its less risky nature (Chang et al., 2009), and prefer debt in an attempt to avail tax benefit on interest payments (Sheikh & Wang, 2011). In contrast, POT signifies negative association with the notion that profitable companies prefer internal funding for financing (Qiu & La, 2010; Hergli & Teulon, 2014; Touil & Mamoghli, 2020; Lee et al., 2020).

TOT asserted a positive association between liquidity and leverage as lenders are more willing to provide loans to firms with high liquid assets due to low associated liquidity risk (Vo, 2017). According to POT, liquidity is negatively associated with leverage as highly liquid companies choose internal earnings rather than external borrowing. A high current ratio and quick ratio show that the firm is in a better position to repay all short and long-term obligations on due dates. Hence, the above enlightenment guided the derivation of the following hypotheses.

H1: Firm size has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

H2: Asset structure has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

H3: Firm Age has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

H4: Growth opportunity has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H5: Profitability has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

H6: Liquidity has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

14.2.2 Industry Dynamics

The leverage of firms varies (Smith et al., 2015), owing to particular traits of each industry (Frank & Goyal, 2009) such as requisites for technical innovation, operational cost, and risk factors and economic importance of a particular industry (De Jong et al., 2008; Wahlen et al., 2011). Firms functioning in highly technical, costly and risky industries are found to be less leveraged (Miao, 2005). According to Larry and Islam (2018), a positive association exists between industries' GDP contribution and leverage, as firms that belong to economic-oriented industries get more investment and credit incentives from policymakers. The Hirschman Herfindahl Index (HHI) is used to gauge industry concentration concerning the market share of top firms in each industry and measured with a sum of the square of the market share of firms within a given industry, where market share is a ratio of firm sale to the total sale of industry. According to MacKay and Phillips (2005), industries with higher HHI are highly leveraged in contrast to less concentrated industries with lower HHI. The firms that operate within industries with higher concentrations are usually more profitable, riskier, and of bigger size (Brander & Lewis, 1986). This shows HHI and firm leverage are positively related to each other. Hence, the above enlightenment guided the derivation of the following hypotheses:

H7: GDP contribution has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H8: HHI has a significantly positive and meaningful impact on the capital structure (leverage) of non-financial firms.

14.2.3 Macroeconomic Dynamics

According to Antoniou et al. (2005), the capital structure decisions of firms are not only affected by internal characteristics but also by the contiguous environment. The surrounding environment may affect the firm's capital structure for reasons such as the deterioration or the improvement in the state of the economy, the existence of a stock market, and the size of the banking sector. The macroeconomic factors also greatly impact the leverage configuration of firms (Lee et al., 2020) as they influence the availability of debt (Levy & Hennessy, 2007). Economic growth leads to a decline in debt funding as firms generate sufficient internal resources to fund investments

(Alyousfi, 2020). According to (Bopkin, 2009), economic growth bears positive as well as negative impacts on firm capital structure decisions.

Inflation affects capital structure in both positive and negative ways depending on the prevailing economic condition (Feldstein et al., 1978). Dewally & Shao (2014) investigated the influence of GDP growth and inflation on leverage and found a positive association (Frank & Goyal, 2009). Studies also found high inflation and GDP growth as indications of a prosperous economy that leads firms to avail more debt (Lee et al., 2020). Lending interest rates are the rates at which the banks lend short and medium-term loans. These lending rates vary according to the credibility of borrowers and the purpose of funding. Lending interest rates also affect capital structure through changes in bankruptcy costs and tax rates. Hence, firms prefer loans at lower interest rates to avail tax benefits, which show a negative association of lending interest rates with leverage (Ramli et al., 2019). According to Lee et al. (2020), increased interest not only increases the cost of debt but also discourages investment, hence decreasing the need for financing. This established a negative association between leverage and lending interest rates.

Studies found a significant impact of government borrowing as one of the macroeconomic determinants of capital structure decisions in firms (Mokhova & Zinecker, 2014; Dincergok & Yalciner, 2011). Budget deficits persuade governments to borrow from the local market which curtails the fund's availability for other industrial sectors, particularly developing countries (Rehman, 2016). Government borrowing tends to tackle an economic predicament in the short run, but long-term leads to crowding out of corporate debt (Ayturk, 2017). Graham et al. (2015) also found a significant impact on the U.S. firm in this context.

FDI greatly affects leverage in domestic companies, as an upsurge in competition in the local market due to the influx of foreign firms may affect major determinants of capital structure in local firms, i.e. profitability and growth opportunity (Anwar & Sun, 2014; Kayo & Kimura, 2011). Precisely, FDI enhances both debt and equity investments with a resulting surge in market competition. Leverage and FDI are positively related if the rise in debt financing is greater than investment (both debt and equity), but there is a negative association if this rise in debt financing is less than investment growth. There is no association observed if debt and investment surge at the same rate. Hence, the above enlightenment guided the derivation of the following hypotheses:

H9: Economic growth has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H10: Inflation has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H11: Lending interest rates have a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H12: Government borrowing has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

H13: FDI has a significantly negative and meaningful impact on the capital structure (leverage) of non-financial firms.

Above literature illustrates the mixed impact of firm, industry, and macroeconomic determinants of capital structure and fails to identify the determinant of prime importance, this lacuna in research demands managerial attention towards identification of the most important determinant of capital structure. Hence, the above enlightenment guided the derivation of the following hypotheses for importance-performance matrix analysis:

H14: There is a difference in the importance and performance of the firm, industry, and macroeconomic determinants of capital structure decisions in non-financial firms.

H15: There is a difference in the importance and performance of the firm, industry, and macroeconomic determinants of capital structure decisions in non-financial firms over different periods.

14.3 Research Design

The current chapter employed deductive approach with balanced panel data, which is more explanatory and deliberate, constitutes greater degrees of freedom, reduces endogeneity issues (Lynch & Brown, 2011), assumes heterogeneity and unpredictability in data (Singh & Bagga, 2019), and equally weighted each observation in the dataset. Furthermore, the component-based structural equation modelling technique will be employed for the current chapter as a substitute to traditional regression analysis as PLS-SEM investigates composite relationships in models with multiple constructs and indicators, provides partial least square regression without the assumption of normally distributed data, imparts robust path relationship with missing data and outliers, and analyses multiple data in a single model by generating groups (Latan & Noonan, 2017; Ramli et al., 2018).

14.3.1 Trial Sample

The research population comprised 625 non-financial and financial firms listed on PSX, with 367 non-financial firms (including 92 defaulter firms with missing data). Financial firms were excluded from the study due to their particular legal capital structure requirements and regulations (Duran & Lozano-Vivas, 2015) unlike non-financial firms (Ripamonti, 2020) where capital structure decisions are based on the market forces and macroeconomic indicators. Hence, with convenient sampling technique, the final sample comprised of balanced panel data of 269 PSX listed firms (73.2% of total non-financial firms from 14 sectors) with the 94,150 observations

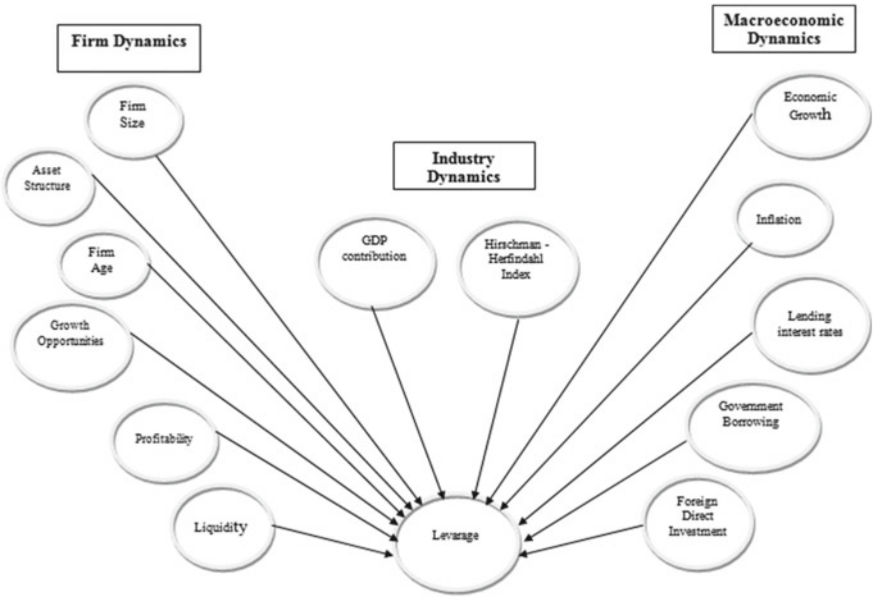

Fig. 14.1 Conceptual framework

(269 firms * 25 indicators * 14 years) for effective parameter estimation, mitigation of multicollinearity and unobserved heterogeneity issues (Chadha & Sharma, 2015; Chaklader & Chawla, 2016; Chakrabarti & Chakrabarti, 2019). Furthermore, panel data are divided into two subsets for testing the difference in most important determinant over different periods (2006–2012 and 2013–2019).

As mentioned in Fig. 14.1, conceptual framework is a reflective model with nine different unobserved constructs representing the firm and macroeconomic dynamics with 20 different observed variables or indicators and five single item constructs representing industry and macroeconomic indicators. Current study employed firm, industry and macroeconomic factors as exogenous or independent constructs while capital structure decision is the endogenous or dependent construct (Tables 14.1 and 14.2).

14.3.2 Measures

14.3.3 Data Analysis

We employed secondary balanced panel data consisted of artefacts and exhibited non-normal distribution (Table 14.9, see Appendix) with high degree of skewness (distribution requirement for normally distributed data is symmetrical and bell-shaped with

Table 14.1 Independent and dependent dynamics

Variable	Indicators	Indicator measure	Reference(s)
Firm Size	Log of firm sales Log of total asset	Log (firm sales) Log (Total Asset)	Daskalakis and Psillaki (2008), Ramli et al. (2018)
Asset Structure	Tangibility collateral value	Net fixed asset/total asset Inventory + gross plant & equipment/total assets	Al-Najjar (2011), Ramli et al. (2018)
Growth Opportunities	MV/BV Tobin's Q	Closing stock price*no of ordinary shares/ stockholder equity Financial debt + MV of equity/total asset	Baker and Wrugler (2002), Ramli et al. (2018, Lee et al.(2020)
Profitability	ROA ROE	Net income/total asset Net income/stockholder equity	Jaisinghani and Kanjilal (2017)
Firm Age	Log of Firm Age since incorporation The log of 1 plus year since incorporation	Log (Firm Age since incorporation) Log (1 plus year since incorporation)	Chakrabarti and Chakrabarti (2019), Li et al. (2018)
Liquidity	Current ratio Quick ratio	Current assets/current liability current assets–inventory/ current liability	Chaklader and Chawla (2016), Ghasemi and Razak (2016)
GDP Contribution	RGDPC	Total industry sales/ annual real GDP	De Jong et al. (2008)
Hirschman—Herfindahl Index	HHI	The sum of the square of the market share of firms within a given industry (market share is a ratio of firm sale to the total sale of industry)	
Economic Growth	GDP GDI	Annual % growth in GDP Annual GDI as % of GDP	Ramli et al. (2018)
Inflation:	GDP deflator CPI	Variation in the Consumer Price index over the years The growth rate of GDP implicit deflator	Ramli et al. (2018)
Lending Interest Rates	LINTR	Real lending interest rates offered by financial institutes	Ramli et al. (2018)
Government Borrowing	GB	Total government borrowing from institutions as % of GDP	Panda and Nanda (2020)

(continued)

Table 14.1 (continued)

Variable	Indicators	Indicator measure	Reference(s)
Foreign Direct Investment	FDI	Net inflow as % of GDP	Panda and Nanda (2020)
Capital structure decision	TD/TA	Total debt/total asset	Chakrabarti and Chakrabarti (2019)
Capital structure decision	LTD/TA	Long term debt/total asset	Chakrabarti and Chakrabarti (2019)
Capital structure decision	STD/TA	Short term debt/total asset	Ahsan (2017)
Capital structure decision	LTD/TD	Long term debt/total debt	Cull et al. (2018)

Table 14.2 Firm and industry statistics

Sector	Industry	No firms	%	
1	Sugar	26	9.7	Manufacturing
2	Other Manufacturing n.e.s	27	10	Manufacturing
3	Information, Comm. and Transport	10	4	Services
4	Paper, Paperboard and Products	06	2	Manufacturing
5	Textile, Made-up Textile, Other Textiles n.e.s	114	42	Manufacturing
6	Other Non-Metallic Mineral Products Cement	12	5	Manufacturing
7	Chemicals and Pharmaceuticals	29	11	Manufacturing
8	Mineral Products	06	2	Manufacturing
9	Fuel & Energy	13	5	Manufacturing
10	Other Food Products	11	4	Manufacturing
11	Coke & Refined Petroleum Products	09	3.3	Manufacturing
12	Other Services Activities	06	2	Services
	Total	269	100%	

equivalent values of mean, median, and mode, i.e. mean of 0 and standard deviation 1, non-zero values of skewness and kurtosis also exhibit an absence of normality in the data). The data analysis approach PLS-SEM (variance approach) was used for significant estimations of path relationships and determination of importance-performance matrix analysis for the evaluation of comparative importance versus performance of determinants of capital structure as it is highly desirable for extraordinary non-normal secondary data analysis (Hair & Alamer, 2022), promotes unrestrained use of single indicators in the model (Hair et al., 2014, 2021; Hair & Alamer, 2022) as research related to business secondary data consists mostly of artefacts such as financial ratios and other firm-specific factors (Henseler, 2017) and provides robust out of sample predictions. PLS-SEM can also recognize significant relationships existing in a population (Sarstedt & Mooi, 2019), run the regression for multiple variable relationships, and also minimize the issues of multicollinearity (Avkiran, 2018) with robust statistical power to give true significant path estimations (Hair et al., 2017; Sarstedt & Mooi, 2019).

14.4 Results

Using software SmartPLS 4, the descriptive statistics (Table 14.9, see Appendix) shows that the values of mean and standard deviation are not 0 and 1, respectively, hence data are not normally distributed whereas the standard criteria for normally distributed data are zero mean and a standard deviation one. Furthermore, non-zero values of skewness and kurtosis also exhibit an absence of normality with the presence of extreme outliers in the data which depict that distribution is leptokurtic as the kurtosis value for all indicators is far from 3. Hence data are non-normal and the use of the PLS-SEM method is most appropriate for analysis of the PLS path model.

14.4.1 Measurement Model Assessment

Standard criteria for measurement model need to be fulfilled in a PLS-SEM before assessment of structural model (Hair et al., 2019) hence interpretation of result is based on established parameters given the study context (Hair et al., 2019). The first step is an analysis of the measurement model, which is also called an outer model and consists of association of latent constructs with respective observed indicators (Esposito Vinzi, 2010; Lathan & Noonan, 2017; Ramli et al., 2018; Hair et al., 2019). The second step is a structural model also called an inner model and examines the relationship between the exogenous (independent) and endogenous (dependent) constructs (Ramli et al., 2018) i.e. inner model. PLS algorithm is employed as the study is prediction oriented where both PLS algorithm and consistent algorithm are equally significant (Roemer, 2016) (Fig. 14.2).

Assessment of the outer model encompasses indicator loading, internal consistency reliability, convergent and discriminant validity. Indicator loading shows the reliability of the item for a particular construct. The desirable value for indicator (item) loading is 0.708, which shows that the construct explains more than 50% of the variance in its items. Table 14.3 shows that indicator loadings for firm size, tangibility, firm age, growth opportunity, profitability, liquidity and inflation established good item reliability. The observed indicators CV, GDI, Td/TA are deleted as the indicator loading is less than 0.5, while the indicators RGDP, Ltd/Td, Ltd/TA, Std/TA are retained with satisfactory indicator reliability. The constructs such as HHI, GDP contribution, FDI and Government borrowing with a single item could easily provide pragmatic evidence for any association (Ramli et al., 2018), hence does not stipulate measurement evidence (Hair & Sarstedt, 2021).

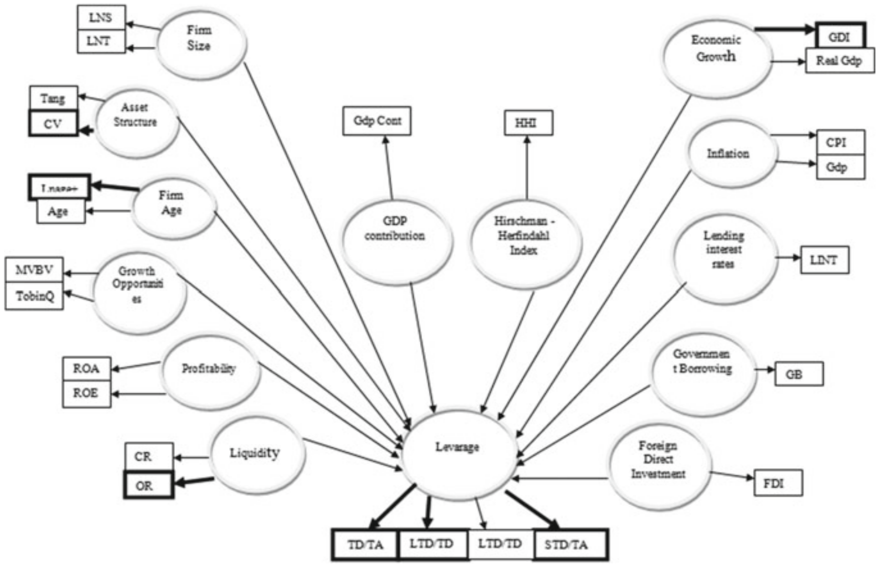

Fig. 14.2 Measurement model assessment PLS algorithm

Internal consistency reliability is a measure of consistency among items of each construct. For exploratory research, values between 0.6 and 0.7 are considered satisfactory, values within the range of 0.7–0.9 are considered adequate to good, and values of 0.95 and above are not desirable, showing that items are superfluous and could negatively affect construct validity (Diamantopoulos et al., 2012). Cronbach's alpha is a traditional measure of internal consistency reliability but gives less accurate results as indicators are not weighted with threshold value 0.7 or higher. The Cronbach's alpha value for all firm-specific latent constructs such as firm size, asset structure, firm age, profitability, and liquidity exceeds the threshold value, which shows good internal consistency reliability. Cronbach's alpha for observed indicator growth opportunity is 0.649, which shows more than 60% of internal consistency among items. Internal consistency reliability is also established for macroeconomic-specific latent constructs economic growth and inflation. Composite reliability is an improved measure of internal consistency reliability, more significant and accurate as it imparts weights to individual indicator loading and gives substantial results hence higher reliability as compared to Cronbach's alpha. The composite reliability for firm size, growth opportunity, inflation and profitability are all above the threshold of 0.7, which shows good internal consistency reliability. The convergent validity (average variance extracted, AVE) measures the extent to which the latent construct explains variance in respective observed indicators with threshold value 0.5 or above (Hair et al., 2016; Rasoolimanesh et al., 2017), which shows that the latent construct explains at least 50% of the variance in indicators. The AVE values for all latent constructs exceed the threshold of 0.5 hence convergent validity is established.

Table 14.3 Outer loadings

Variable	Indicators	Outer loadings	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)
		>0.70	0.70–0.90	>0.70	>0.50
Asset structure	Tang **Cv**	0.899 **0.112**	1.000	1.000	1.000
Economic growth	Real GDP **GDI**	1.000 **0.083**	1.000	1.000	1.000
Firm age	Age Age + 1	0.998 0.990	1.000	1.000	1.000
Firm size	Lns Lnta	0.921 0.898	0.809	0.904	0.826
Foreign direct investment	FDI	1.000	1.000	1.000	1.000
GDP contribution	GDP Contribution	1.000	1.000	1.000	1.000
Government Borrowing	GB	1.000	1.000	1.000	1.000
Growth opportunities	MVBV TobinQ	0.629 0.984	0.649	0.804	0.682
Herfindhal index	HHI	1.000	1.000	1.000	1.000
Inflation	CPI GDP Deflator	0.693 0.999	0.791	0.846	0.739
Lending Interest rate	LINT	1.000	1.000	1.000	1.000
Leverage	Ltd/Td Ltd/TA Std/TA **Td/TA**	0.904 0.631 0.856 **0.367**	1.000	1.000	1.000
Liquidity	Cr Qr	0.985 0.981	1.000	1.000	1.000
Profitability	ROA ROE	0.976 0.862	0.844	0.917	0.848

Note CV, GDI and Td/TA are deleted due to lower scores than acceptable for outer loading

Heterotrait-Monotrait ratio as recommended by Henseler (2014) is a consistent measure of discriminant validity and demarcated as "mean value of item correlations across constructs relative to mean of average correlation of item measuring the same construct". According to Henseler et al. (2015), the standard cut-off value for HTMT is 0.85 for the abstractly discrete construct. An HTMT value of up to 0.9 is acceptable in the case of theoretically analogous constructs. Greater values of HTMT than the threshold show the absence of a discriminant value (Ngah et al., 2018). HTMT2 is an advanced measure of discriminant validity based on geometric mean rather than arithmetic mean as in HTMT and provides more robust and less biased estimations predominantly with heterogeneous indicators. Table 14.4 shows established discriminant validity for all the constructs with values less than 0.85.

14.4.2 Structural Model Assessment

Variance inflation factor (VIF) is used to check for multicollinearity in the model. The structural model standard value for VIF is less than 3, which shows no issue of multicollinearity. VIF values greater than 5 show the existence of multicollinearity issues, greater than 10 shows acute multicollinearity issues (Hair et al., 2019). Indicators such as Age plus 1, quick ratio, Ltd/TA, Std/TA and Td/TA omitted to multicollinearity issues while Table 14.5 shows that VIF values for rest of the items are less than 3 hence there is no collinearity issue in the model.

The R^2 is the explanatory power or in-sample predictive power of the model. The R^2 values range from 0 to 1 as higher values show good in-sample predictive power. However, R^2 values are sensitive to the number of exogenous variables in the model hence its interpretation is based on the study context. Based on the study's perspective, R^2 values up to 0.10 are also considered satisfactory in some cases (Raithel et al., 2012). Inferences for R^2 values are always concerned with research in similar context and model intricacy (Hair et al., 2019). Table 14.5 shows that the R^2 value for the proxy of leverage (Long-term debt to total debt) is 23.6%, which is not too strong as only one proxy for leverage is retained and the rest are deleted by the model. Studies done by Ramli et al. (2018) on capital structure with the same complex model and study context showed an R^2 value of 0.07. Comparatively, the R^2 value of the current study of 23.6% is satisfactory for the currently employed panel data; this shows statistically significant explanatory power or in-sample predictive power of the model.

Adjusted R^2 altered the model for the number of exogenous constructs. Table 14.5 shows that with multiple exogenous variables in the model, the adjusted R^2 value for the leverage is 23.3%, which is quite satisfactory for panel data.

The f^2 value (effect size metric) in the structural model shows the meaningfulness of the impact of the exogenous construct on the endogenous construct in ranking order. Table 14.5 depicts that the f^2 value of asset structure is the highest of other exogenous constructs, with a value of 0.176. Thus, the relationship between asset structure and leverage is meaningful at a medium level. The f^2 value for economic growth and liquidity is 0.023 and 0.026, respectively, illustrating the weak effect size, hence the relationship is weakly meaningful. The effect size for the rest of the construct was found not meaningful.

SRMR computes the difference between estimated and observed covariance with standard threshold value 0.08, values above 0.08 show issues with model fit. Table 14.5 shows that the SRMR in the estimated model is distinctly less than 0.08, i.e. 0.054, hence showing a good model fit as there is no discrepancy between estimated and observed covariance.

Table 14.4 Discriminant validity: Heterotrait-Monotrait Ratio (HTMT)

	Asset structure	Economic growth	Firm age	Firm size	Foreign direct investment	GDP contribution	Government borrowing	Growth opportunities	Herfindah l index	Inflatio n	Lending interest rate	Lever age	Liqui dity	Profitabili ty
Asset structure														
Economic growth	0.002													
Firm age	0.025	0.012												
Firm size	0.149	0.046	0.045											
Foreign direct investment	0.062	0.440	0.195	0.076										
GDP contribution	0.236	0.001	0.039	0.354	0.020									
Government borrowing	0.053	0.124	0.229	0.097	0.496	0.061								
Growth opportunities	0.127	0.044	0.048	0.072	0.030	0.025	0.011							
Herfindhal index	0.258	0.016	0.044	0.284	0.000	0.505	0.008	0.153						
Inflation	0.038	0.301	0.231	0.075	0.680	0.027	0.426	0.051	0.028					
Lending interest rate	0.006	0.482	0.151	0.056	0.086	0.028	0.216	0.039	0.034	0.508				
Leverage	0.381	0.207	0.025	0.078	0.138	0.111	0.006	0.060	0.055	0.049	0.050			

(continued)

Table 14.4 (continued)

	Asset structure	Economic growth	Firm age	Firm size	Foreign direct investment	GDP contribution	Government borrowing	Growth opportunities	Herfindahl index	Inflatio n	Lending interest rate	Lever age	Liqui dity	Profitabili ty
Liquidity	0.094	0.007	0.016	0.130	0.009	0.010	0.005	0.010	0.019	0.015	0.024	0.020		
Profitability	0.068	0.019	0.009	0.021	0.032	0.011	0.030	0.108	0.049	0.068	0.055	0.020	0.015	

	Firm age	Growth opportunitie	Asset structure	Economic growth	Foreign direct investment	GDP contribution	Govemment borrowing	Hirschman-Herfindahl index	Inflation	Lending interest rates	Levarage	Liquidity Liquidity	Profitability	Firm size
Growth opportunitie	0.104													
Asset structurenitie	0.023	0.223												
Economic growthrenitie	0.011	0.075	0.001											
Foreign direct investmentenitie	0.196	0.048	0.056	0.441										
GDP contribution	0.038	0.038	0.233	0.000	0.019									
Govemment borrowing	0.230	0.017	0.049	0.125	0.496	0.060								
Hirschman-Herfindahl index	0.041	0.141	0.265	0.016	0.000	0.505	0.008							
Inflation	0.233	0.037	0.028	0.300	0.680	0.027	0.426	0.028						
Lending interest rates	0.152	0.048	0.002	0.482	0.084	0.027	0.216	0.035	0.506					
Levarage	0.025	0.151	0.369	0.207	0.140	0.108	0.006	0.049	0.045	0.053				
Liquidity	0.121	0.017	0.186	0.050	0.044	0.008	0.125	0.000	0.167	0.161	0.077			
Profitability	0.035	0.066	0.090	0.038	0.045	0.066	0.055	0.114	0.085	0.077	0.015	0.093		
Firm size	0.050	0.069	0.141	0.049	0.077	0.346	0.100	0.290	0.080	0.059	0.084	0.047	0.163	

Table 14.5 Structural model

		VIF	f^2*Square*	R^2 Square	R^2Square Adjusted
Asset structure	Tang	1.000	0.176		
Economic Growth	Real GDP	1.000	0.023		
Firm Age	Age	1.000	0.000		
Firm Size	Lns Lnta	1.857 1.857	0.015		
Growth Opportunities	MVBV TobinQ	1.300 1.300	0.007		
Herfindhal Index	HHI	1.000	0.008		
Foreign Direct Investment	FDI	1.000	0.003		
GDP Contribution	GDP Contri	1.000	0.004		
Government Borrowing	GB	1.000	0.006		
Inflation	CPI GDP Def	1.750 1.750	0.000		
Lending Interest rate	LINT	1.000	0.003		
Leverage	Ltd/Td	1.000		0.236	0.233
Liquidity	Cr	1.000	0.026		
Profitability	Roa Roe	2.142 2.142	0.000		
	Saturated Model			**Estimated Model**	
SRMR	0.054			0.054	

The f^2 value ≥0.02 shows weak, ≥0.15 shows mediocre and ≥ 0.35 shows high effect sizes (Cohen, 1988). Age + 1, STD/TA, LTD/TA, TD/TA & QR deleted due to multicollinearity issue

14.4.3 Testing of Hypotheses

The current study used a complete bootstrapping, a non-parametric approach to determine the statistical significance of path relationship with 5000 subsamples, weighting scheme path, parallel processing, bias-corrected and accelerated type with one tail test at 95% confidence interval to obtain significance values for all the metrics.

Regression coefficient beta value for asset structure depicts that a 1 unit change in it will bring positive 40.2% change in leverage. Economic growth shows negative 18% impact, firm size shows 11.6%, FDI shows negative 12%, GDP contribution shows negative 9%, Government borrowing negative 5.8%, growth opportunity is negative 5.5%, HHI positive 8%, lending interest rate positive 6% and liquidity depicts positive 14% impact on leverage. All of the path relationships were found statistically significant except firm age, inflation and profitability where path relationships were found statistically insignificant (Table 14.6).

Table 14.6 Path coefficients

	Beta (β)	Standard deviation	t-statistics	p-value	2.5%	97.5%
Asset structure -> Leverage	0.402	0.019	21.202	0.000	0.364	0.438
Economic Growth -> Leverage	−0.182	0.020	8.955	0.000	−0.224	−0.144
Firm Age -> Leverage	−0.011	0.016	0.687	0.246	−0.044	0.020
Firm Size -> Leverage	0.116	0.024	4.788	0.000	0.069	0.165
Foreign Direct Investment -> Leverage	−0.120	0.023	5.258	0.000	−0.162	−0.073
GDP Contribution -> Leverage	−0.093	0.018	5.071	0.000	−0.128	−0.057
Government Borrowing -> Leverage	−0.058	0.018	3.144	0.001	−0.092	−0.020
Growth Opportunities -> Leverage	−0.055	0.014	3.958	0.000	−0.082	−0.028
Herfindhal Index -> Leverage	0.081	0.022	3.661	0.000	0.039	0.125
Inflation -> Leverage	0.027	0.024	1.096	0.137	−0.023	0.071
Lending Interest rate -> Leverage	0.061	0.019	3.145	0.001	0.022	0.098
Liquidity -> Leverage	0.149	0.022	6.665	0.000	0.105	0.192
Profitability -> Leverage	0.013	0.023	0.596	0.275	−0.050	0.040

14.4.4 Importance-Performance Map Analysis

Table 14.7 shows that unit increase in performance of asset structure from 47.052 to 48.052 will lead to a positive 0.402 unit increase in performance of endogenous construct leverage, which is equal to the total effect of the exogenous construct asset structure. Likewise, a unit increase in performance of economic growth and firm age from 67.658 and 72.713 will lead to a negative increase in leverage performance of 0.182 and 0.011, respectively. Growth opportunity and government borrowing also show negative 0.055 and 0.058 unit increase in performance of leverage with a unit change. Firm size shows positive increase in leverage of 0.116 with a unit change

Table 14.7 IPMA-construct/indicator total effects and performances for [Leverage]

Variable	Leverage	Performances	Indicator	Leverage	Performances
Asset structure	0.402	47.052	Tang	0.402	47.052
Economic growth	−0.182	67.658	Rel GDP	−0.182	67.658
Firm age	−0.011	72.713	Fage	−0.011	72.713
Firm size	0.116	71.674	Lns Lnta	0.051 0.076	68.495 72.907
Foreign direct	−0.120	28.767	FDI	−0.120	28.767
GDP contribution	−0.093	5.022	GDP Contri	−0.093	5.022
Government Borrowing	−0.058	28.606	GB	−0.058	28.606
Growth Opportunities	−0.055	14.600	MVBV TobinQ	−0.033 −0.027	31.157 2.562
Herfindhal index	0.081	19.137	HHI	0.081	19.137
Inflation	0.027	29.748	CPI GDP DEF	0.000 0.027	35.978 29.732
Lending interest rate	0.061	60.600	RINT	0.061	60.600
Liquidity	0.149	46.187	CR	0.149	46.187
Profitability	0.013	68.178	ROA ROE	0.014 −0.003	66.062 37.513

that is negative for foreign direct investment and GDP contribution (−0.120 FDI and −0.093 GDP contribution), while lending interest rate, liquidity and profitability, inflation and HHI illustrate positive increase with a unit change in performance.

On indicator level, a unit increase in tangibility performance leads to positive increase in performance of LTD/TD by 0.402 units, which is negative for FDI, Fage, Government borrowing, GDP contribution, MV/BV, ROE, Real GDP and Tobin's Q. CPI exhibit zero change in performance with a unit change whilst CR, GDP deflator, HHI, Lns, Lnta, Lint, ROA shows positive change in performance which is nearly negligible. IPMA for two different time periods (2006–2012 and 2013–2019) also shows that asset structure is the most important determinant of capital structure in the mentioned periods (Tables 14.10 and 14.11, see Appendix).

Table 14.8 depicts a statistically significant and positive association of capital structure with firm size, asset structure, liquidity, Herfindahl Index, inflation, lending interest rate, and negative association with firm age, growth opportunity, GDP contribution, economic growth, FDI and government borrowing while the insignificant association was found for profitability but effect size f^2 signify that only relationships of asset structure, liquidity and economic growth are meaningful. Using IPMA technique, it is also found that asset structure with observed variable tangibility is the most important determinant of the capital structure decision with the exhibition of less performance even for two different time periods and need managerial attention.

The positive value of Q^2 predict (0.217) depicts a lesser prediction error of the PLS path model as compared to the prediction error of mean values (0.218), thus displaying enhanced predictive performance. Furthermore, an exhibition of equal

Table 14.8 Hypotheses summary

		Beta p-value	f^2 value	Decision
H[1]	Firm Size -> Leverage	0.000	0.015	Rejected
H[2]	***Asset structure -> Leverage***	0.000	*0.176*	***Retained***
H[3]	Firm Age -> Leverage	0.246	0.000	Rejected
H[4]	Growth Opportunities -> Leverage	0.000	0.004	Rejected
H[5]	Profitability -> Leverage	0.275	0.000	Rejected
H[6]	***Liquidity -> Leverage***	*0.000*	*0.026*	***Retained***
H[7]	GDP Contribution -> Leverage	0.000	0.008	Retained
H[8]	Herfindhal Index -> Leverage	0.000	0.006	Rejected
H[9]	***Economic Growth -> Leverage***	0.000	*0.023*	***Retained***
H[10]	Inflation -> Leverage	0.137	0.000	Rejected
H[11]	Lending Interest rate -> Leverage	0.001	0.003	Rejected
H[12]	Government Borrowing -> Leverage	0.001	0.003	Rejected
H[13]	Foreign Direct Investment -> Leverage	0.000	0.007	Rejected
H[14]	**There is a difference in the importance and performance of the firm, industry, and macroeconomic determinants of capital structure decisions in non-financial firms**.			***Retained***
H[15]	There is a difference in the prospect of importance and performance of the firm, industry, and macroeconomic determinants of capital structure decisions in non-financial firms over different periods.			Rejected

Note Retained/rejected decision on basis of effect size and meaningful relationship

values of RMSE (0.190) and MAE (0.146) for every indicator in the data set by PLS path analysis as the LM approach shows that the PLS path model displays medium predictive power of the model (Hair et al., 2019).

14.4.5 Discussion of Results

The current study offers mixed pragmatic indications in support of both trade-off and pecking order theory as firm size, growth opportunity and asset structure support trade-off order theory while economic growth, GDP contribution, FDI, and government borrowing are in favour of pecking order theory. The findings further specify that non-financial firms in Pakistan prefer long-term debt funding as compared to short term in support of trade-off theory and contrast to pecking order theory (Legesse & Guo, 2020). According to trade-off theory, highly profitable firms are more creditworthy and obtained debt at favourable terms while pecking order theory presents the view that profitable and resourceful firms prefer short-term debt over the long term due to sufficient short-term financial resources. The study found a positive and statistically significant association of firm size with leverage (LTD/TD) but effect size is not meaningful, hence rejecting hypothesis H1.

Therefore, the current findings submitted that bigger size firms listed on PSX choose more long-term debt in the capital structure as compared to small firms following TOT and agency cost theory and are also analogous to other studies (Rajan & Zingales, 1995; Anwar & Sun, 2014; De Jong et al., 2008; Hergli &

Teulon, 2014; Touil & Mamoghli, 2020) as such firms are potentially more profitable with expanded operations in international markets, less predisposition to bankruptcy, enjoy benefits such as established economies of scale, an approach to the credit market, lower risk, and access to international markets. The positive association of firm size with LTD/TD is in contradiction to POT due to the existence of an unpredictable equity market in Pakistan hence even bigger firms prefer debt over equity despite less information asymmetry but the relationship is not meaningful. Non-financial firms are asset-intensive, bear good creditworthiness with less default risk, and lead to a decrease in agency cost, hence prefer more debt.

The observed variable tangibility for the latent construct asset structure shows a positive and statistically significant impact on LTD/TD with the endorsement of significant effect size following trade-off, agency, and Pecking order theory at parallel with other studies in the context of European countries (Bandyopadhyay & Barua, 2016; Moradi & Paulet, 2018) and the Pakistan context (Ahsan et al., 2016) and in contrast to other studies, found a positive and significant association of long-term debt with tangibility (Li & Islam, 2019; Alyousufi, 2020). Hence, the result shows that non-financial firms in Pakistan bearing more tangible assets favour long-term debt for malleable capital structure due to lower default risk and unpredictable credit market with medium effect size and strongly retained hypothesis H2.

According to POT, information asymmetry indicates an inverse liaison of firm age with debt financing, as substantial relevant information is accessible for older companies that mitigate the issue of information asymmetry to encourage investors, thus older companies prefer equity financing rather than debt as compared to new firms. Studies in the Pakistan context also found a positive relationship in this context (Ahsan et al., 2016). On the contrary, other studies found a negative association with leverage (Berger & Udell, 1995; Bandyopadhyay & Barua, 2016). According to path estimates, this relationship is negative and insignificant and the effect size is also not meaningful. Hence, hypothesis H3 is rejected.

In the perspective of growth opportunity, researchers found mixed results such as studies conducted in Australia, Indonesia, Singapore, and Malaysia found negative (Deesomsak et al., 2004) while others found positive impact (Lee et al., 2020). The observed variables for growth opportunity are MV/BV and Tobin's Q, which are statistically significant and negatively associated with leverage (LTD/TD) following trade-off and agency theory and other studies (Frank & Goyal, 2009; Rajan & Zingles, 1995; Shah & Khan, 2007; De Jong et al., 2008; Guner, 2016; Moradi & Paulet, 2018; Jermias & Yigit, 2018; Touil & Mamoghli, 2020) and in contrast to studies (Dewally & Shao, 2014; Vo, 2017; Karpavicius & Yu 2019; Liu & Zhang, 2019; Lee et al., 2020; Alyousufi, 2020) The results also follow market timing theory by availing more long term debt with a high market-to-book ratio (Baker & Wrugler, 2002), but effect size is not meaningful hence rejected hypothesis H4.

Path analysis shows the insignificant association of profitability with LTD/TD, similar to findings of Olarewaju (2019) for a study conducted in Nigerian context without any evidence for an association between firm leverage and profitability, which is in contrast to other studies (Chang et al., 2009; Legesse & Guo, 2020; Sheikh & Wang, 2011) following TOT and POT and related studies (Qiu & La, 2010; Sheikh &

Wang, 2011; Lemma & Negash 2013; Hergli & Teulon, 2014; Ahsan et al., 2016; Touil & Mamoghli, 2020; Lee et al., 2020), hence hypothesis H5 is rejected.

Path analysis shows a positive association of liquidity with LTD/TD consistent with the trade-off theory and following other studies and in contrast to pecking order theory, which suggests a negative association in this setting (Deesomsak et al., 2004; Sheikh & Wang, 2011; Guner, 2016; Ahsan et al., 2016; Chakrabarti & Chakrabarti, 2019). However, the effect size f^2 shows that this relationship is weakly meaningful hence retained hypothesis H6.

For industries-related factors, GDP contribution depicts a negative and statistically significant association in contrast with other studies (Larry & Islam, 2018), where a positive association is found as firms with more contribution towards economic growth get incentives for investment. The negative association found in the current study shows that firms with a major GDP contribution towards the economy tend to avoid LTD/TD, which may be due to costly debts and unfavourable policies towards debt provisions but effect size is not meaningful, hence H7 is rejected.

The path estimates for Hirschman Herfindahl Index show positive and significant association with LTD/TD following the study of MacKay and Phillips (2005) and in contrast to studies for emerging economies like Pakistan where a negative association is found. Furthermore, effect size shows that this relationship is not meaningful following the study of Kayo and Herbert (2011) where an insignificant effect was observed for developed countries, hence the study rejects hypothesis H8.

Path estimates for economic growth show that GDP is negatively and statistically significantly related to LTD/TD following POT and similar studies (Alyousfi, 2020) and in contrast to TOT and related studies (Ahsan et al., 2016; Dewally & Shao, 2014; Lee et al., 2020) as during high economic growth decline in interest rates activate firms to lock and borrow more long-term loans at lower interest cost to facilitate investments, hence hypothesis H9 is retained with weakly meaningful effect size.

Path estimates for inflation show a positive and a statistically insignificant association with LTD/TD following the study of Frank and Goyal (2009) and Dewally and Shao (2014) and in contrast to a study in the Pakistan context (Fan et al., 2010; Ahsan et al., 2016). Furthermore, the effect size shows that this relationship is not meaningful, hence hypothesis H10 is rejected.

Path analysis for lending interest rates shows a positive and significant association with LTD/TD in contrast to the negative association found in other studies (Ramli, 2018, Lee et al., 2020) with the non-meaningful effect size, hence H11 is rejected.

Path estimates exhibit a negative and significant association of Government borrowing with a significant effect size. This finding is parallel to other studies that depict that long-term borrowing is more affected by government borrowing especially for creditworthy firms (Graham et al., 2014; Badoer & James, 2015; Ayturk, 2016; Rehman, 2016; Zinecker, 2014; Ayturk, 2016), but effect size is not meaningful, hence hypothesis H12 is rejected.

Path estimates for FDI show a significant negative association between FDI and LTD/TD. Such results are similar to other studies with a negative association in this context (Anwar & Sun, 2014; Kayo & Kimura, 2011), which shows that investment growth is less than the increase in Foreign direct investment but effect size is not meaningful. Hence, H13 is rejected.

The finding of IPMA shows that there is a difference in importance and performance of the firm, industry, and macroeconomic determinants of capital structure, and asset structure is the most important determinant for the non-financial sector in Pakistan exhibiting less performance with tangibility as the indicator of the main focus for managerial attention for better planning of capital structure decision, hence H14 is retained.

Moreover, asset structure is also found as the most important determinant for two different periods, hence H15 is rejected.

14.5 Conclusion

The study used PLS-SEM for obtaining path estimates and effect sizes of path relationships in line with the research design and achieved precision through selection of secondary data for non-financial firms from SBP and other authentic sources, with techniques to check the robustness of results. In contrast to earlier studies, the current estimation shows that the asset structure, liquidity and economic growth bear statistically significant and meaningful relationship with capital structure for PSX listed non-financial firms while the relationship of firm size, growth opportunity, HHI, GDP contribution, FDI, Government borrowing and lending interest rates with leverage is either statistically insignificant or not meaningful. However, asset structure appears to be of utmost importance over the span of studied period to positively regulate the capital structure trend in non-financial firms in Pakistan. Moreover, the current study supports the idea that asset structure, liquidity, and economic growth are widely involved in determining the trend of leverage for PSX-listed non-financial firms. The outcomes also exhibit that non-financial firms rely more on long-term debt in the capital structure for financing investment, which may be due to the unpredictable and unstable financial market in Pakistan.

14.5.1 Practical Implications

The above results show that improving tangible assets in the infrastructure will lead to encouragement of the non-financial sector towards more investment through the use of financing. The approach to debt financing at favourable terms is a major issue faced by many firms in the non-financial sector so there is a need for policymakers to focus greatly on the financing opportunities for the non-financial sector to achieve enhancement in investments and technological advancement in infrastructure. To go on, the study also provides a platform for managerial attention to strategic planning for sustaining appropriate asset structure to obtain debt on favourable terms, keeping in view opportunities and threats due to macroeconomic conditions such as economic growth, FDI, and government borrowing. The current study offers valued commendation for policymakers to provide a favourable external business environment and incentives to increase production and service provision by the non-financial sector for the growth of the economy as a whole. As a result, provision of long-term debt on favourable terms could lead to an increase in investments and GDP contribution from non-financial firms, and also boost financial markets. The IPMA technique tends to expedite focused decision-making by financial managers by identifying the opportunity for improvement to achieve optimal capital structure, which is very useful for appropriate strategic planning keeping in view both internal and external factors affecting the business environment. The observations of the current study direct financial managers to focus on improving tangibility in the asset structure to improve creditworthiness and to obtain long-term debt on favourable terms. Furthermore, IPMA technique provides a platform for policymakers as well as financial managers to identify the key exogenous construct to improve the performance of the target endogenous construct keeping in view strength, weakness, opportunities and threats in external and internal business environment in various business disciplines.

14.5.2 Limitation and Future Research Recommendations

The current study focused only on non-financial PSX-listed firms due to the unavailability of financial data for the private non-financial sector. Non-financial sector comprises both manufacturing and non-manufacturing sectors that exhibit different industrial traits and might reflect different behaviours if assessed separately.

Opportunities existed for future research to study a difference in capital structure trends and comparison of important determinants of capital structure decisions within different sectors using importance-performance map analysis for manufacturing and non-manufacturing firms or different periods through the use of panel data. Future research could also compare different industries and even different countries through multi-group analysis techniques (MGA). There is also room concerning the comparison of important determinants of capital structure decisions for non-financial and financial firms for policy implications in the broader context.

Appendix

(See Tables 14.9, 14.10 and 14.11).

Table 14.9 Descriptive statistics

	Mean	Median	Min	Max	Standard deviation	Excess Kurtosis	Skewness
Lns	6.279	6.443	0	9.075	1.356	10.512	−2.753
Lnta	6.488	6.456	0	8.885	0.819	6.222	−0.734
Tang	0.469	0.472	0	1.918	0.232	−0.052	0.051
Cv	1.188	0.974	0	181.394	4.79	1120.518	32.553
MV BV	4.187	0.509	−154.776	1060	41.433	453.308	20.013
TobinQ	2.59	0.583	0	719.217	22.922	578.095	22.06
Age	1.478	1.477	0.301	1.919	0.204	1.322	−0.596
Lnage+	2.478	2.477	1.301	2.919	0.204	1.322	−0.596
TD TA	2.556	0.619	0	1450.348	37.348	812.856	26.256
LTD TA	0.486	0.133	0	197.791	6.541	692.829	25.753
STD TA	2.07	0.423	0	1450.323	34.162	1018.226	28.995
LTD TD	0.272	0.242	0	1	0.215	0.058	0.73
Cr	1.316	0.848	−11.781	316.832	7.397	1228.46	32.776
Qr	0.934	0.402	−11.781	316.832	7.334	1275.59	33.607
ROA	0.418	0.067	−36.5	185.098	4.817	841.809	25.217
ROE	0.519	0.125	−112.469	188.2	6.757	428.194	13.519
Real GDP	4.04	4.05	0.36	5.8	1.402	0.99	−1.071
GDI	2.638	1.61	1.41	15.611	3.602	9.042	3.318
GB	64.581	63.3	56.4	85	6.868	2.94	1.738
FDI	1.326	0.82	0.38	3.67	1.079	−0.103	1.262
LINT	3.041	4.035	−5.079	8.321	3.774	0.055	−0.944
GDP DEF	3.632	2.9	1.83	7.89	1.792	−0.172	0.968
CPI	8.918	7.921	2.529	20.286	4.572	0.387	0.818
HHI	0.093	0.066	0	0.483	0.11	0.793	1.191
GDP contribution	0.001	0	0	0.015	0.002	28.113	5.297

Table 14.10 Construct and indicator total effects and performances for [Leverage] (2006–2012)

	Levarage	Performance	Indicator	Levarage	Performance
Asset structure	0.313	46.150	Tang	0.313	46.606
Economic growth	−0.171	70.225	Rel GDP	−0.171	70.225
Firm age	0.004	60.020	Fage	0.004	60.020
Firm size	0.206	72.290	Lns Lnta	0.106 0.120	67.859 74.216
Foreign_direct investment	−0.105	13.785	FDI	−0.105	13.785
GDP contribution	−0.057	3.824	GDP Contri	−0.057	3.824
Government borrowing	−0.107	39.850	GB	−0.107	39.850
Growth opportunities	−0.071	15.850	MVBV TobinQ	−0.045 −0.033	31.496 2.859
Hirschman—Herfindahl index	0.042	21.645	HHI	0.042	21.645
Inflation	0.118	20.541	CPI GDP DEF	0.021 0.112	41.606 19.153
Lending interest rates	0.012	36.740	RINT	0.012	36.740
Liquidity	0.174	29.808	CR	0.174	29.808
Profitability	−0.050	79.553	ROA ROE	−0.012 −0.041	66.298 85.842

Table 14.11 Construct and indicator total effects and performances for [Leverage] (2013–2019)

	Levarge	Performance	Indicator	Levarge	Performance
Asset structure	0.505	48.840	Tang	0.505	48.840
Economic growth	−0.189	62.966	Rel GDP	−0.189	62.966
Firm age	−0.022	69.267	Fage	−0.022	69.267
Firm size	−0.028	66.026	Lns Lnta	−0.036 0.011	69.622 74.470
Foreign_direct investment	−0.192	41.640	FDI	−0.192	41.640
GDP contribution	−0.062	5.769	GDP Contri	−0.062	5.769
Government borrowing	−0.024	57.387	GB	−0.024	57.387
Growth opportunities	−0.052	10.165	MVBV TobinQ	−0.030 −0.028	22.325 2.320
HHI	0.099	18.216	HHI	0.099	18.216
Inflation	0.023	43.514	CPI GDP DEF	0.003 0.022	34.550 44.048
Lending interest rates	0.053	49.170	RINT	0.053	49.170
Liquidity	0.161	48.141	CR	0.161	48.141
Profitability	0.021	28.558	ROA ROE	−0.008 0.021	29.951 33.996

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