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Putting the "Person" in the Center: Review and Synthesis of Person-Centered Approaches and Methods in Organizational Science

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Abstract

This article provides a review and synthesis of person-centered analytic (i.e., clustering) methods in organizational psychology with the aim of (a) placing them into an organizing framework to facilitate analysis and interpretation and (b) constructing a set of practical recommendations to guide future person-centered research. To do so, we first clarify the terminological and conceptual issues that still cloud person-centered approaches. Next, we organize the diverse kinds of person-centered analyses into two major statistical approaches, algorithmic and latent-variable approaches. We then present a literature review that quantifies how these two approaches have been used within our field, identifying trends over time and typical study characteristics. Out of this review, we construct a unifying taxonomy of the five ways in which clusters are differentiated: (1) construct-based patterns, (2) response-style patterns, (3) predictive relations, (4) growth trajectories, and (5) measurement models. We also provide a set of practical guidelines for researchers and highlight a few remaining questions and/or areas in which future work is needed for further advancing person-centered methodologies.

Keywords

profile analysis, cluster analysis, latent class analysis, latent class growth models

The "person-centered" approach has become an increasingly used concept within the organizational sciences. Recent publications (e.g., Morin, Meyer, Creusier, & Biétry, 2016) and a 2011 special issue of *Organizational Research Methods* (Wang & Hanges, 2011) have either used or explicated person-centered analytic frameworks. However, this term has also been used to simultaneously

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describe a number of other research paradigms and approaches that are substantially different (albeit related), engendering confusion in what it means to be *person-centered*. This conceptual ambiguity together with the lack of methodological integration and coherence have limited advancement in research and theory on person-centered approaches. Paralleling developments in multilevel approaches within organizational science (Chan, 1998; Kozlowski & Klein, 2000), there is a need for an overarching framework for understanding how the person-centered approach is conceptualized (e.g., implicit theories, choice of topics, scope of study), articulated (e.g., explicit theories and hypotheses), and methodologically implemented (e.g., study design and data analysis). In the current article, we aim to clarify the core features of person-centered approaches in organizational research from both conceptual and methodological angles and summarize various person-centered analytic methods used in past studies into an integrative framework to assist researchers conducting person-centered work. With such a framework, we can better develop future research directions and insights for advancing person-centered research.

We begin this article by discussing the terminological and conceptual issues that still cloud person-centered approaches. These include explicating differences in how *person-centered* is conceptualized and its relationship to the idiographic-nomothetic research distinction. Next, we organize the diverse kinds of person-centered analyses into two major statistical approaches, algorithmic and latent-variable approaches. We then present a literature review that quantifies how these two approaches have been used within our field, identifying trends over time and average study characteristics (e.g., sample size, number of indicators). Out of this review, we construct a unifying taxonomy of cluster interpretations that consists of five ways in which subpopulations are differentiated: (1) construct-based patterns, (2) response-style patterns, (3) predictive relations, (4) growth trajectories, and (5) measurement models. Using this taxonomy and examples from the literature, we provide a set of practical guidelines for researchers in deciding whether and how to identify person-centered research questions, how to choose analytic options appropriate for addressing those questions, and how to validate their findings. We close with a discussion of remaining questions and/or areas in which future work is needed for further advancing person-centered methodologies.

Part 1: What Constitutes a Person-Centered Approach?

In organizational research, the term *person-centered* has a number of variations, such as *person-oriented*, *person-centric*, *employee-centered*, and *employee-centric*. All of these terms have been used to describe a diverse array of theoretical and analytical approaches. From an extensive review of the literature, we propose that the differences among them can be grouped into three major themes.

Definition 1: The Characteristics of Individuals (as Opposed to Situations)

The first person-centered perspective focuses on personal rather than situational factors in explaining organizational phenomena (e.g., Dierdorff, Rubin, & Morgeson, 2009; Kanfer & Ackerman, 2005; Schneider, Goldstein, & Smith, 1995) and has the longest history of the three. A study or a theoretical perspective can be called person-centered simply because its theoretical focus is placed on the characteristics of people (e.g., personality, values, knowledge, skills, abilities) rather than those of situations (e.g., organizational structure, pay system, labor market conditions) in explaining and predicting outcomes of interest (e.g., turnover, performance). This terminological tradition, although frequently invoked in the literature, may not be useful for all types of organizational researchers. This is because a large portion of theoretical and empirical work already focuses on the properties of individuals (e.g., personality traits, job attitudes, work performance) rather than structural or environmental factors, and thus adhering to this conception of person-centered would result in the inclusion of too many studies and theories for it to be a meaningful distinguisher. That said, this conception of the term may be useful for the community of organizational behavior researchers when "the micro-macro divide" is based on whether the level of analysis is the individual versus the organizational level (Molloy, Ployhart, & Wright, 2011).

Definition 2: The Subjectivity of Worker Experience

Another way in which the concept of person-centered has been used in organizational research was explicated by Weiss and Rupp (2011). Their article, "Experiencing Work: An Essay on a Person-Centric Work Psychology," described a new wave of scholarly interests within our field that focuses on the subjective experience of workers rather than treating each employee as an object with a collection of properties (like a "box" with height and weight). Predating Weiss and Rupp, there were similar mentions of the concept for focusing on individual experiences (e.g., Dalal, 2005; Liu, Zhan, & Wang, 2011) in areas where the person-centric viewpoint has been used for many years to study phenomena grounded in the personal, subjective experiences of workers—for example, well-being, burnout (Maslach, Schaufeli, & Leiter, 2001), work detachment and affect (Sonnentag, Binnewies, & Mojza, 2008), and work stress and work-family conflict (Liu, Wang, Zhan, & Shi, 2009). As pointed out by Weiss and Rupp, person-centric work psychology can (and should) cover a variety of different topics and methodological choices. Therefore, we suggest that it is most appropriate to understand this particular terminological tradition strictly on a philosophical level, which allows a sufficient diversity in the ways in which empirical studies are conducted and theoretical advances are made on a given topic.

Definition 3: The Clustering of Persons

Finally, the term *person-centered* is used to describe a variety of analytic strategies that cluster individuals (or other units) based on their shared characteristics instead of clustering (or factor-analyzing) variables. The collective aim of such strategies is to identify subgroups within populations (e.g., Foti, Thompson, & Allgood, 2011; Liu et al., 2011; Wang & Hanges, 2011) either theoretically or empirically (or both). As such, the concept of person-centered research has been most commonly applied under the "clustering" tradition, where the researcher's goal is to use individual-level attributes to identify subpopulations, types, or profiles of persons, such as emotional labor strategies (e.g., surface and deep acting; Gabriel, Daniels, Diefendorff, & Greguras, 2015), organizational commitment mindsets (e.g., affective, normative, and continuance; Meyer & Morin, 2016), and turnover antecedents (e.g., turnover intentions and job search behaviors; Woo & Allen, 2014). This focus is also referred to as *pattern-oriented*, *configural*, or *typological* as it considers patterns or configurations of variables that describe various types of persons. Clusters of individuals are most often derived from empirical quantitative data using statistical techniques, following a model of inductive theory building (e.g., Gabriel et al., 2015; Woo & Allen, 2014). Statistical examples of the person-centered (i.e., clustering) approach include cluster analysis, latent class/profile analysis, latent class regression analysis, latent transition analysis, and growth mixture modeling, and they collectively diverge from traditional "variable-centered" analytic models (Muthén & Muthén, 2000). Clustering can also be done qualitatively (e.g., Klotz & Bolino, 2016) or theoretically (e.g., Hom, Mitchell, Lee, & Griffeth, 2012), but in those cases, the authors do not tend to call their approach person-centered and instead use words like *profiles* or *styles* to describe the person clusters of interest.

We suggest that defining the person-centered approach as "clustering of people as opposed to variables" is the most appropriate option of the three aforementioned traditions if the goal is to maximize the level of precision in *methodological* discussions within organizational research.

Therefore, hereafter in the present article, we will use the term *person-centered* interchangeably with *clustering* when discussing it as a methodological approach.[1]

In the rest of this article, we systematically review various person-centered methods within organizational science by delineating their types, usage, and popularity over time and offer practical guidelines for conducting and evaluating person-centered research. However, before doing so, we seek to further clarify the conceptual space of person-centered methods by shedding light on two additional sources of confusion we have observed in academic literatures.

Clarification 1: The Person- Versus Variable-Centered ≠ Idiographic Versus Nomothetic

The distinction between person- and variable-centered perspectives is often (incorrectly) equated to the idiographic versus nomothetic distinction present at the founding of scientific psychology (Hurlburt & Knapp, 2006; Münsterberg, 1899; Windelband, 1894/1998). Person-centered analyses are frequently assumed to be idiographic, namely, being focused on the uniqueness of a handful of individuals or "describing and explaining particular phenomena" (Robinson, 2011, p. 32). Idiographic approaches analyze *intra*individual (as opposed to *inter*individual) variation and are thus longitudinal in nature, being "firmly based on adequate time series analysis" (Molenaar, 2004, p. 216). However, in the clustering of persons, the source of variation can be *intra*individual and/or *inter*individual, and thus not all clustering approach can be said to be idiographic.

Variable-centered analyses are viewed as nomothetic, the "Galtonian," group-based approach of identifying patterns and consistencies and then espousing principles that account for them beyond the individuals in a particular sample (Robinson, 2011, p. 33). However, this is also the case for most (if not all) person-centered analyses. Large samples are often used to derive generalizable principles, such as the number and interpretation of latent classes (or subpopulations) underlying a phenomenon and the predictive relationships of class membership.

Clarification 2: In Defense of Clustering Methods

Other issues in need of clarity are two overarching criticisms of clustering methods that have appeared in the psychological and organizational literatures. The first is that categorizing individuals into discrete, nominal clusters results in the loss of meaningful variance among individuals within clusters (Asendorpf & van Aken, 2003; Costa, Herbst, McCrae, Samuels, & Ozer, 2002). What this means is that while classification into types is a convenient label for descriptive purposes, it comes at the high cost of discarding those unique attributes of individuals that do not fit within the defining attributes of the cluster. In this way, person-centered approaches could be argued to be *counter* to the idiographic approach delineated previously. Our response to this is twofold. First, we fully acknowledge the validity within the argument, that a solitary focus on clustering will often discard potentially psychologically illuminating information. However, person-centered approaches do not at all seek to replace the insights to be gained from idiographic research; the two provide complementary information. While the categorization process omits a certain degree of information, it allows a parsimonious representation of structure in the form of groupings. Classification schemes are conceptually useful, and categories are a natural feature of cognition due the efficiency and simplicity they provide (Macrae & Bodenhausen, 2000). It should also be noted that person-centered analyses can be extended to include longitudinal data to incorporate more idiographic information and that recent developments in mixture modeling approaches allow the estimation of within-profile variability.

The second criticism against clustering concerns a lack of current evidence that it can explain variance in manifest variables above and beyond what can be explained by conventional regression models (e.g., Schmitt et al., 2007). An immediate response to this is that issues of incremental validity have not been sufficiently investigated to justify these claims; empirical research has begun to suggest that a clustering approach does help with prediction (e.g., Donnellan & Robins, 2010; Garver, Williams, & Taylor, 2008; Roth & von Collani, 2007). Also, even in cases where there is no large degree of incremental prediction, it does not necessarily void the conceptual usefulness of typologies. Again, typologies give a highly useful representation of structure (Costa et al., 2002). Person-centered clustering methods are not a replacement of the regression approach but ask different questions by approaching phenomena from a different statistical and substantive perspective that yields significant benefits to theory and practice (see e.g., Gabriel et al., 2015).

Part 2: An Integrative Review and Taxonomic Framework for Person-Centered Methods

While clarifying terminology and concept is useful, the statistical aspect of clustering also has layers and nuances that require clarification. In this part of the article, we provide an integrative review of how person-centered methods have been used within organizational sciences. Our review begins by delineating two major approaches to clustering: algorithmic and latent-variable approaches. We then present the overall results of our literature review, summarizing the frequencies, trends, and substantive details of person-centered analytic methods within our field. After this, to guide future person-centered research effort, we propose a unifying taxonomic framework to better understand the substantive implications of various person-centered analytic methods. Specifically, we propose that clustering methods can be classified into five categories based on how the subpopulations to be explored/tested are differentiated: by (1) patterns of construct-level variables, (2) patterns of response styles, (3) predictive relationships, (4) growth trajectories over time, and (5) parameters for measurement models.

Two Statistical Approaches to Clustering

From a statistical vantage point, it is helpful to distinguish between two major kinds of person-centered analyses: (a) *algorithmic approaches*, which comprise the traditional “cluster analyses,” and (b) methods that are based in latent-variable models (*latent-variable approaches*).[2] While both approaches seek to identify the number of classes and categorize individuals within them, they differ in significant ways that are important to understand (e.g., how cases are clustered, the types of input data, and mathematical form of the analysis).

Algorithmic Approaches

Mathematically, the algorithmic approaches are often simpler than latent-variable approaches; they are nonparametric and do not posit a formal probability model of the data. Instead, they rely on distinct algorithms to derive their category structure. The two major examples of algorithmic approaches for continuous variables are k-*means* clustering (quick clustering) and *hierarchical* clustering.

In the *k*-means approach, the number of classes is specified before the analysis. The cluster locations are randomly assigned, and cases are sorted into the nearest cluster (Celebi, Kingravi, & Vela, 2013; Jain, 2010; Xu & Wunsch, 2010). After this, clusters are relocated, with locations being the means of the data points currently assigned to them. These steps (i.e., reassignment and relocation) are repeated until a criterion for terminating the algorithm is reached (e.g., little to no reassignment of cases, minimal reduction in squared error) and a single *k*-cluster solution is found.

As opposed to returning one solution with *k*-clusters, hierarchical clustering offers many different solutions with varying numbers of clusters (Alam, Dobbie, Koh, Riddle, & Ur Rehman, 2014;

Xu & Wunsch, 2010). The two major ways of doing hierarchical clustering are *divisive* and *agglomerative*. Divisive clustering starts with all the data points in a single large cluster, which is then divided into smaller clusters at each step based on dissimilarity values ("top-down"). Agglomerative clustering, by contrast, starts with every data point as its own unique cluster. At each step, the two nearest clusters are merged, a process that repeats until only a single cluster remains ("bottom-up"). In both types of clustering, each step produces a unique solution for the analyst to select from. These solutions are often represented as a tiered, tree-like structure called a *dendrogram*.

Both *k*-means and hierarchical clustering are designed for continuous variables, but there are also methods for handling discrete categorical variables. Clustering for these data types is more difficult because clustering works on distances between objects, and categorical variables by definition lack quantitative distance. However, several solutions do exist. For hierarchical clustering, one can include categorical variables using Gower's (1971) distance. Here, similarity values between cases are set to 1 if the two individuals are in the same category and 0 if they are not. A variation of *k*-means, called *k*-modes, is also suitable for categorical variables (Huang, 1998, 2009). Instead of means, the modes of the categorical variables determine the cluster centers, and dissimilarities between cases are defined as the number of times they are in different categories ("simple matching"). When extended to mixed data, this algorithm is called *k*-purposes and combines both *k*-means and *k*-modes. More information can be found in Huang (1998, 2009).

Overall, algorithmic clustering approaches are popular for a variety of reasons. The *k*-means approach is simple to understand and implement, is computationally inexpensive, and works well for many purposes. Hierarchical clustering is more computationally demanding but provides a rich visual representation of many different cluster solutions; it allows the researcher to understand the entire hierarchical structure of the data to identify the optimal cluster solution. Aldenderfer and Blashfield (1984) and Milligan and Cooper (1987) provide short introductions to these methods for social scientists, whereas Kaufman and Rousseeuw (1990) offer a more thorough treatment.

Latent-Variable Approaches

Another family of person-centered analyses is the latent-variable approach, which conceives group membership as an unobserved categorical variable whose true value indicates what group the individual belongs to. Latent-variable approaches are all model-based; that is, they propose a formal statistical model of the data. As a result, they offer several advantages over algorithmic approaches, such as the ability to include covariates, model longitudinal change (and associated error structures), account for measurement error, and conduct statistical tests of model fit and variable associations. (A fuller discussion of pros and cons of algorithmic vs. latent-variable approaches is provided later in this article.)

Within the latent-variable approach, it is helpful to make finer distinctions among statistical models. The classic person-centered latent-variable model is *latent class analysis* (Lazarsfeld, 1950) or *latent class cluster analysis* to distinguish it from algorithmic clustering methods (Vermunt & Magidson, 2002). Some also distinguish between *latent class analysis* and *latent profile analysis* (Bartholomew, 1987)—with the former involving categorical (either dichotomous or polytomous) response indicators and the latter involving continuous response indicators (though these terms are often used interchangeably). Individuals are classified based on the pattern of their responses, and the optimal number of latent classes is determined by comparing models that have different numbers of latent classes.

Classifying individuals based on cross-sectional responses is sufficient in many cases, but in others, the researcher may want to incorporate other features. Consequently, one extension to the classic latent class model is *mixture regression*, or *latent class regression* (also occasionally referred to as *clusterwise regression*, although this label does not limit to model-based methods; see Brusco, Cradit, Steinley, & Fox, 2008). These models identify subpopulations based on predictive relations between variables, and individuals with similar regression slopes are classified together. This is done by incorporating a regression equation within the latent class model. Another extension for longitudinal data is *growth mixture modeling*. This analysis estimates a growth trend for each individual, who is then classified based on his or her trajectories over time. A special case of growth mixture modeling is *latent class growth analysis*. This is simply a restricted case of growth mixture modeling in which all growth trajectories within a class are set to be homogeneous, leading to greater model parsimony and less complicated estimation. *Latent transition analysis* is also an analysis for longitudinal data and is appropriate in cases when the latent group membership variable itself is hypothesized to change over time (i.e., dynamic latent variables). Finally, *mixed-measurement modeling* involves blending of latent class analysis with item response theory (IRT) or (confirmatory) factor analysis, where subjects are grouped based on item–latent trait relations (e.g., item response parameters such as location and discrimination or factor loadings). More detailed summaries, potential research questions, and suggested readings of each of these methods are presented in Table 1. In addition, we recommend two introductory chapters by Morin (2016) and Morin and Wang (2016) for those seeking to learn more about mixture models in general.

Literature Review of Clustering Methods Used in Organizational Sciences

To understand how all of these methods have been used in our field, we surveyed the organizational sciences literature for studies that used person-centered approaches. Our main goals were to identify their prevalence, research trends over time, and characteristics of the studies that implemented them (e.g., level of analysis, sample size, and composition).

We conducted our search according to the standards of the PRISMA (2009) checklist. Included studies met the eligibility criteria of being published or in press from any year. Our information sources comprised 15 of the most prominent journals in our field: *Academy of Management Journal*, *Administrative Science Quarterly*, *Organization Science*, *Organizational Research Methods*, *Organizational Behavior and Human Decision Processes*, *Journal of Management*, *Journal of Organizational Behavior*, *Journal of Vocational Behavior*, *Journal of Applied Psychology*, *Journal of Business and Psychology*, *Personnel Psychology*, *Journal of Occupational and Organizational Psychology*, *European Journal of Work and Organizational Psychology*, *Journal of Occupational Health Psychology*, and *Journal of Personnel Psychology*. Although what truly constitutes the "organizational sciences literature" can be debated, the practice of using journals to delimit it is common to many reviews (e.g., Aguinis, Pierce, Bosco, & Muslin, 2009). All studies identified that met the aforementioned requirements were included.

With regard to our specific search terms, for algorithmic person-centered approaches, we searched for the term *cluster*. However, the full-text option produced an unmanageable number of results (e.g., 387 for *Academy of Management Journal*, 158 for *Journal of Applied Psychology*). It also included studies that did not necessarily use cluster analyses as the primary method but merely as a minor step in the overall analysis. Therefore, we altered our approach and searched only for papers that had *cluster* as a subject term, resulting in a more manageable set of papers in which clustering played a central role. We found 43 of these studies, and the results of this review are provided in the Supplementary Materials (Table S1, available in the online version of the journal). The table provides study characteristics (e.g., samples, indicators, identified groups), and entries are sorted first by study year and then author last name.

For searches related to latent-variable approaches, we used the full-text option for the following terms: *latent class*, *latent profile*, *latent transition*, *growth mixture*, *mixed measurement*, *mixture regression*, *factor mixture*, and *mixture-SEM*. (Note that the *latent class* term covered latent class

Table 1. Commonly Used Analytic Methods for Clustering.

Analytic Method	Summary, Distinctive Features, and Research Questions	Suggested Reading
Hierarchical clustering	Overview ○ Involves the repeated partitioning of observations into different sets of clusters in one of the following two ways: – Bottom-up (agglomerative): start from *N* clusters (each observation as its own cluster); the two nearest clusters are joined at each step; repeats until a single cluster contains all the data, and each step represents a possible cluster solution – Top-down (divisive): from a single cluster to *N* clusters Researcher decisions before clustering: ○ A measure of distance between observations (typically, Euclidean distances) ○ The criterion for how two clusters will merge (e.g., the lowest average distance between clusters) Methods for choosing a cluster solution: ○ Agglomeration schedule ○ Visualizations (dendrogram, scree plots, icicle plots) ○ Distance statistics (variance ratio criterion) Research questions (applicable to all other analyses) ○ How many clusters/classes are in the data? ○ What is the prevalence (size) of each cluster? ○ How are clusters different (e.g., different variable means)? ○ What variables predict group membership? ○ How do other outcomes differ across groups?	• Aldenderfer and Blashfield (1984) • Gore (2000) • Ketchen and Shook (1996) • Yim and Ramdeen, (2015)
k-means clustering	Overview ○ Requires that the number of clusters be supplied prior to the analysis (only a classification procedure). ○ The starting locations of each cluster center are assigned randomly, and the distance from each observation is calculated. ○ Observations are grouped into the nearest cluster, minimizing the within-cluster sum of squares error (SSE). ○ New locations for each cluster center are calculated based on the mean of their observations, and observations are reclassified into different clusters if necessary. This process repeats until observations are no longer reclassified or prespecified number of iterations has passed. Research questions ○ Same as hierarchical clustering	Same as hierarchical clustering
Latent class/ profile analysis	Overview ○ The basic person-centered latent variable models. ○ Instead of a single distribution, observations are viewed as coming from several subpopulations, represented as a weighted sum (a "mixture") of probability distributions.	• Collins and Lanza (2010) • Magidson and Vermunt (2004, 2005) • McCutcheon (1987)

(continued)

Table 1. (continued)

Analytic Method	Summary, Distinctive Features, and Research Questions	Suggested Reading
	○ Each subdistribution represents a unique class, and its weight indicates its size. Classes are differentiated based on the parameter values of their distributions (e.g., Group A has mean of 10 and variance of 4, whereas Group B has a mean of 15 and variance of 1). ○ Classification is modal membership (case is assigned to the group with the highest probability of membership) Statistics for model selection ○ Likelihood ratio tests (Vuong-Lo-Mendell-Rubin likelihood ratio test, bootstrap likelihood ratio test) ○ Information criteria (Akaike Information Criterion [AIC], Bayesian Information Criterion [BIC], sample size–adjusted BIC) ○ Entropy (degree of separation between classes) Research questions ○ Same as hierarchical clustering	• Nylund, Asparouhov, and Muthén (2007) • Vermunt and Magidson (2002)
Mixture regression	Overview ○ An extension of the latent class model that respecifies the distribution means as a linear function of predictors (i.e., a linear regression model) ○ Classes are identified based on their different patterns of association with predictors. Research questions ○ Are there different patterns of association between variables that can be grouped into classes?	• Brusco, Cradit, Steinley, and Fox (2008) • Collins and Lanza (2010) • Chénard-Poirier, Morin, and Boudrias (2017) • Garver, Williams, and Taylor (2008) • Magidson and Vermunt (2004) • Van Horn et al. (2009)
Growth mixture modeling	Overview ○ An extension of latent growth modeling to include latent classes ○ In latent growth models, the slope (change over time) and intercept (initial standing) are modeled as latent variables. These latent variables have a single mean and variance that describe the overall growth trajectory (i.e., all are pooled into a single group). ○ Growth mixture models allow multiple classes of growth trajectories that have different means and variances for their slopes and intercepts. Research questions ○ How many different types of growth trajectories are there? ○ How much do these trajectories vary within classes?	• Jung and Wickrama (2008) • Muthén and Muthén (2000) • Nylund et al. (2007) • Ram and Grimm (2009) • Wang and Bodner (2007)
Latent class growth analysis	Overview ○ Same as growth mixture modeling except that all trajectories within classes are constrained to be equal. Research questions ○ Same as growth mixture modeling aside from questions on how trajectories vary within classes.	Same as growth mixture modeling

(continued)

Table 1. (continued)

Analytic Method	Summary, Distinctive Features, and Research Questions	Suggested Reading
Latent transition analysis	Overview ○ An extension of latent class/latent profile analysis that allows class membership to change over time (exclusively for longitudinal data). The latent classes are called *latent statuses* because they can change. ○ Important estimated parameters are the (a) proportion of individuals within each status at each timepoint, (b) transition probabilities (the probabilities of going to another status given the current status), and (c) the parameter values of each status (e.g., means). Research questions ○ Are there different latent statuses present in the data? ○ How stable are these statuses (i.e., how do their frequencies change over time)?	• Collins and Lanza (2010) • Lanza, Patrick, and Maggs (2010) • Velicer, Martin, and Collins (1996)
Mixed-measurement modeling	Overview ○ An extension of item response theory (IRT) or factor analysis to include latent classes ○ Mixed-measurement models add in the possibility that there may be groups for which the item behaves differently (e.g., has different IRT parameter values or different factor loadings). ○ IRT or factor models with different numbers of latent classes are compared to find the most appropriate model. Research questions ○ Are there classes for how items or item responses behave across individuals? ○ Does measurement equivalence exist across latent (and/or observed) subgroups? ○ Are latent measurement classes distributed differently among hierarchical units (e.g., teams, firms, countries)?	• Baker and Kim (2004) • Carter, Dalal, Lake, Lin, and Zickar (2011) • Maij-de Meij, Kelderman, and van der Flier (2008) • Tay, Newman, and Vermunt (2011) • Tay, Diener, Drasgow, and Vermunt (2011) • Zickar, Gibby, and Robie (2004)

growth analysis as well as latent class regression.) This yielded a set of 64 studies. A summary of how these person-centered approaches were used is reported in the second table in the Supplementary Materials (Table S2, available in the online version of the journal), the entries sorted by study year and then author name.

Overall Prevalence and Trends Over Time

For algorithmic approaches, hierarchical clustering was by far the most common method (25 studies), followed by *k*-means clustering (9 studies) and several other methods that were used in earlier decades prior to more sophisticated clustering approaches (e.g., clustering based on inspecting correlations). Figure 1 shows the number of publications over time for algorithmic clustering approaches with a nonparametric trendline fitted to the data. Because of the many years in the series, observations were binned into 5-year intervals, with the x-axis labels showing the upper bin limits (the years 2016-2017 were added to 2015). As seen, these clustering methods have been used

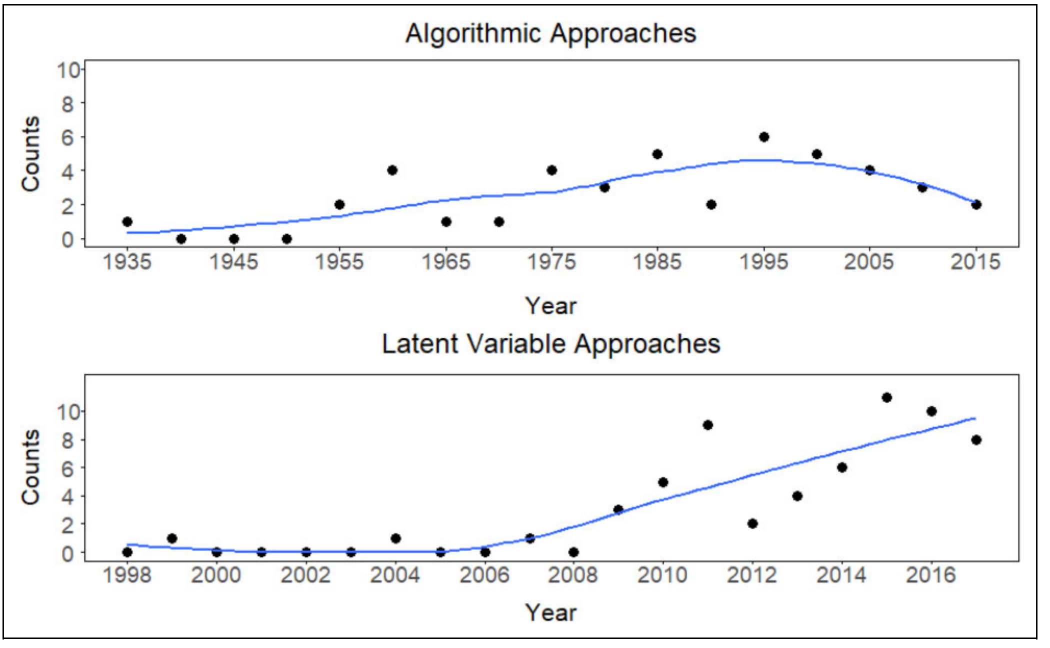

Figure 1. Plots of the use of algorithmic and person-centered latent-variable approaches over time. Years for algorithmic approaches had a much larger span (1935-2017) and have been binned into 5-year increments (years given are the upper limit of each 5-year bin, and 2015 includes 2016-2017).

consistently since approximately 1975. There appears to be a slight downward trend toward the end of the series after 1995.

For latent-variable approaches, we found that 23 studies used latent profile analysis, 14 used latent class analysis, 2 used mixture regression, 15 used growth mixture modeling, 7 used mixed-measurement modeling, and 4 used latent transition analysis. Figure 1 shows the number of publications over time for these approaches with a nonparametric trend line fitted to the data. (Observations here are not binned due to fewer years in the series.) Articles in press were not plotted but are included in all statistics. Prior to 2009, there were only three studies that used person-centered approaches (i.e., Hernández, Drasgow, & González-Romá, 2004; Pearce & Osmond, 1999; Wang, 2007). However, since then, there has been a notable and consistent increase in their use. Sixty-one such studies (95%) were conducted in or after 2009, indicating a growing interest and application of these methods within the organizational sciences.

Study Characteristics

Specific descriptive characteristics of the reviewed studies are shown in Table 2. There were both similarities and differences among algorithmic versus latent-variable approaches. On average, latent-variable methods used larger sample sizes. There was an overall median sample size of $N = 678$, and for each model subtype, the median sample size was at least 300 participants. However, the range also indicated that there were less than 100 participants in some studies. Studies using algorithmic methods, in contrast, had an overall median sample size of $N = 180$, and the Ns ranged between 180 and 280 for specific algorithms. Some studies had fewer than 20 participants, which were usually cases when the researcher was clustering higher-level units like firms or regions. Despite sample sizes differences, both algorithmic and latent-variable approaches seemed to identify similar numbers of subpopulations, with an average of 4 to 5 clusters per study. Algorithmic

Table 2. Descriptive Statistics of the Person-Centered Studies in Organizational Sciences.

Algorithmic Approaches										
		Sample Size			Number of Classes			Number of Indicators		
Algorithm	*N*	Median	Range	*SD*	Mean	Range	*SD*	Mean	Range	*SD*
All	43	180	9-2,771	447	5.40	1-12	2.48	27.36	2-139	32.27
Hierarchical	25	226	19-970	288	5.19	1-10	2.63	19.53	2-97	27.64
k-means	9	279.50	20-2,771	901	4.25	3-6	1.04	35.69	6-68	35.54
Other	12	101	9-685	226.	6.47	3-12	2.39	45.89	5-139	41.65

Latent Variable Approaches										
		Sample Size			Number of Classes			Number of Indicators		
Model Type	*N*	Median	Range	SD	Mean	Range	*SD*	Mean	Range	*SD*
All	64	678	17-121,740	14,175	4.23	2-8	1.22	4.75	2-22	1.37
Latent profile analysis	23	481	132-1,362	323	4.32	2-6	1.11	4.77	2-18	3.32
Latent class analysis	14	786	17-20,074	6,103	4.56	2-7	1.26	7.46	3-22	5.16
Mixture regression	2	337	201-474	193	5	4-6	1.41	7.50	7-8	0.71
Latent transition analysis	4	994	255-1,744	608	4.50	4-5	0.58	5.75	3-9	2.75
Growth mixture modeling	15	837	72-7,661	1,825	4.13	2-8	1.30	1.00	—	—
Mixed-measurement modeling	7	1,669	262-121,740	45,280	3.13	2-5	1.13	11.60	4-24	7.40

Note: — indicates cases where there was no variability. For studies in the review that fit multiple models (e.g., Hernández, Drasgow, & González-Romá, 2004, fit 16 separate mixed-measurement models to 16 personality scales), the within-study average was taken so as to not outweigh studies with only single models.

approaches showed slightly more variation in the number of clusters identified (overall $SD = 2.48$ vs. 1.22). Finally, algorithmic approaches had significantly more indicators as compared to latent-variable approaches (overall $M = 27.36$ vs. 4.75) and much more variation in the number of indicators (overall $SD = 32.27$ vs. 1.37). This is not surprising given that latent-variable approaches are more computationally demanding than algorithmic approaches.

Five Cluster Meanings: Synthesizing the Reviews Into a Unified Taxonomy

Our review showed an upward trajectory of person-centered methodology, which is most likely due to the increasing complexity and diversity of the analytic techniques that are available (e.g., growth mixture modeling, mixed-measurement modeling). Although this signals progress, without proper guidance, this growth could lead to inconsistencies and confusion when conducting and interpreting these analyses. For person-centered research to better flourish, we see the need for a common framework that allows researchers to articulate and understand the substantive meanings of the *clusters* they identify (which may be also referred to as *profiles*, *classes*, *groups*, and *subpopulations*). Thus, in this current section, we offer a unifying taxonomy of cluster meanings, or interpretations. As displayed in Table 3, we found that the different clusters gained from person-centered methods can be summarized into five major categories based on the substantive nature of the clustering: construct-based groups, response-style groups, predictive groups, trajectory groups, and measurement groups. The current section provides an overview of each group type to (a) better

Table 3. A Unifying Framework for Person-Centered Research Questions, Methods, and Examples.

Meaning of Clusters	Similarity in	Form of Indicators	Analytic Methods	Examples
Construct-based groups	Construct patterns	Construct scores	*k*-means or hierarchical cluster analysis Latent class/profile analysis Latent transition analysis	• Given the types of motivation posited by self-determination theory (e.g., internal, integrated), how many distinct motivational profiles are there? (Moran, Diefendorff, Kim, & Liu, 2012) • How many faultlines (i.e., group divisions based on demographics) are there within an organization? (Lawrence & Zyphur, 2011)
Response-style groups	Response patterns	Item-level responses	*k*-means or hierarchical cluster analysis Latent class/profile analysis Latent transition analysis	• Are there distinct cultural patterns of item responses (i.e., response styles) to items that measuring promotion focus? (Tay, Woo, Klafehn, & Chiu, 2010) • Are there different responses of firm commitment to the natural environment? (Henriques & Sadorsky, 1999)
Predictive groups	Regression relations	Construct scores	Mixture-SEM Mixture-regression	• Do family resources (parent free time, adequate finances) relate to academic achievement in children differently across classes? (Van Horn et al., 2009) • Are there different classes for how reflective judgment is predicted by high school and college GPA? (Brusco, Cradit, Steinley, & Fox, 2008)
Trajectory groups	Growth patterns	Scores over time	Growth mixture modeling	• What are the different growth trajectories for career satisfaction and engagement in early career phases? (Upadyaya & Salmela-Aro, 2015) • What are the trajectories of absenteeism over time? (Magee, Caputi, & Lee, 2015)
Measurement groups	Item-parameters or marginal probability of responding	Item-level responses	Mixed-measurement modeling	• Are there classes of individuals that are measurement equivalent for a scale of union citizenship? (Tay, Newman, & Vermunt, 2011) • Are there classes of individuals that are measurement equivalent who respond differently to middle categories, such as "?," "not sure," and "undecided"? (Hernández, Drasgow, & González-Romá, 2004)

Note: Examples were taken from the organizational sciences literature or related fields.

organize the growing area of person-centered analysis and (b) aid organizational researchers in identifying and interpreting the groups they derive. After this, we provide even more practical guidelines for assessing the validity of cluster solutions in Part 3.

Construct-Based Groups

The first group type is when the indicators (or manifest variables) represent theoretical constructs. In these cases, the inputs to the analysis are construct scores, and the substantive interpretations of the groups are based on the different constructs that are inputted to the analysis—namely, *construct-based groups*. Construct-based groups are by far the most common group type as contemporary organizational science is decidedly theory-driven, and cases where the indicators were construct scores comprised the majority of studies in our literature review. Importantly, theoretical interpretations of these groups must be equally sensitive to *all* of the construct indicators. Ignoring one or several in theoretical interpretation leads to inaccurate descriptions and, potentially, inferences.

As an example of this using an algorithmic approach, Sestito et al. (2015) conducted a two-step clustering analysis to identify subtypes of vocational identity status (i.e., identities in pursuing career and academic objectives). The authors had five inputs to the analysis, the subscales of the Vocational Identity Status Assessment: commitment making, identification with commitment, flexibility, self-doubt, exploration in breadth, and exploration in depth. Taking into account the levels of these variables per each class, the authors assigned substantive meaning to the six groups they found. For instance, the cluster labeled *undifferentiated* was characterized by moderate scores on all the identity dimensions, whereas *searching moratorium* was a class with moderately high scores in commitment, high scores on self-doubt, and modestly low scores on exploration in breadth.

In an example using a latent-variable approach, Gabriel et al. (2015) used latent profile analysis to derive five profiles of emotional labor strategies based on two types of emotional labor: deep and surface acting. The interpretation of the derived groups was based on these two construct indicators: nonactors (very low levels of both deep and surface acting), low actors (low levels of both indicators), surface actors (high in surface acting and low in deep acting), deep actors (low in surface acting and high in deep acting), and regulators (high on both indicators). Graves, Cullen, Lester, Ruderman, and Gentry (2015) also used latent profile analysis to uncover types of managerial motivational profiles. The indicators used were four distinct motivational constructs: external, introjected, identified, and intrinsic (the last three representing internal motivations). Six groups were uncovered and then interpreted based on their patterns of these motivational types: very low internal (lowest in all three internal motivations), low internal (second lowest in internal), moderately low internal (third lowest in internal), high internal, and self-determined (high in identified and intrinsic motivation).

Response-Style Groups

Another type of clustering describes situations where the goal is to examine response styles to scale items or a set of observed variables; these may or may not represent some overarching theoretical construct. Further, these groupings do not have an underlying *continuous* latent variable. Latent class/profile analysis is used to see if there are unique *response-style groups*. For example, Tay, Woo, Klafehn, and Chiu (2010) conducted latent class cluster analysis to examine distinct patterns of responses to items measuring promotion focus, roughly describable as eagerness for achievement, in a sample of American and Chinese students. The authors found two latent classes with respect to how subjects responded: a middle-point and end-point group. For those high in promotion focus, middle-point responders were just as likely to be American or Chinese (56% vs. 44%). However, for those high in promotion focus, end-point responders were largely American (88% vs. 12%), and those low in promotion focus, middle-point responders were largely Chinese (79% vs. 21%), aligning with prior researching showing that the Chinese are more likely to use middle scale points but also showing that Americans also use middle scale points. The authors concluded that there exist groups that are similar across nations but also "culturally unique response patterns" across these two countries (p. 193). These types of groups can also be derived using algorithmic approaches.

Predictive Groups

In the basic person-centered latent-variable models, observations are categorized based on the raw values of the manifest variables. However, in many cases, what defines the phenomenon in question is not so much the raw values themselves but how these manifest variables relate to important covariates. In such applications, individuals can be clustered based on differences in associations between predictors and outcomes. These models can be seen as extensions to traditional person-centered models and include (a) mixture regression (or latent class regression) for observed covariates and (b) mixture-SEM for predictor variables that are latent. The theoretical meaning imbued to any class depends on the nature of the variable relations; the interpretation is rooted in the pattern of associations between predictors and its outcome variables (i.e., *predictive groups*). For example, Garver et al. (2008) used mixture regression to analyze theoretical hypotheses related to chronic turnover in a sample of truck drivers. Several variables had been posited as strong explanatory factors of this phenomenon, such as the relationship with top management, pay, relationship with dispatch, and equipment. After analyzing the data, the authors found that a four-class solution resulted in a 40% increase in variance explained relative to traditional multiple regression (i.e., a one-class model). The uncovered groups were differentiated based on how strongly the set of attitudinal variables related to the intent to stay. The largest group within the sample (62%) had 47% of intent to stay variance being explained by top management, dispatch, and pay factors. The second largest group (16%) also had significant relations with these three variables, but they explained a much greater percentage of the intent to stay variance (90%). Intent to stay in the third group was a function of equipment and pay (83% variance explained), whereas intent to stay in the smallest group (7%) was influenced only by pay (41% variance explained).

Trajectory Groups

So far, we have only considered models for cross-sectional data in which substantive interpretations of groups do not need to consider dynamic relations and the influence of time.[3] However, most organizational phenomena have important time-based effects (Ancona, Goodman, Lawrence, & Tushman, 2001; Mitchell, James, & James, 2011), and longitudinal designs and analyses have significantly grown in prevalence in the past decade (Aguinis et al., 2009). Person-centered latent-variable models have also been developed to accommodate longitudinal data, namely, growth mixture modeling (and its restricted case of latent class growth analysis). However, given that the input data are longitudinal, the interpretation of classes must fundamentally change as well. In these cases, the interpretation of the classes are different *trajectory groups* that are described by different growth parameters (i.e., intercept and slopes). The specific interpretation for each group must be based on the exact form of change over time, considering all of the timepoints under study. For instance, in a study examining psychological well-being in two samples of retirees, Wang (2007) uncovered three distinct types of latent growth patterns. The first group consistently showed a high level of well-being with the estimated growth curve displaying essentially no change. This group was labeled the *maintaining pattern* because of the lack of any significant change in well-being over the retirement course under study. By contrast, well-being in the second group was significantly lower at the onset of retirement. However, their well-being levels rose over time with a positive linear trend, and this trajectory group was called the *recovering pattern* given the nature of this change. Finally, the third group trajectory group displayed an initial decrease in well-being over time followed by a subsequent increase and was labeled the *U-shaped* group.

Measurement Groups

In our review, we also identified cases where person-centered approaches have been applied to measurement models for latent variables. This is the case for mixed-measurement modeling, a fusion of latent class analysis with IRT or (confirmatory) factor analysis where individuals are grouped by virtue of their different item-trait relationships. This constitutes the final type of group interpretation, namely, *measurement groups*, or unobserved measurement equivalence (see Lubke & Muthén, 2005; Tay, Newman, & Vermunt, 2011). These differ from response-style groups in that their interpretation is based on different item–(continuous) latent variable relations, whereas response-style groups are defined by differences in response patterns without an additional continuous latent variable. The substantive goal of measurement groups is to obtain groupings that are measurement invariant. In mixed-measurement models, interpreting these groups is somewhat more complex than in the other cases because there are various ways in which measurement groups might differ from one another and how one might test for such measurement invariance. For instance, the defining difference across classes may be different estimates of item response parameters, such as different location and discrimination parameter estimates. Tay et al. (2011) examined measurement equivalent groups for a scale of union citizenship (McShane, 1986) using mixed-measurement modeling. Two classes emerged, differentiated by how levels of the latent trait of union citizenship were related to different probabilities of item endorsement. Specifically, in the latent class labeled *politico*, higher union citizenship levels led to greater probabilities of endorsing items that were related to running for political office (e.g., "Have you been, or are you now, an elected officer in the local Association?"). Within the other group (*non-politico*), these same items did not discriminate levels of latent union citizenship. The authors interpreted these as reflecting qualitative differences in how higher levels of union citizenship manifest behaviorally.

In addition to parameters of the item response models, latent groups can also be defined by the probabilities of responding to given response options. Hernández et al. (2004) used Rost's (1991) mixed-measurement model for polytomous response data to detect subclasses of how individuals responded to the middle categories (e.g., "?") in the Sixteen Personality Factor Questionnaire (Cattell, Cattell, & Cattell, 1993). They found that a two-class model fit best for 13 of these personality scales. While not distinguishable by item response parameters, the groups differed in their marginal probabilities of endorsing the middle response category (e.g., ?), suggesting that this middle category does not function the same for everyone and that the same score across the two groups does not necessarily correspond to the same latent trait level (i.e., not measurement equivalent).

Part 3: Practical Guidelines for Cluster Validation in Person-Centered Research

In addition to delineating the general meanings of clusters, we see the need for further guidance on more tangible issues that arise while designing, conducting, and reporting person-centered research. Therefore, in this part we offer recommendations and/or key points to consider regarding researchers' decisions over (a) whether and how to articulate person-centered research questions, (b) what data collection and analytic methods to use in addressing those questions, and (c) how to select, interpret, and further establish the cluster solutions. These three issues are closely intertwined and together influence the issue of cluster validity in the person-centered research paradigm.

In the variable-centered paradigm, connecting analytic procedures and results to an underlying theory is closely related to the question of construct validity: Is there a close correspondence between the measurement (observable variables or indicators) and the theory (i.e., latent factor variables or constructs)? Similarly, in person-centered research, one can speak of a hypothetical, explanatory concept that represents multiple groups (or clusters) of people (e.g., a latent class variable). Furthermore, the specific features of clusters resulting from the analysis require substantive interpretations and theory-building efforts to ensure the content relevance of the clusters in light of existing theory and/or toward a new theoretical development. Broadly put, *cluster validity*—much analogous to construct validity—can be established based on the quality of analytic practices in capturing the clusters of individuals that are meaningfully differentiated from one another. However, just as a variable-centered construct validation involves establishing multiple types of validity evidence (e.g., content relevance, factorial structure, and relationships with other variables; Cronbach & Meehl, 1955; Hinkin, 1998; Landy, 1986; Messick, 1995), a person-centered, *cluster validation* process also entails some careful considerations and steps to follow.

Step 1: Articulate a Person-Centered Research Purpose

Whether the nature of one's person-centered investigation is inductive or deductive, any study needs to begin with a clear purpose (Woo, O'Boyle, & Spector, 2017). Therefore, prior to conducting a person-centered study, the researcher must deliberate on whether it is reasonable to expect the presence of multiple clusters in the population of interest in the first place and how such clusters may be differentiated from one another (e.g., by construct patterns, response-style patterns, regression relations, growth patterns, or measurement models; see Table 3). Based on how confidently one can answer these questions, the study purpose will be either more exploratory or confirmatory. Specifically, we can think of three general circumstances. First, when there is little known about a given topic, researchers may take an open-ended, exploratory approach by asking the following questions: "Are there multiple clusters/types/subpopulations of ______? How are these clusters characterized?" (e.g., Gabriel et al., 2015; Moran, Diefendorff, Kim, & Liu, 2012; Woo & Allen, 2014). This can be framed as a loose form of hypothesis testing without specific predictions at the cluster level (e.g., Jermier, Slocum, Fry, & Gaines, 1991). Second, there may be a good theoretical reason to specify a specific cluster(s) of individuals within the entire population of interest but without knowing exactly how the rest of the population may be clustered (e.g., Kam, Morin, Meyer, & Topolnytsky, 2016; Nielsen et al., 2009; Woo, 2011). Third and last, the most specific, restrictive form of hypothesis testing may be posing a specific number of clusters to be expected along with the detailed description of how they may be differentiated from one another (e.g., O'Neill, McLarnon, Hoffart, Woodley, & Allen, 2018; Sinclair, Tucker, Cullen, & Wright, 2005; Wang, 2007).

Step 2: Determine the Analysis and Collect Data

Once a research purpose is specified and the corresponding research questions and/or hypotheses articulated, the researcher faces a series of important decisions, including the type and amount of data to collect and an analytic strategy to implement given the research question. Oftentimes these decisions are further complicated by practical constraints, such as restricted control over data sources, limited time to gather survey responses, and so on. The particular research questions also provide strong analytic direction (e.g., growth mixture modeling for questions about trajectory classes). Therefore, rather than prescribing one best course of actions for all cases, in the following, we review and discuss (a) key differences between algorithmic and latent-variable approaches and (b) issues associated with statistical power (and sample size) in implementing clustering methods.

Algorithmic Versus Latent-Variable Approaches: Pros and Cons

A key issue in person-centered analysis is whether to select an algorithmic or laten-variable approach to data analysis. However, this choice will largely be determined by the research question and types of groups one seeks to identify. Algorithmic approaches are only used for clustering individuals into construct-based or response-style groups.[4] By contrast, latent-variable methods are more flexible and can also uncover predictive groups, trajectory groups, and measurement groups.

For research questions about construct-based or response-style groups, there are important differences between algorithmic versus latent-variable approaches that make one or the other preferable within a certain context. First, algorithmic approaches tend to involve greater levels of subjectivity than latent-variable approaches (Shore & Barksdale, 1998; Vermunt & Magidson, 2002). Latent-variable approaches are model-based and allow one to fit a number of different models (hypothesizing varying numbers of clusters) and then compare them using fit statistics. It is also possible to test and evaluate a particular model in a more confirmatory fashion using these statistics. By contrast, the process of determining clustering solutions for algorithmic approaches is less formal as there are "judgmental processes used in evaluating the number of clusters to retain" (Shore & Barksdale, 1998, p. 737).[5] In addition, there are a number of algorithmic clustering methods available, and researchers must make a series of related analytic decisions, such as the specific clustering algorithm to use (e.g., hierarchical vs. *k*-means), distance measure, and linkage criteria for forming clusters. Some arbitrariness is present in these choices and can lead to inconsistent results (Von Eye, Mun, & Indurkhya, 2004). One of the most cited advantages of latent-variable methods is that they avoid such choices.

However, latent-variable methods have drawbacks as well. The biggest limitation is that they require that the data conform to a specific distribution. For instance, analyses with continuous indicators assume that the data are distributed according to the multivariate normal distribution within each of the extracted profiles. If this distributional assumption is incorrect, the model is misspecified, and the results may not be accurate. Moreover, there is also subjectivity in choosing which fit statistics to use and how to use them. Although one can consult prior work and methodological recommendations, certain fit statistics can offer conflicting conclusions regarding model selection. In these cases, researchers must ensure that their decisions are judicious (discussed more in the following step). Latent-variable methods can also run into estimation problems. This is especially true of more complex models, such as those with greater numbers of latent classes and those that relax the assumption of local independence. To estimate such models, either more data must be collected or certain free parameters must become fixed. Researchers ought not to implement constraints that are not substantively tenable to simply meet model estimation needs. Finally, latent-variable approaches are often more mathematically sophisticated than algorithmic approaches and tend to involve higher degrees of computational complexity. Because of this, generic statistical software programs (e.g., SPSS) offer a variety of clustering algorithms (e.g., *k*-means, hierarchical) but have limited or no capabilities for conducting model-based clustering analyses. As of today, latent-variable approaches can only be implemented in some of the more specialized statistical packages such as Mplus, R, and Latent GOLD. This practical constraint is also important to consider when selecting an approach (Sharpe, 2013).

Statistical Power and Appropriate Sample Size

Another key question posed in person-centered data analysis is "What is the required or appropriate sample size?" There are several issues to consider in responding to this question. First, if the goal is a purely descriptive analysis where the researcher simply seeks to describe sample characteristics, there is often no minimum requirement beyond the basic requirements for computation of a solution.

Often this descriptive approach is taken in algorithmic analyses, and past research has used sample sizes of as low as 9 students (Ross, Dardano, & Hackman, 1959) and 20 executives (Priem, Love, & Shaffer, 2002).

Second, if the goal is generalizing the properties of the clusters from the sample to a wider population (i.e., statistical inferences), it usually involves an evaluation of an appropriate sample size. The specific numbers can vary, but one can rely on shared experience and expertise, rules of thumb, and power calculations. Drawing on shared experience, past organizational research in Table 1 has used a median sample size of $N = 180$ for algorithmic approaches and $N = 678$ for latent-variable approaches, which are reasonable requirements. Drawing on "classic" rules of thumb, Formann (1984) recommended a minimum sample size of 2^m, where m is the number of clustering variables for algorithmic approaches. For example, with $m = 5$ variables, one would require a minimum sample size of 32 individuals. On the other hand, a widely cited paper by Nylund, Asparouhov, and Muthén (2007) simulated a variety of latent class analysis and growth mixture models with three sample sizes: 200, 500, and 1,000. It was found that across conditions, a minimum sample size of about 500 yielded good accuracy in identifying the right number of latent classes.

While cutoffs and rules of thumbs are useful, they are also potentially crude given the variety of models and multiplicity of factors that can influence sample size requirements, particularly in latent-variable approaches. In latent-variable approaches, it has been recognized that factors such as the reliability of variables, number of response variables, strength of associations between latent variables and response variables, and class sizes can all affect the extent one can recover the true number of classes (e.g., Muthén & Muthén, 2002; Tekle, Gudicha, & Vermunt, 2016). Beyond this, sample size requirements based on statistical power can differ based on how one decides the number of classes (e.g., likelihood ratio, information criteria; e.g., Tekle et al., 2016), whether an indicator is significantly associated with a latent class (e.g., Gudicha, Tekle, & Vermunt, 2016), or if transition probabilities are significant in latent Markov analysis (e.g., Gudicha, Schmittmann, & Vermunt, 2014). These studies point to minimum sample sizes for adequate power ranging from 200 to more than 2,000. Similarly, it has been noted that "depending on these factors, analyses for very simple latent class models may be carried out probably with as few as 30 subjects, whereas other analyses require thousands of subjects" (Lubke, 2010, p. 215). Given this, we recommend the use of Monte Carlo approaches to calculate estimated power for a given sample size (or estimated sample size requirement for a given power level) where possible in Latent GOLD (e.g., Gudicha et al., 2014; Gudicha, Schmittmann, Tekle, & Vermunt, 2016; Gudicha, Tekle, et al., 2016; Tekle et al., 2016) or generalizing syntax from latent factor approaches in MPlus (Muthén & Muthén, 2002; Wolf, Harrington, Clark, & Miller, 2013).

Step 3: Select, Interpret, and Establish the Clusters

Selecting, interpreting, and establishing a cluster solution represents a complex process of cluster validation. Importantly, the processes through which clusters are selected, interpreted, and established are neither entirely sequential nor mutually exclusive of one another. Rather, cluster validation is best conceived as an iterative process, which involves multiple sources of information simultaneously informing the researcher in identifying the most appropriate/valid cluster solution. That said, for the sake of simplicity, we organize the issues related to this critical step into three separate (albeit interrelated) categories.

Selecting a Cluster Solution

One of the most fundamental issues in person-centered analysis is identifying what number of clusters best describes the data (i.e., which solution or model to choose). Before delving into specific statistics, it is necessary to state that the most important factor in choosing a solution is theory. Theory constrains solutions in a number of ways. First, to be theoretically meaningful, each cluster should have different parameter values associated with it. If the means between two groups are indistinguishable, then the theoretical interpretation will not be different, which implies that the number of clusters should be reduced. Plotting these means as profiles on a line graph may be particularly helpful. Second, each cluster should be large enough to be considered a meaningful class. If a cluster only comprises a small number of individuals, then the analyst should seriously consider whether that cluster is worth retaining—even if it is actually present within the population (practical significance vs. statistical significance). A third consideration is what prior research has to say about the expected numbers of classes. With the rise in person-centered methods, it will become increasingly likely that some prior theoretical expectation exists about the number of classes. This can take several forms, such as when there is a direct replication (analyzing job satisfaction profiles a second time), investigating a phenomenon related to a previous one (job engagement profiles informed by work on satisfaction profiles), or a person-centered extension (a latent transition analysis of satisfaction informed by a prior latent profile analysis). At the same time, it is important to note that sole reliance on a priori expectations to guide the cluster selection process may preclude the researcher from discovering novel yet potentially meaningful clusters that are yet to be explicated.

In addition to theory, there are different statistical methods for selecting optimal cluster solutions. For algorithmic approaches, choosing the correct number of classes pertains to hierarchical clustering only as *k*-means requires the number of clusters to be prespecified. This selection process for hierarchical clustering is based on the distances at which clusters are combined at each step, and this information is presented graphically in several different ways. The most basic of these graphics is the *dendrogram*, described earlier as the tiered diagram of cluster solutions. Here, the length between levels represents the distances between the clusters that are combined at each step. Using this visualization technique, one can identify where the distances between clusters start to become large and "cut" the tree (choose a solution) before dissimilar clusters are combined.

The agglomeration schedule, in contrast, presents this same information but in a table. This table lists every step in the algorithm, the two clusters that are combined at that step, and the distances between them (as coefficients). Another important visualization is the scree plot. Scree plots are usually used in exploratory factor analysis to determine the number of factors to retain. In that context, eigenvalues (variance explained) are plotted on the y-axis against each factor on the x-axis (1 to *m* factors). When a break in the plot occurs (an "elbow"), it reveals the point at which more factors no longer explain significant variance. In cluster analysis, the scree plot is used in a similar way. Different numbers of clusters are placed on the x-axis, and the distances between the clusters combined at each step are shown on the y-axis. When a break in the plot occurs, then another step would combine dissimilar clusters, suggesting that the optimal solution occurs just before the break. For more information on choosing a solution, the reader can enlist the resources listed in Table 1.

It is worth noting that these methods for hierarchical clustering are largely visual and involve higher levels of subjective judgment than those used for latent-variable methods. However, instead of a drawback, subjective judgement is a necessary part of data analysis; graphics can communicate much more information than single statistics (Jebb, Parrigon, & Woo, 2017; Tay, Parrigon, Huang, & LeBreton, 2016; Tukey, 1977), and qualitative data checks often identify mistakes made by automatic procedures (Gelman, 2004). Thus, with skillful application, optimal solutions can certainly be found. For instance, in their study on motivational profiles, Moran et al. (2012) found that a dendrogram supported two to five clusters as six or more produced clusters having just one observation. The agglomeration schedule and scree plot suggested between five and seven clusters (more clusters only resulted in minor improvements). Thus, the authors selected the five-cluster solution favored by both methods, and cluster means were examined to confirm that each class was theoretically distinguishable.

In contrast to algorithmic approaches, latent-variable approaches rely on a variety of statistical model evaluation criteria. In this process, more complex models (i.e., more classes) are compared to less complex models. Ideally, for a more complex model to be preferred, likelihood ratio tests should be significant (chi-square difference test, Vuong-Lo-Mendell-Rubin likelihood ratio test, bootstrap likelihood ratio test), information criteria should be lower (Akaike Information Criterion [AIC], Consistent AIC [CAIC], Bayesian Information Criterion [BIC], and sample size–adjusted BIC), and entropy values should be higher (how well separated the classes are).[6] The analyst should use many indices together to determine the optimal model as indices may at times diverge from the others (for further discussion, see Nylund et al., 2007). For instance, Gabriel et al. (2015) selected a five-profile model based on the results of seven fit statistics. They chose this solution even though the six-profile solution had slightly lower AIC and sample size–adjusted BIC. This was because the likelihood ratio tests for this more complex model were nonsignificant (the Lo-Mendell-Rubin likelihood ratio test and bootstrap likelihood ratio test) and its entropy was lower. By contrast, when comparing the five-profile solution to simpler models, its likelihood ratio tests were all significant and information criteria were all smaller (AIC, BIC, and sample size–adjusted BIC).

In an example with longitudinal data, Hirschi (2011) used four fit indices to determine the proper growth mixture model of adolescent career readiness: the BIC, entropy, Lo-Mendell-Rubin likelihood ratio test, and bootstrap likelihood ratio test. A four-class solution was ultimately chosen despite the five-class solution having significant likelihood ratio tests. Overriding these significance tests was the fact that the four-class model had a lower BIC value and higher entropy. More importantly, the fifth class was not different theoretically than the other classes (i.e., high initial levels of readiness and subsequent increase over time); the author described it as merely a "variation of an already existing group" (p. 345). This case displays the clear importance of using both theory and multiple statistics when evaluating latent-variable models. Further information on comparisons of model fit can be found in the resources listed in Table 1 (which include slightly different criteria for mixed-measurement IRT models).

Interpreting the Clusters

Answering the question of whether (and how much) the derived clusters are theoretically interpretable is analogous to providing two types of construct validity evidence found in the *Standards for Educational and Psychological Testing*: (a) evidence related to test content and (b) convergent-discriminant relationships (American Educational Research Association [AERA], American Psychological Association, & National Council on Measurement in Education, 2014).

In relation to content, assessing the meaningfulness of cluster differences entails examining the ability of the indicator content in capturing key differences across the clusters. Like content relevance in tests, this is typically examined in a qualitative and theoretical manner. By contrast, with respect to convergent-discriminant relations, one investigates how clusters produce different associations with theoretically meaningful covariates (as antecedents or correlates). This requires empirical data, and greater differences in associations imply that clusters are more importantly distinguished. Possible analytic strategies for such investigations are: comparing mean scores of external variables across the selected clusters (e.g., Cortina & Wasti, 2005) and conducting multinomial logistic regressions to predict classification probabilities across classes from variables usually theorized as antecedents of cluster membership (e.g., Bennett, Gabriel, Calderood, Dahling, & Trougakos, 2016; Gabriel et al., 2015; Meyer, Morin, & Vandenberghe, 2015). Through these theoretical and empirical means, the researcher can "make sense" out of the observed cluster configurations for improving an overall understanding of the phenomenon of interest.

In Step 1, we outlined three ways in which a particular research purpose might be more inductive or deductive in its structure. These lead to three different possible scenarios in which the meanings of cluster solutions are interpreted. First, if the researcher's purpose is inductive theory building (e.g., Woo & Allen, 2014), then a cluster solution identified as most reliable and replicable from the analysis should be given the closest examination for their theoretical merit (note: the issue of reliability and replicability is particularly critical for inductive research; Woo et al., 2017). In doing so, the researcher is encouraged to engage in a careful abductive reasoning process in which they examine how the observed configuration of clusters relates to prior theory and findings and whether the interpretation of clusters requires developing a new theory or revising/synthesizing existing ones. Second, when the researcher's focus is on identifying a specific set of clusters that are theoretically expected from prior research, then the primary attention should be given to finding the hypothesized clusters. The remaining clusters can be subject to post hoc interpretations/investigations for subsequent theory enrichment as needed (see e.g., Nielsen et al., 2009; Woo, 2011). Lastly, the strictest form of hypothesis testing on a particular set of subpopulations requires a close match between the observed configurations/features of each cluster within a solution and those that were explicitly hypothesized; any deviance from the hypothesized patterns in the observed cluster features should be explicitly discussed (see e.g., see O'Neill et al., 2018; Wang, 2007).

Establishing the Clusters

Once a cluster solution is (initially) selected and interpreted, the researcher is encouraged to further establish the validity of the clusters. One way of doing so entails investigating whether the clusters have differing levels of outcomes that are of theoretical and/or practical importance, such as performance (e.g., Howard, Gagné, Morin, & Van den Broeck, 2016; Moran et al., 2012), well-being (e.g., Gabriel et al., 2015), and turnover (e.g., Meyer et al., 2015). This is analogous to yet another type of construct validity evidence outlined in the *Standards* (AERA et al., 2014): test-criterion relationships. Further, sometimes (although not always), a researcher's ultimate goal of identifying subpopulations is to help clarify inconsistent findings of predictive relationships in variable-centered research. In such cases, it helps to present findings from both person-centered and variable-centered approaches and illustrate that certain predictive relationships that are theoretically noteworthy can only emerge when using a person-centered analysis (e.g., Gabriel et al., 2015).

Another important task to undertake for further establishing the cluster validity is examining its generalizability/replicability across different samples, contexts, and timepoints (see e.g., Gabriel et al., 2015; Hirschi & Valero, 2015; Kabins, Xu, Bergman, Berry, & Wilson, 2016; Meyer et al., 2015; Sinclair et al., 2005; Woo & Allen, 2014). For algorithmic approaches, Breckenridge (1989) evaluated and compared three possible ways of replicating clustering analyses in a Monte Carlo study. On the other hand, Morin and colleagues (2016) recently provided comprehensive guidance on how the replicability of cluster solutions can be systematically examined in the latent-variable approaches, focusing on the case of latent profile analysis conducted across two national samples. Specifically, the authors introduced a multiple-groups latent profile analysis approach to evaluate the similarity of latent profiles across groups or timepoints, which integrates latent profile analysis into the generalized structural equation modeling framework (Muthén, 2002). However, as further elaborated in the following, person-centered research in our field has implemented a wide variety of approaches to replication that are greatly varied in rigor and precision, and the literature does not provide a sufficient guidance on choosing the right type of replication strategy in a given research context/purpose.

Part 4: Future Research Agenda

To advance the person-centered methodological paradigm, the current article has attempted to offer a number of key contributions: a clarification of definitional and philosophical issues, a classification of techniques, a review of their use in our field, a typology for standardizing the interpretation of latent groups, and concrete recommendations for conducting analysis. All of these contributions are intended to assist researchers understanding the role of person-centered research and encourage further rigorous study with and development of these methods. At the same time, there are many other issues left open that will become the task of future work.

One important issue is generalizability. Clustering analyses are frequently done in an inductive fashion for a specific context or sample. This exploratory nature can be beneficial and even necessary (Jebb et al., 2017), but there is an increasing interest to understand if these groupings are replicable—or if we even need to replicate them in the first place. In our review, some studies (e.g., Gabriel et al., 2015; Kam et al., 2016) conducted replications of the found solution, but they were certainly not the majority. We highlight a number of critical aspects that need to be addressed in this regard. First of all, there needs to be a clear argument for whether these groups are *expected* to be generalizable or not. If not, one method of replication is through a holdout sample. If generalizable, one should proceed to collect data from additional contexts to show that these groupings are generalizable. Also, methodologically, work has begun to develop confirmatory approaches for latent class clustering methods (Finch & Bronk, 2011) and clear criteria for equivalence across samples (Morin et al., 2016) or timepoints (Morin & Litalien, 2017).

Further, there needs to be clear information on sample size recommendations as this can often influence the number of groups that are derived and the stability of the groupings (due to error). From our review, the sample sizes varied considerably across studies. Although the median sample size was an ample 678 participants for latent-variable approaches, half the studies had fewer subjects. It is not fully known how sample size influences the accuracy and replicability of uncovered classes. Are classes of some organizational phenomenon more stable than others? Does the stability vary based on what kind of groups they are (i.e., measurement groups vs. trajectory groups)? An issue that may be even more relevant than sample size to replicability is sample *representativeness*. How stable are the solutions across different types of samples? Do cultural and/or demographic effects matter? Morin et al. (2016) provided an important contribution in this regard, but future person-centered work can continue to examine these questions, which bear on the validity of the scientific inferences.

Another area needing more work is to systematically understand the relation between unobserved and observed characteristics. The development of these different types of groups (e.g., response, measurement, predictive, and trajectory) requires convergence and further understanding through observable characteristics of individuals, teams, or organizations. Methodologically, there is the question of whether grouping should be derived together with covariates or without covariates. Groupings derived with covariates use covariate information (e.g., race/ethnicity, gender, age, etc.) to establish class membership. How does this affect the determination of latent class membership both theoretically and statistically? And what determines covariate selection? Are certain covariates preferred to others—and if so, based on what factors? Tentatively, we can state that the use of these covariates should be theoretically informed. Where there is past work or theory suggesting that these groupings are related to observed demographic variables, then one should include these covariates as part of clustering. However, if these are not, then the "purest" form of clustering is to use the exclusive information (e.g., item or variable responses) that one seeks to maximize clustering on.

Further conceptual and methodological research is also needed for guiding analytic decisions between latent factor versus latent class approaches. This is a complex topic, and an in-depth discussion is beyond the scope of the paper. However, we note some themes in this decision process.

While the two approaches are conceptually different (latent factor clusters variables, whereas latent class clusters individuals), there is less distinction statistically as the k-class latent class model is structurally equivalent to the k–1 latent factor model based on model-implied covariances (Bartholomew, 1987). Given this, one perspective is that this choice may be purely driven based on conceptual grounds (e.g., Meehl, 1992). In other words, if there is a reasonable rationale to examine clusters of individuals, one should proceed with latent class analysis. On the other hand, there are also concerns that a latent factor approach may be the more parsimonious, and so there needs to be competitive testing and adjudication by statistical methods (for specific approach using factor mixture models, see Lubke & Neal, 2006). The implication is when one seeks a more exploratory approach to the data, it may be critical to compare models as there is no strong a priori theoretical rationale. More recently, it has been advocated that we consider them as complementary approaches in which latent class approaches need to be anchored on initial latent factor approaches, at least in terms of evaluating psychometric properties of measures (see overview by Morin et al., 2017). In general, this area of work is burgeoning, and we expect to see more development in the years to come.

Closing Remarks

In empirical science, substantive knowledge is bound to the underlying methodology used (Greenwald, 2012; Zyphur, 2000). The organizational sciences are no exception. The rapid growth of SEM methods and software in the 1970s (MacCallum & Austin, 2000) led to an increase in researchers developing and testing complex theoretical models that posited relationships among unobserved latent variables (Scandura & Williams, 2000; Stone-Romero, Weaver, & Glenar, 1995). By accommodating both micro and macro processes and the hierarchical nature of organizational data, multilevel modeling has engendered nothing less than a "paradigm shift" in organizational theory and research (Kozlowski & Klein, 2000; Mathieu & Chen, 2011, p. 610). Likewise, person-centered approaches offer a new way of conceiving and studying organizational topics. They are remarkably diverse, able to be paired with the two paradigms just referenced (e.g., mixture-SEM and multilevel latent class analysis) as well as other analytic frameworks (e.g., with item-response theory in mixed-measurement modeling, with latent growth curves in growth mixture modeling).

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Supplemental Material

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Notes

1. It is important to note that clustering approaches can be used for collective units beyond individual persons (e.g., firms, nations, environments); in such cases, terms like *clustering* and *configural* are more appropriate than the term *person-centered*.
2. In this paper, we use the terms *algorithmic* and *latent variable* to denote these two approaches to clustering. However, as one reviewer noted, latent-variable methods involve estimation algorithms (e.g., expectation-maximization), and algorithmic approaches can uncover latent variables. Although we decided that our

labels were intuitive for most organizational researchers, others could certainly be used as well (e.g., parametric vs. nonparametric).

3. Latent transition analysis also takes into account the dynamic nature of latent class membership by modeling movements across different cluster membership categories over time. However, the core theoretical meaning of clusters in this case is the same as those of response-style groups or construct-based groups, and thus we do not specify a separate cluster meaning associated with this analysis.
4. A few exceptions are: *k*-means approaches to longitudinal clustering (e.g., Genolini, Alacoque, Sentenac, & Arnaud, 2015; Genolini & Falissard, 2010) and non-model–based algorithms for partitioning data sets based on the heterogeneity of regression functions (e.g., Späth, 1991).
5. There is always some degree of subjectivity (as opposed to arbitrariness) involved in the way cluster solutions are ultimately selected, regardless of whether an algorithmic or a latent-variable approach is used. This is because determining the number of clusters not only depends on the statistical results per se but also on their interpretability, theoretical meaningfulness, and practical utility. At the same time, the arbitrary nature of decisions over specific clustering methods—possibly leading to inconsistent results—can and should be mitigated by implementing several strategies for cluster validation as outlined later in this article.
6. As described by Morin, Meyer, Creusier, and Biétry (2016), with very large samples, these fit indices may favor increasingly complex models without a stopping point (e.g., likelihood ratio tests never reaching nonsignificance). In these cases, the authors recommend that these statistics be mapped onto an elbow plot just like in hierarchical clustering. When the slope of the plot becomes flat, then no more significant changes in model fit are occurring and the most parsimonious model at that point should be chosen.

References

Aguinis, H., Pierce, C. A., Bosco, F. A., & Muslin, I. S. (2009). First decade of *Organizational Research Methods*. *Organizational Research Methods*, *12*(1), 69-112.

Alam, S., Dobbie, G., Koh, Y. S., Riddle, P., & Ur Rehman, S. (2014). Research on particle swarm optimization based clustering: A systematic review of literature and techniques. *Swarm and Evolutionary Computation*, *17*, 1-13.

Aldenderfer, M. S., & Blashfield, R. K. (1984). *Cluster analysis* (Sage University Paper Series on Quantitative Applications in the Social Sciences, No 07-044). Beverly Hills, CA: Sage.

American Educational Research Association, American Psychological Association, & National Council on Measurement in Education. (2014). *Standards for educational and psychological testing*. Washington, DC: American Educational Research Association.

Ancona, D. G., Goodman, P. S., Lawrence, B. S., & Tushman, M. L. (2001). Time: A new research lens. *Academy of Management Review*, *26*(4), 645.

Asendorpf, J. B., & van Aken, M. A. G. (2003). Personality-relationship transaction in adolescence: Core versus surface personality characteristics. *Journal of Personality*, *71*, 629-666.

Baker, F. B., & Kim, S.-H. (2004). *Item response theory*. Boca Raton, FL: CRC.

Bartholomew, D. J. (1987). *Latent variable models and factor analysis*. London: Charles Griffin.

Bennett, A. A., Gabriel, A. S., Calderwood, C., Dahling, J. J., & Trougakos, J. P. (2016). Better together? Examining profiles of employee recovery experiences. *Journal of Applied Psychology*, *101*(12),1635-1654.

Breckenridge, J. N. (1989). Replicating cluster analysis: Method, consistency, and validity. *Multivariate Behavioral Research*, *24*(2), 147-161.

Brusco, M. J., Cradit, J. D., Steinley, D., & Fox, G. L. (2008). Cautionary remarks on the use of clusterwise regression. *Multivariate Behavioral Research*, *43*(1), 29-49. doi:10.1080/00273170701836653

Carter, N. T., Dalal, D. K., Lake, C. J., Lin, B. C., & Zickar, M. J. (2011). Using mixed-model item response theory to analyze organizational survey responses: An illustration using the Job Descriptive Index. *Organizational Research Methods*, *14*(1), 116-146. doi:10.1177/1094428110363309

Cattell, R. B., Cattell, A. K., & Cattell, H. E. P. (1993). *16PF fifth edition questionnaire*. Champaign, IL: IPAT.

Celebi, M. E., Kingravi, H. A., & Vela, P. A. (2013). A comparative study of efficient initialization methods for the *k*-means clustering algorithm, *Expert Systems With Applications*, *40*(1), 200-210.

Chan, D. (1998). Functional relations among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology*, *83*, 234-246. doi:10.1037/0021-9010.83.2.234

Chénard-Poirier, L. A., Morin, A. J. S., & Boudrias, J. S. (2017). On the merits of coherent leadership empowerment behaviors: A mixture regression approach. *Journal of Vocational Behavior*, *103*, 66-75. doi:10.1016/j.jvb.2017.08.003

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. Hoboken, NJ: John Wiley & Sons, Inc.

Cortina, L. M., & Wasti, S. A. (2005). Profiles in coping: Responses to sexual harassment across persons, organizations, and cultures. *Journal of Applied Psychology*, *90*, 182-192.

Costa, P. T., Herbst, J. H., McCrae, R. R., Samuels, J., & Ozer, D. J. (2002). The replicability and utility of three personality types. *European Journal of Personality*, *16*, S73-S87.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*(4), 281-302.

Dalal, R. S. (2005). A meta-analysis of the relationship between organizational citizenship behavior and counterproductive work behavior. *Journal of Applied Psychology*, *90*, 1241-1255.

Dierdorff, E. C., Rubin, R. S., & Morgeson, F. P. (2009). The milieu of managerial work: An integrative framework linking work context to role requirements. *Journal of Applied Psychology*, *94*, 972-988. doi:10.1037/a0015456

Donnellan, M. B., & Robins, R. W. (2010). Resilient, overcontrolled, and undercontrolled personality types: Issues and controversies. *Social and Personality Psychology Compass*, *4*(11), 1070-1083. doi:10.1111/j.1751-9004.2010.00313.x

Finch, W. H., & Bronk, K. C. (2011). Conducting confirmatory latent class analysis using Mplus. *Structural Equation Modeling*, *18*, 132-151.

Formann, A. K. (1984). *Die latent-class-analyse: Einfuhrung in die theorie und anwendung*. Beltz: Weinheim.

Foti, R. J., Thompson, N. J., & Allgood, S. F. (2011). The pattern-oriented approach: A framework for the experience of work. *Industrial and Organizational Psychology*, *4*(1), 122-125.

Gabriel, A. S., Daniels, M. A., Diefendorff, J. M., & Greguras, G. J. (2015). Emotional labor actors: A latent profile analysis of emotional labor strategies. *Journal of Applied Psychology*, *100*(3), 863-879.

Garver, M. S., Williams, Z., & Taylor, G. S. (2008). Employing latent class regression analysis to examine logistics theory: An application of truck driver retention. *Journal of Business Logistics*, *29*(2), 233-257. doi:10.1002/j.2158-1592.2008.tb00094.x

Gelman, A. (2004) Exploratory data analysis for complex models. *Journal of Computational and Graphical Statistics*, *13*(4), 755-779. doi:10.1198/106186004X11435

Genolini, C., Alacoque, X., Sentenac, M., & Arnaud, C. (2015). kml and kml3d: R Packages to cluster longitudinal data. *Journal of Statistical Software*, *65*(4), 1-34. doi:10.18637/jss.v065.i04

Genolini, C., & Falissard, B. (2010). KmL: k-means for longitudinal data. *Computational Statistics*, *25*(2), 317-328.

Gore, P. (2000). Cluster analysis. In H. Tinsley & S. Brown (Eds.), *Handbook of applied multivariate statistics and mathematical modeling* (pp. 298-318). San Diego, CA: Academic Press.

Gower, J. C. (1971). A general coefficient of similarity and some of its properties. *Biometrics*, *27*, 857-874.

Graves, L. M., Cullen, K. L., Lester, H. F., Ruderman, M. N., & Gentry, W. A. (2015). Managerial motivational profiles: Composition, antecedents, and consequences. *Journal of Vocational Behavior*, *87*, 32-42. doi:10.1016/j.jvb.2014.12.002

Greenwald, A. G. (2012). There is nothing so theoretical as a good method. *Perspectives on Psychological Science*, *7*(2), 99-108. doi:10.1177/1745691611434210

Gudicha, D. W., Schmittmann, V. D., Tekle, F. B., & Vermunt, J. K. (2016). Power analysis for the likelihood-ratio test in latent Markov models: Short-cutting the bootstrap *p*-value based method. *Multivariate Behavioral Research*, *51*, 649-660.

Gudicha, D. W., Schmittmann, V. D., & Vermunt, J. K. (2014). Power computation for likelihood ratio tests for the transition parameters in latent Markov models. *Structural Equation Modeling*, *23*, 234-245.

Gudicha, D. W., Tekle, F. B., & Vermunt, J. K. (2016). Power and sample size computation for Wald tests in latent class models. *Journal of Classification*, *33*, 30-51.

Henriques, I., & Sadorsky, P. (1999). The relationship between environmental commitment and managerial perceptions of stakeholder importance. *Academy of Management Journal*, *42*(1), 87-99. doi:10.2307/256876

Hernández, A., Drasgow, F., & González-Romá, V. (2004). Investigating the functioning of a middle category by means of a mixed-measurement model. *Journal of Applied Psychology*, *89*(4), 687-699. doi:10.1037/0021-9010.89.4.687

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods*, *1*(1), 104-121. doi:10.1177/109442819800100106

Hirschi, A. (2011). Career-choice readiness in adolescence: Developmental trajectories and individual differences. *Journal of Vocational Behavior*, *79*(2), 340-348. doi:10.1016/j.jvb.2011.05.005

Hirschi, A., & Valero, D. (2015). Career adaptability profiles and their relationship to adaptivity and adapting. *Journal of Vocational Behavior*, *88*, 220-229. doi:10.1016/j.jvb.2015.03.010

Hom, P. W., Mitchell, T. R., Lee, T. W., & Griffeth, R. W. (2012). Redefining employee turnover: Focusing on proximal psychological states and an expanded criterion. *Psychological Bulletin*, *138*, 831-858. doi:10.1037/a0027983

Howard, J., Gagné, M., Morin, A. J. S., & Van den Broeck, A. (2016). Motivation profiles at work: A self-determination theory approach. *Journal of Vocational Behavior*, *95-96*, 74-89. doi:10.1016/j.jvb.2016.07.004

Huang, Z. (1998). Extensions to the *k*-means algorithm for clustering large data sets with categorical values. *Data Mining and Knowledge Discovery*, *2*, 283-304.

Huang, Z. (2009). Clustering categorical data with k-modes. In J. Wang (Ed.), *Encyclopedia of data warehousing and mining* (2nd ed., pp. 246-250). Hershey, PA: Information Science Reference.

Hurlburt, R. T., & Knapp, T. J. (2006). Münsterberg in 1898, not Allport in 1937, introduced the terms "idiographic" and "nomothetic" to American psychology. *Theory & Psychology*, *16*(2), 287-293. doi:10.1177/0959354306062541

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, *31*(8), 651-666. doi:10.1016/j.patrec.2009.09.011

Jebb, A., Parrigon, S., & Woo, S. E. (2017). Exploratory data analysis as a foundation of inductive research. *Human Resource Management Review*, *27*, 265-276.

Jermier, J. M., Slocum, J. W., Fry, L. W., & Gaines, J. (1991). Organizational subcultures in a soft bureaucracy: Resistance behind the myth and facade of an official culture. *Organization Science*, *2*, 170-194. doi:10.1287/orsc.2.2.170

Jung, T., & Wickrama, K. A. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass*, *2*(1), 302-317. doi:10.1111/j.1751-9004.2007.00054.x

Kabins, A. H., Xu, X., Bergman, M. E., Berry, C. M., & Willson, V. L. (2016). A profile of profiles: A meta-analysis of the nomological net of commitment profiles. *Journal of Applied Psychology*, *101*(6), 881-904. doi:10.1037/apl0000091

Kam, C., Morin, A. J. S., Meyer, J. P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? *A latent transition analysis.* Journal of Management, *42*(26), 1462-1490. doi:10.1177/0149206313503010

Kanfer, R., & Ackerman, P. L. (2005). Work competence: A person-oriented approach. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 336-353). New York, NY: Guilford Press.

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data*. New York, NY: Wiley

Ketchen, D., & Shook, C. (1996). The application of cluster analysis in strategic management research: An analysis and critique. *Strategic Management Journal*, *17*(6), 441-458.

Klotz, A. C., & Bolino, M. C. (2016). Saying goodbye: The nature, causes, and consequences of employee resignation styles. *Journal of Applied Psychology*, *101*(10), 1386-1404.

Kozlowski, S. W., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In K. J. Klein & S. W. Kozlowski (Eds.), *Multilevel theory, research, and methods in organizations* (pp. 3-90). San Francisco, CA: Jossey-Bass.

Landy, F. J. (1986). Stamp collecting versus science: Validation as hypothesis testing. *American Psychologist*, *41*(11), 1183-1192. doi:10.1037/0003-066X.41.11.1183

Lanza, S. T., Patrick, M. E., & Maggs, J. L. (2010). Latent transition analysis: Benefits of a latent variable approach to modeling transitions in substance use. *Journal of Drug Issues*, *40*(1), 93-120.

Lawrence, B. S., & Zyphur, M. J. (2011). Identifying organizational faultlines with latent class cluster analysis. *Organizational Research Methods*, *14*(1), 32-57. doi:10.1177/1094428110376838

Lazarsfeld, P. F. (1950). The logical and mathematical foundation of latent structure analysis & The interpretation and mathematical foundation of latent structure analysis. S. A. Stouffer (Ed.), *Measurement and prediction* (pp. 362-472). Princeton, NJ: Princeton University Press.

Liu, S., Wang, M., Zhan, Y., & Shi, J. (2009). Daily work stress and alcohol use: Testing the cross-level moderation effects of neuroticism and job involvement. *Personnel Psychology*, *62*, 575-597.

Liu, S., Zhan, Y., & Wang, M. (2011). Person-centric work psychology: Additional insights on its tradition, nature, and research methods. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *4*, 105-108.

Lubke, G. H. (2010). Latent variable mixture modeling. In G. R. Hancock & R. O. Mueller (Eds.), *The reviewer's guide to quantitative methods in the social sciences* (pp. 283-297). New York, NY: Routledge.

Lubke, G. H., & Muthén, B. O. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods*, *10*, 21-39.

Lubke, G. H., & Neale, M. C. (2006). Distinguishing between latent classes and continuous factors: Resolution by maximum likelihood? *Multivariate Behavioral Research*, *41*, 499-532.

MacCallum, R., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology*, *51*, 201-226.

Macrae, C. N., & Bodenhausen, G. V. (2000). Social cognition: Thinking categorically about others. *Annual Review of Psychology*, *51*, 93-120.

Magee, C. A., Caputi, P., & Lee, J. K. (2015). Distinct longitudinal patterns of absenteeism and their antecedents in full-time Australian employees. *Journal of Occupational Health Psychology*, *21*(1), 24-36. doi:10.1037/a0039138

Magidson, J., & Vermunt, J. (2004). Latent class models. *Latent Variable Models and Factor Analysis*, (617), 157-189. doi:10.1002/9781119970583.ch6

Magidson, J., & Vermunt, J. K. (2005). A nontechnical introduction to latent class models. *DMA Research Council Journal*, 1-15.

Maij-de Meij, A. M., Kelderman, H., & van der Flier, H. (2008). Fitting a mixture item response theory model to personality questionnaire data: Characterizing latent classes and investigating possibilities for improving prediction. *Applied Psychological Measurement*, *32*(8), 611-631. doi:10.1177/0146621607312613

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, *52*, 397-422.

Mathieu, J. E., & Chen, G. (2011). The etiology of the multilevel paradigm in management research. *Journal of Management*, *37*(2), 610-641. doi:10.1177/0149206310364663

McCutcheon, A. L. (1987). *Latent class analysis*. Newbury Park, CA: Sage Publication

McShane, S. L. (1986). The multidimensionality of union participation. *Journal of Occupational Psychology*, *59*, 177-187.

Meehl, P. E. (1992). Factors and taxa, traits and types, differences of degree and differences in kind. *Journal of Personality*, *60*, 117-174.

Messick, S. (1995). Validity of psychological assessment. *American Psychologist*, *50(9)*, 741-749.

Meyer, J. P., & Morin, A. S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*(4), 584-612. doi:10.1002/job.2085

Meyer, J. P., Morin, A. J. S., & Vandenberghe, C. (2015). Dual commitment to organization and supervisor: A person-centered approach. *Journal of Vocational Behavior*, *88*, 56-72. doi:10.1016/j.jvb.2015.02.001

Milligan, G. W., & Cooper, M. C. (1987). Methodological review: Clustering methods. *Applied Psychological Measurement*, *11*, 329-354.

Mitchell, T. R., James, L. R., & James, R. (2011). Time and the better theory: Building of when things happen specification. *Academy of Management Review*, *26*(4), 530-547. doi:10.2307/3560240

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201-218. doi:10.1207/s15366359mea0204_1

Molloy, J. C., Ployhart, R. E., & Wright, P. M. (2011). The myth of "the" micro-macro divide: Bridging disciplinary and system-level divides. *Journal of Management*, *37*, 581-609.

Moran, C. M., Diefendorff, J. M., Kim, T. Y., & Liu, Z. Q. (2012). A profile approach to self-determination theory motivations at work. *Journal of Vocational Behavior*, *81*(3), 354-363. doi:10.1016/j.jvb.2012.09.002

Morin, A. J. S. (2016). Person-centered research strategies in commitment research. In J. P. Meyer (Ed.), *The handbook of employee commitment* (pp. 490-508). Cheltenham, UK: Edward Elgar.

Morin, A. J. S., Boudrais, J.-S., Marsh, H. W., McInerney, D. M., Dagenais-Desmarais, V., Madore, I. . . . Litalien, D. (2017). Complementary variable- and person-centered approaches to the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology*, *32*(4), 395-419.

Morin, A. J. S., & Litalien, D. (2017). *Webnote: Longitudinal tests of profile similarity and latent transition analyses*. Retrieved from https://smslabstats.weebly.com/uploads/1/0/0/6/100647486/lta_distributional_similarity_v02.pdf

Morin, A. J. S., Meyer, J. P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254. doi:10.1177/1094428115621148

Morin, A. J. S., & Wang, J. C. K. (2016). A gentle introduction to mixture modeling using physical fitness data. In N. Ntoumanis & N. Myers (Eds.), *An introduction to intermediate and advanced statistical analyses for sport and exercise scientists* (pp. 183-210). London: Wiley.

Münsterberg, H. (1899). Psychology and history. *Psychological Review*, *6*, 1-31.

Muthén, B. O. (2002). Beyond SEM: General latent modeling. *Behaviormetrika*, *29*, 81-117.

Muthén, B. O., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analysis: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, *24*, 882-891.

Muthén, B. O., & Muthén, L. K. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, *9*, 599-620.

Nielsen, M. B., Skogstad, A., Matthiesen, S. B., Glasø, L., Aasland, M. S., Notelaers, G. . . . Einarsen, S. (2009). Prevalence of workplace bullying in Norway: Comparisons across time and estimation methods. *European Journal of Work and Organizational Psychology*, *18*(1), 81-101. doi:10.1080/13594320801969707

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535-569.

O'Neill, T. A., McLarnon, M. J. W., Hoffart, G. C., Woodley, H. J. R., & Allen, N. J. (2018). The structure and function of team conflict state profiles. *Journal of Management*, *44*(2), 811-836.

Pearce, C. L., & Osmond, C. P. (1999). From workplace attitudes and values to a global pattern of nations: An application of latent class modeling. *Journal of Management*, *25*(5), 759-778. doi:10.1177/014920639902500507

Priem, R. L., Love, L. G., & Shaffer, M. (2002). Executives' perceptions of uncertainty sources: A numerical taxonomy and underlying dimensions. *Journal of Management*, *28*(6), 725-746.

PRISMA. (2009). *PRISMA checklist*. Retrieved from http://prisma-statement.org/

Ram, N., & Grimm, K. J. (2009). Growth mixture modeling: A method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioural Development*, *33*(6), 565-576.

Robinson, O. C. (2011). The idiographic/nomothetic dichotomy: Tracing historical origins of contemporary confusions. *History and Philosophy of Psychology*, *13*, 32-39.

Ross, S., Dardano, J., & Hackman, R. C. (1959). Conductance levels during vigilance task performance. *Journal of Applied Psychology*, *43*(1), 65-69. doi:10.1037/h0043246

Rost, J. (1991). A logistic mixture distribution model for polychotomous item responses. *British Journal of Mathematical and Statistical Psychology*, *44*, 75-92.

Roth, M., & von Collani, G. (2007). A head-to-head comparison of big-five types and traits in the prediction of social attitudes. *Journal of Individual Differences*, *28*(3), 138-149. doi:10.1027/1614-0001.28.3.138

Scandura, T. A, & Williams, E. A. (2000). Research methodology in management: Current practices, trends, and implications for future research. *Academy of Management Journal*, *43*(6), 1248-1264.

Schmitt, N., Oswald, F. L., Kim, B. H., Imus, A., Merritt, S., Friede, A. . . . Shivpuri, S. (2007). The use of background and ability profiles to predict college student outcomes. *Journal of Applied Psychology*, *92*(1), 165-179. doi:10.1037/0021-9010.92.1.165

Schneider, B., Goldstein, H. A., & Smith, D. B. (1995). The ASA framework: An update. *Personnel Psychology*, *48*, 747-773.

Sestito, A. L., Sica, L. S., Ragozini, G., Porfeli, E., Weisblat, G., & Di Palma, T. (2015). Vocational and overall identity: A person-centered approach in Italian university students. *Journal of Vocational Behavior*, *91*, 157-169. doi:10.1016/j.jvb.2015.10.001

Sharpe, D. (2013). Why the resistance to statistical innovations? Bridging the communication gap. *Psychological Methods*, *18*, 572-582.

Shore, L. M., & Barksdale, K. (1998). Examining degree of balance and level of obligation in the employment relationship: A social exchange approach. *Journal of Organizational Behavior*, *19*(S1), 731-744.

Sinclair, R. R., Tucker, J. S., Cullen, J. C., & Wright, C. (2005). Performance differences among four organizational commitment profiles. *Journal of Applied Psychology*, *90*(6), 1280-1287. doi:10.1037/0021-9010.90.6.1280

Sonnentag, S., Binnewies, C., & Mojza, E. J. (2008). "Did you have a nice evening?" A day-level study on recovery experiences, sleep, and affect. *Journal of Applied Psychology*, *93*, 674-684.

Späth, H. (1991). *Mathematical algorithms for linear regression*. San Diego, CA: Academic.

Stone-Romero, E. F., Weaver, A. E., & Glenar, J. L. (1995). Trends in research design and data analytic strategies in organizational research. *Journal of Management*, *21*(1), 141-157.

Tay, L., Diener, E., Drasgow, F., & Vermunt, J. K. (2011). Multilevel mixed-measurement IRT analysis: An explication and application to self-reported emotions across the world. *Organizational Research Methods*, *14*(1), 177-207. doi:10.1177/1094428110372674

Tay, L., Newman, D. A., & Vermunt, J. K. (2011). Using mixed-measurement item response theory with covariates (MM-IRT-C) to ascertain observed and unobserved measurement equivalence. *Organizational Research Methods*, *14*(1), 147-176. doi:10.1177/1094428110366037

Tay, L., Parrigon, S., Huang, Q., & LeBreton, J. M. (2016). Graphical descriptives: A way to improve data transparency and methodological rigor in psychology. *Perspectives on Psychological Science*, *11*(5), 692-701.

Tay, L., Woo, S. E., Klafehn, J., & Chiu, C.-Y. (2010). Conceptualizing and measuring culture. In G. Walford, E. Tucker, & M. Viswanathan (Eds.), *The SAGE handbook of measurement* (pp. 177-203). London: Sage.

Tekle, F. B., Gudicha, D. W., & Vermunt, J. K. (2016). Power analysis for the bootstrap likelihood ratio test for the number of classes in latent class models. *Advances in Classification and Data Analysis*, *10*, 209-224.

Tukey, J. W. (1977). *Exploratory data analysis*. Reading, MA: Addison Wesley

Upadyaya, K., & Salmela-Aro, K. (2015). Development of early vocational behavior: Parallel associations between career engagement and satisfaction. *Journal of Vocational Behavior*, *90*, 66-74. doi:10.1016/j.jvb.2015.07.008

Van Horn, M. L., Jaki, T., Masyn, K., Ramey, S. L., Smith, J. A., & Antaramian, S. (2009). Assessing differential effects: Applying regression mixture models to identify variations in the influence of family resources on academic achievement. *Current Opinion in Rheumatology*, *45*(5), 1298-1313. doi:10.1037/emo0000122.Do

Velicer, W. F., Martin, R. A., & Collins, L. M. (1996). Latent transition analysis for longitudinal data. *Addiction*, *91*, S197-S209.

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied latent class analysis* (pp. 89-106). Cambridge, MA: Cambridge University Press.

Von Eye, A., Mun, E. Y., & Indurkhya, A. (2004). Typifying developmental trajectories—a decision making perspective. *Psychology Science*, *46*, 65-98.

Wang, M. (2007). Profiling retirees in the retirement transition and adjustment process: Examining the longitudinal change patterns of retirees' psychological well-being. *Journal of Applied Psychology*, *92*(2), 455-474. doi:10.1037/0021-9010.92.2.455

Wang, M., & Bodner, T. E. (2007). Growth mixture modeling: Identifying and predicting unobserved subpopulations with longitudinal data. *Organizational Research Methods*, *10*(4), 635-657.

Wang, M., & Hanges, P. J. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods*, *14*, 24-31.

Weiss, H., & Rupp, D. E. (2011). Experiencing work: An essay on a person-centric work psychology. *Industrial and Organizational Psychology: Perspectives on Science and Practice*, *4*, 83-97.

Windelband, W. (1998). History and natural science. *Theory and Psychology*, *8*(1), 5-22. (Original work published 1894)

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. M. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, *73*, 913-934.

Woo, S. E. (2011). A study of Ghiselli's hobo syndrome. *Journal of Vocational Behavior*, *79*(2), 461-469. doi:10.1016/j.jvb.2011.02.003

Woo, S. E., & Allen, D. G. (2014). Toward an inductive theory of stayers and seekers in the organization. *Journal of Business and Psychology*, *29*, 683-703. doi:10.1007/s10869-013-9303-z

Woo, S. E., O'Boyle, E. H., & Spector, P. E. (2017). Best practices in developing, conducting, and evaluating inductive research. *Human Resource Management Review*, *27*, 255-264.

Xu, R. X. R., & Wunsch, D. C. D. C. (2010). Clustering algorithms in biomedical research: A review. *IEEE Reviews in Biomedical Engineering*, *3*, 120-154. doi:10.1109/RBME.2010.2083647

Yim, O., & Ramdeen, K. T. (2015). Hierarchical cluster analysis: Comparison of three linkage measures and application to psychological data. *The Quantitative Methods for Psychology*, *11*(1), 8-21.

Zickar, M. J., Gibby, R. E., & Robie, C. (2004). Uncovering faking samples in applicant, incumbent, and experimental data sets: An application of mixed-model item response theory. *Organizational Research Methods*, *7*(2), 168-190. doi:10.1177/1094428104263674

Zyphur, M. J. (2000). When mindsets collide: Switching analytical mindsets to advance organization science. *Academy of Management Review*, *34*(4), 677-688.

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