Computers & Education 128 (2019) 13–35

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education

Ronny Scherer[a,*], Fazilat Siddiq[b], Jo Tondeur[c]

[a] Department of Teacher Education and School Research (ILS) and Centre for Educational Measurement at the University of Oslo, Faculty of Educational Sciences, University of Oslo, Norway
[b] University of South-Eastern Norway (USN), Drammen, Norway
[c] Vrije Universiteit Brussel & Ghent University, Belgium

ARTICLE INFO

Keywords:
Meta-analysis
Teacher education
Technology acceptance model (TAM)
Technology adoption

ABSTRACT

The extent to which teachers adopt technology in their teaching practice has long been in the focus of research. Indeed, a plethora of models exist explaining influential factors and mechanisms of technology use in classrooms, one of which—the Technology Acceptance Model (TAM) and versions thereof—has dominated the field. Although consensus exists about which factors in the TAM might predict teachers' technology adoption, the current field abounds in some controversies and inconsistent findings. This meta-analysis seeks to clarify some of these issues by combining meta-analysis with structural equation modeling approaches. Specifically, we synthesized 124 correlation matrices from 114 empirical TAM studies (N = 34,357 teachers) and tested the fit of the TAM and its versions. Overall, the TAM explains technology acceptance well; yet, the role of certain key constructs and the importance of external variables contrast some existing beliefs about the TAM. Implications for research and practice are discussed.

1. Introduction

Technology pervades almost all areas in society. Considering education, at least two trends can be observed: First, educational systems around the world are incorporating digital competences in curricula and assessments (Beller, 2013; Flórez et al., 2017; Siddiq, Hatlevik, Olsen, Throndsen, & Scherer, 2016). Second, teachers and teacher educators are encouraged to include technology in their teaching—as a tool to facilitate learning or as a means to formative assessment (Shute & Rahimi, 2017; Straub, 2009). It has become the designated aim of education to help students to become digitally literate citizens who can cope with the complexities and dynamics in today's societies (Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014). This development, however, necessitates the meaningful inclusion of technology in teaching and learning contexts (OECD, 2015; Siddiq, Scherer, & Tondeur, 2016). An extensive body of literature has dealt with the factors associated with this inclusion by focusing on teachers' adoption of technology (Straub, 2009). One model though has dominated the research landscape—the Technology Acceptance Model (TAM). The TAM comprises several variables explaining behavioral intentions and the use of technology directly or indirectly (i.e., perceived usefulness, perceived ease of use, attitudes toward technology), and has been extended by external variables, such as self-efficacy, subjective norms,

* Corresponding author. University of Oslo, Faculty of Educational Sciences, Department of Teacher Education and School Research (ILS), Postbox 1099 Blindern, NO-0317, Oslo, Norway.
E-mail address: ronny.scherer@cemo.uio.no (R. Scherer).

https://doi.org/10.1016/j.compedu.2018.09.009
Received 9 April 2018; Received in revised form 12 September 2018; Accepted 16 September 2018
Available online 18 September 2018
0360-1315/

and facilitating conditions of technology use (Schepers & Wetzels, 2007). The TAM has gained considerable prominence, particularly due to its transferability to various contexts and samples, its potential to explain variance in the intention to use or the use of technology, and its simplicity of specification within structural equation modeling frameworks (e.g., King & He, 2006; Marangunić & Granić, 2015). Besides, the TAM is a powerful vehicle to describe teachers' technology adoption next to other models.

Despite its prominence, however, the existing body of research does not draw a clear picture about specific relations within the TAM: Whereas some studies confirmed the hypothesized relations fully, others did not (King & He, 2006; Šumak, Heričko, & Pušnik, 2011). This finding is further substantiated by significant variation of TAM relations across studies and samples, and consequently calls for a systematic synthesis. Furthermore, whereas previous meta-analyses on the TAM included a large variety of samples from multiple occupations and domains (Hsiao & Yang, 2011; Ritter, 2017; Schepers & Wetzels, 2007), a systematic review of the TAM for teachers in educational contexts is, to our best knowledge, lacking. It is important to synthesize the existing findings on teachers' technology acceptance though, because they provide further insights into the possible mechanisms behind technology acceptance—insights relevant to teacher education and professional development. The current meta-analysis consequently reviews studies presenting the TAM for teacher samples. We take a meta-analytic structural equation modeling (MASEM) approach to synthesizing entire correlation matrices instead of single correlations and further quantify their variation across teacher samples, particularly for pre- and in-service teachers. Besides, we explore model fit, moderation effects, and the effects of external variables within the TAM.

1.1. Technology acceptance in education

Education has always lived in tension between two functions: education as a matter of assuring continuity and as a matter of fostering creativity and change. Within these, technology brings a new set of challenges and pressures for educational institutions (Romeo, Lloyd, & Downes, 2013). The speed with which the evolution of technology has taken place is phenomenal. Today, school teachers in many countries around the world are working with "digital natives" who are growing up with new technologies as a non-remarkable feature of their life. Technology allows us to (co-)create, collect, store and use knowledge and information; it enables us to connect with people and resources all over the world, to collaborate in the creation of knowledge and to distribute and benefit from knowledge products (Spector, 2008; von Davier, Hao, Liu, & Kyllonen, 2017).

The question remains as to what degree teachers integrate technology into teaching and learning activities. Research reveals that integrating technology is a complex process of educational change, and the extent of technological applications in schools is still extremely varied (Bishop & Spector, 2014; Fraillon et al., 2014). Clearly, emerging educational technology usage in (teacher) education has increased in recent years, but technology acceptance and usage continue to be problematic for educational institutions (Berrett, Murphy, & Sullivan, 2012; Straub, 2009). In the literature, the question is repeatedly put forward as to what variables determine technology integration in education. Measuring user acceptance of technology is a way of determining the teacher's intentions toward using new technologies in their educational practice. Over the last decades, a series of models have been proposed to describe the mechanism behind and factors affecting technology adoption, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model. These models have emerged from well-established psychological theories, including the Theory of Reasoned Action (Fishbein, 1979) and the Theory of Planned Behavior (Ajzen, 1991). The UTAUT, for example, describes four core determinants of the user intentions and the actual use of technology, namely performance and effort expectancy, social influence, and facilitating conditions (Venkatesh, Morris, Davis, & Davis, 2003). The effects of these determinants are hypothesized to be moderated by respondents' gender, age, experience, and the voluntariness of technology use (Williams, Rana, & Dwivedi, 2015). The setup of the UTAUT is comparable to that of the TAM, and the determinants share similarities in their conceptualization (Nistor & Heymann, 2010). Although it is more difficult to test than the TAM (due to the hypothesized moderation effects), this model is considered another, powerful model describing technology acceptance. The TAM and the UTAUT are only two examples of technology acceptance models; several extensions and alternatives have evolved over time (for a comprehensive overview, please review Taherdoost, 2018). Despite the variety of models, the TAM has dominated the research landscape as the most commonly used model to describe use intentions and actual technology use (Hsiao & Yang, 2011; King & He, 2006; Marangunić & Granić, 2015).

At the same time, the TAM falls short of conceptualizing what it means to accept and integrate technology in classrooms. More specifically, the model does not specify which types of professional knowledge about teaching and learning with technology teachers must have in order to integrate technology meaningfully. These types of knowledge are specified in the so-called Technological Pedagogical Content Knowledge (TPACK) framework, a framework that defines different kinds of knowledge domains teachers need to become proficient in for successfully integrating digital technology in teaching and learning processes (Koehler, Mishra, Kereluik, Shin, & Graham, 2014). These knowledge domains comprise content knowledge, pedagogical knowledge, and pedagogical content knowledge in the context of technology, as well as the mere technological knowledge (Mishra & Koehler, 2006). Koehler and Mishra (2009) argued that, for technology integration to occur in education, teachers must be competent in these forms of knowledge, but more importantly, they must be able to integrate all types of knowledge. In other words, TPACK emphasizes the importance of preparing pre-service teachers to make sensible choices in their uses of technology when teaching particular content to a specific target group, as it can lead to a better understanding about how teachers make decisions that affect technology acceptance and integration into teaching and learning processes. From this perspective, it is anticipated that teachers will be likely to "accept" a new technology once they perceive it as relevant for specific didactical approaches within their subjects. In addition, Mei, Brown, and Teo (2017) found in their study that teachers who perceived themselves as competent in the TPACK domains were more likely to accept and integrate technology in their teaching. Hsu (2016) further found that both PEU and PU can be predicted by TPACK. Considering

Table 1
Overview of TAM variables and their conceptualization.

TAM variable	Conceptualization
TAM-core variables	
Perceived ease of use (PEU)	The degree to which a person believes that using technology would be free of effort (Davis, 1989)
Perceived usefulness (PU)	The degree to which a person believes that using technology would enhance his or her job performance (Davis, 1989)
Attitudes toward technology (ATT)	A person's evaluation of technology or specific behavior associated with the use of technology (P. Zhang, Aikman, & Sun, 2008)
Outcome variables	
Behavioral intention (BI)	A person's intention to use technology
Technology use (USE)	A person's actual technology use
External variables	
Subjective norm (SN)	A person's perception that most people who are important to him or her think he or she should or should not perform the behavior in question (Martin Fishbein & Ajzen, 1975)
Computer self-efficacy (CSE)	The degree to which a person believes that he or she can perform a specific task using a computer (Compeau & Higgins, 1995)
Facilitating conditions (FC)	The degree to which a person believes that organizational and technical resources exist to support the use of technology (Venkatesh et al., 2003)

this, a link to the TPACK framework could address the shortcoming of the TAM and enhance the understanding of technology acceptance processes.

1.2. The technology acceptance model (TAM)

The Technology Acceptance Model, first proposed by Davis (1985), comprises core variables of user motivation (i.e., perceived ease of use, perceived usefulness, and attitudes toward technology) and outcome variables (i.e., behavioral intentions, technology use). Of these variables, perceived usefulness (PU) and perceived ease of use (PEU) are considered key variables that directly or indirectly explain the outcomes (Marangunić & Granić, 2015). These variables are often accompanied by external variables explaining variation in perceived usefulness and ease of use: Among others, subjective norms (SN), self-efficacy (CSE), and facilitating conditions (FC) were significantly related to the TAM core variables—however, to different degrees (Abdullah & Ward, 2016; Schepers & Wetzels, 2007). These external variables represent personal capabilities next to contextual factors. Their conceptualizations, however, vary across studies and thus necessitate clear definitions in the current meta-analysis. We present the definitions applied to this meta-analysis in Table 1. Overall, perceived ease of use and perceived usefulness, the most important factors in the TAM, refer to the degrees to which a person believes that using technology would be free from effort (PEU) and that using technology would enhance their job or task performance (PU). In this context, "free from effort" means "free from difficulty or great effort", as Davis (1989) in his seminal paper specified. PEU therefore refers to the effort a person estimates it would take to use technology and is closely related to competence beliefs (Scherer, Siddiq, & Teo, 2015). These two perceptions, PEU and PU, directly relate to another TAM-core variable, attitudes toward technology (ATT). Most commonly, the TAM comprises at least one outcome variable: behavioral intention (BI) and/or technology use (USE). Inspired by the Theory of Reasoned Action, the former refers to intended behavior, whereas the latter refers to observable behavior, that is, the actual use of technology. In most versions of the TAM, BI predicts USE—however, the direction of this link is not deterministic because positive user experience may also determine future behavioral intentions (Straub, 2009). Finally, external variables in the TAM refer to perceptions of how important others consider the use of technology (SN), perceptions of one's own capabilities of mastering computer- or technology-related tasks (CSE), and perceptions of external control, that is, the organizational support for technology use (FC) in terms of organizational resources and support structures (Taylor & Todd, 1995).

Given the variety of variables within the TAM, different versions of the model have been studied empirically (Taylor & Todd, 1995). The most prominent versions are depicted in Fig. 1. Model 1 represents the TAM core and focuses on behavioral intentions as the outcome. Model 2 extends this model by technology use. Nistor (2014) noted that the link between use intentions and actual use is oftentimes missing in empirical studies of the TAM—hence, the extension of Model 1. Models 3 and 4 further add the proposed external variables to Models 1 and 2 as predictors of perceived usefulness and ease of use. This selection of TAM versions represents the typically specified path models exhibiting the hypothesized relations (Marangunić & Granić, 2015; Ritter, 2017).

1.3. Empirical TAM studies and previous meta-analyses

Empirical research on the TAM identified several issues: First, substantial variation in specific paths in the TAM exists (Imtiaz & Maarop, 2014; T. Teo & Paul van Schaik, 2012). For instance, whereas some authors found significant direct relations between perceived usefulness and behavioral intention (e.g., E. Y. M. Cheung & Sachs, 2006; Pynoo et al., 2012), others did not (e.g., Kirmizi, 2014; Teo & Milutinovic, 2015). Second, the role of external variables explaining variation in the TAM core constructs differs (Burton-Jones & Hubona, 2006). For instance, whereas teachers' computer self-efficacy explains considerable variation in perceived usefulness and perceived ease of use, facilitating conditions for technology use at school weakly predict these two variables—these relations vary across studies (e.g., Nam, Bahn, & Lee, 2013; Teo & van Schaik, 2012). Third, a variety of TAM models exist, with or

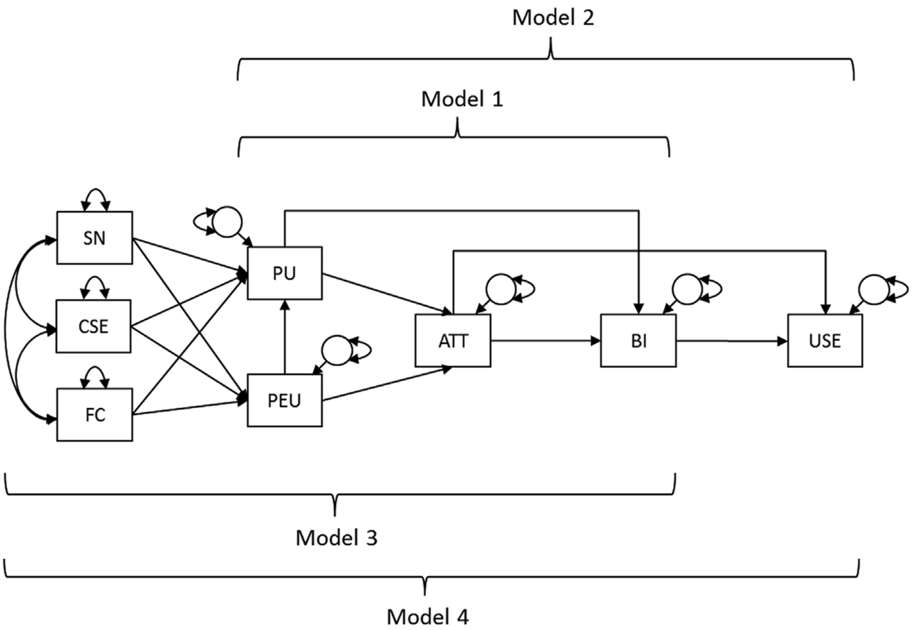

Fig. 1. Models describing teachers' technology acceptance with and without external variables.

without external variables, with or without direct effects of certain variables on outcome variables, with or without variables grouping the teacher samples. To illustrate, Marangunić and Granić (2015) systematically reviewed research on the TAM conducted between 1986 and 2013. They identified at least three different versions of the model, some considering only USE as an outcome variable, others considering BI and USE as outcomes yet excluding ATT. Abdullah and Ward (2016) meta-analyzed a TAM version that contained external variables—the selection of variables, however, differed from that of other meta-analyses (e.g., Schepers & Wetzels, 2007). Fourth, some studies investigated the measurement and structural invariance of the TAM across groups of teachers, including pre- and in-service teachers and different nationalities (Teo, Lee, Chai, & Wong, 2009). Such studies could oftentimes not identify full invariance across groups of teachers, and the resultant findings highlight that the TAM may not fully apply to all contexts and groups of teachers to the same extent. Fifth, variables characterizing persons, contexts, and the measurement of variables may moderate the relations within the TAM (Straub, 2009).

The prominence of the TAM and the availability of primary research studies resulted in several meta-analyses that synthesized the relations and paths within the TAM in various contexts. Table 2 provides a brief account of these meta-analyses. These meta-analyses mainly focused on the TAM core variables (i.e., PEU, PU, and ATT) and outcome variables, such as behavioral intentions and technology use (Marangunić & Granić, 2015). The contexts in which the relations among them were studied vary substantially: Whereas some meta-analyses included any TAM study that had been conducted until the date of review (e.g., King & He, 2006;

Table 2
Overview of selected meta-analyses synthesizing TAM studies.

Meta-analysis	TAM core variables	*k*	Moderators	MASEM approach	Fixed Effects (β)							
					PEU→PU	PEU→ATT	PEU→BI	PU→ATT	PU→BI	ATT→BI	ATT→USE	BI→USE
Gerow et al.	PEU, PU, BI, USE	185	T	Univariate-*r*	0.39*	–	0.16*	–	0.36*	–	–	0.48*
King and He (2006)	PEU, PU, BI	140	U, T	Univariate-β	0.48*	–	0.19*	–	0.51*	–	–	–
Ritter (2017)	PEU, PU, ATT, BI	13	–	cb-TSSEM	0.51*	0.52*	–	0.16*	–	0.61*	–	–
Schepers and Wetzels (2007)	PEU, PU, ATT, BI, USE	63	U, T, C	Univariate-*r*	0.48*	0.26*	0.12*	0.46*	0.38*	0.18*	–	0.55*
Šumak et al. (2011)	PEU, PU, ATT, BI, USE	51	U, T	Univariate-*r*	0.40*	0.29*	0.24*	0.51*	0.40*	0.33*	0.33*	0.44*
Wu & Du	PEU, PU, BI, USE	103	V	Univariate-*r*	0.50*	–	–	–	–	–	–	–
Zhang et al. (2012)	PEU, PU, ATT, BI, USE	58	C	Univariate-*r*	0.27*	0.07	0.17*	0.24*	0.07	0.27*	–	0.24*

Note. k = Number of studies, U = User type, T = Technology type, C = Culture, V = Variables, cb = correlation-based. * $p < .05$.

Schepers & Wetzels, 2007), others included only TAM studies targeted at specific educational contexts, such as e-learning platforms or instruction (e.g., Ritter, 2017; Šumak et al., 2011).

Most meta-analyses described above performed separate meta-analyses and aggregated the resultant correlations between the TAM variables in an overall correlation matrix, thus taking a univariate approach. In addition, one meta-analysis aggregated path coefficients, and one meta-analysis synthesized correlation matrices, however with a very small number of studies ($k = 13$). Although these meta-analyses provided valuable insights into the roles of certain variables in the TAM, possible group differences, and the overall variance explanation of technology use or its intentions, more recent developments of meta-analytic structural equation model (MASEM) may take these findings even further by addressing some of the challenges associated with the univariate approaches (M. W.-L. Cheung, 2015; M. W.-L. Cheung & Chan, 2005). More specifically, the potential of MASEM procedures that combine entire correlation matrices rather than single correlations through separate meta-analyses across studies lies in the provision of more accurate correlation matrices that are further subjected to structural equation modeling. Tang and Cheung (2016), for example, showcased this benefit in the context of testing theories in internal business and warned against using univariate meta-analyses may lead to inaccurate findings.

Once correlations are pooled in previous meta-analyses, the resultant correlations, path coefficients, or correlation matrices are then submitted to moderator analyses—moderating variables target, for instance, types of users, technologies, and cultures. By and large, the effects identified in these meta-analyses suggest: (a) strong relations between PEU and PU; (b) larger effects of PU on BI than of PEU on BI; and (c) mediocre to strong ATT–BI and BI–USE relations. These effects, however, varied considerably across meta-analyses, sometimes ranging from insignificant and close-to-zero effects to strong, positive, and significant effects. This variation, in fact, points to some inconsistencies across meta-analyses, as the following example illustrates: The effects of both perceived ease of use and usefulness on teachers' attitudes toward technology differ considerably. Whereas Ritter (2017) reports a strong positive effect of PEU on ATT ($\beta_{PEU\text{-}ATT} = 0.52$) and a weak positive effect of PU on ATT ($\beta_{PU\text{-}ATT} = 0.16$), Schepers and Wetzels (2007) found the opposite ($\beta_{PEU\text{-}ATT} = 0.26$, $\beta_{PU\text{-}ATT} = 0.46$)—so did L. Zhang, Zhu, and Liu (2012) in their meta-analysis ($\beta_{PEU\text{-}ATT} = 0.07$, $\beta_{PU\text{-}ATT} = 0.24$). Besides methodological differences, the varying focus on certain samples and technologies may have caused these inconsistent findings and makes the findings less informative for education in general and teachers specifically. Hence, the types of samples and the specificity of technology are considered powerful moderators of TAM effects (see Table 2).

1.4. The current meta-analysis

The current meta-analysis synthesizes the existing body of empirical research on the TAM for pre- and in-service teachers. It exploits the potential that lies within multivariate meta-analysis and synthesizes correlation matrices with the help of correlation-based MASEM—a MASEM approach that accounts for the dependencies between correlations within correlation matrices (M. W.-L. Cheung, 2015). We believe that this meta-analysis will stimulate the application of MASEM in educational research. Four interrelated research questions are addressed:

1. To what extent does an overall correlation matrix representing the relations among the TAM constructs show significant variation across studies? *(Fixed-versus random-effects models)*
2. To what extent does the TAM fit the data? Which of the hypothesized relations in the TAM can be established empirically based on the pooled correlation matrix? *(Structural equation models with and without direct effects; Models 1 and 2)*
3. To what extent do sample origin, teacher experience, and the specificity of technology affect the overall fit and the relations exhibited in the TAM? *(Subgroup analyses; Models 1 and 2)*
4. To what extent do external variables, including subjective norms, computer self-efficacy, and facilitating conditions explain variation in perceived usefulness and perceived ease of use? (*External variables; Models 3 and 4*)

Overall, our study follows the core steps of meta-analyses as it synthesizes the measures of associations between the TAM variables and quantifies their variation between studies first (Research Question 1), tests specific assumptions on the structural part of the TAM (Research Question 2), explores possible moderation of these assumptions by considering subgroups of teacher samples (Research Question 3), and finally tests the effects of alternative variables on the key TAM variables (Research Question 4).

2. Method

2.1. Literature search

A search in the following databases was conducted to identify the literature relevant to this meta-analysis: ERIC (Educational Resources Information Center), Learn Tech Lib (Learning & Technology Library), PsycINFO, ScienceDirect, ProQuest Dissertation and Theses Database, IEEE Xplore Digital Library, ACM Digital Library, and Google Scholar (first 100 entries as of March 17, 2017). We used the following search terms and Boolean operators for ERIC and PsycINFO: ("Technology acceptance model" OR TAM* OR "technology acceptance") AND (teacher* OR instructor*). The search in ScienceDirect was restricted to English titles, abstracts, and keywords. For all other databases, we searched for "technology acceptance model" AND teacher. Besides existing databases, we hand-searched the following journals: Australasian Journal of Educational Technology, British Journal of Educational Technology, Computers & Education, Computers in Human Behavior, Computer Science Education, Educational Technology Research and Development, Journal of Computer Assisted Learning, Journal of Educational Computing Research, and the Journal of Research on

Technology in Education. Reference lists of existing reviews and meta-analyses that focused on the TAM were also screened (Imtiaz & Maarop, 2014; King & He, 2006; Legris, Ingham, & Collerette, 2003; Marangunić & Granić, 2015; Schepers & Wetzels, 2007; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). Citation searches for these papers were conducted in the ISI Web of Knowledge databases. Finally, the publication lists of scholars who published at least two journal articles about the TAM were screened for additional, relevant works. The list of scholars contained Timothy Teo, Gary Wong, Viswanath Venkatesh, and Fred D. Davis. All searches were conducted in March 2017 and resulted in 2239 entries. After removing duplicates and constraining the time frame of the relevant publications to 1986–2017 (first publication of the TAM by Davis and colleagues; for details, please refer to Marangunić & Granić, 2015), 1826 publications remained and were subjected to an initial screening.

2.2. Screening, inclusion and exclusion criteria

Fig. 2 summarizes the results of our literature search and screening procedures. The extracted publications were screened in two steps: In the first step, we performed an initial screening of the 1826 extracted titles and abstracts according to the following criteria: (1) *Study context*—only studies were included that addressed school or university teachers' integration or acceptance of technology in educational contexts; (2) *Quantitative nature of the study*—only studies were included that described relations between the TAM constructs quantitatively; conceptual papers, literature reviews, or qualitative studies were excluded; (3) *Language of reporting*—only studies were included that reported the relevant information (i.e., sample characteristics and results) in English. This initial screening resulted in 363 eligible publications.

In the second step, we applied inclusion and exclusion criteria to retrieve only those studies that provided sufficient information on the teacher sample, the constructs relevant to the technology acceptance model, and the quantitative results. For the latter to be sufficient, studies had to report the correlations among manifest or latent variables, the full variance-covariance matrix, or regression coefficients and their standard errors. Overall, we applied the following criteria:

1. *Accessibility—f*ull texts or secondary resources that describe the study in sufficient detail must have been available.
2. *Sample*—the study focused on a sample of in- or pre-service teachers in K-12, college, or university education.
3. *Constructs*—the study assessed at least three of the TAM constructs. These include: (a) Perceived usefulness; (b) Perceived ease of use; (c) Outcome variables such as intentions to use digital technology for teaching (often labelled as behavioral intentions) or actual use or attitudes toward use; (d) External variables such as subjective norms, technology self-efficacy, or facilitating conditions.
4. *Reporting of statistics*—the study reported the statistics necessary to retrieve the correlations among the relevant TAM constructs (see 3.). Minimal reporting included at least one of the following types of information: (a) correlation matrix; (b) variance-covariance matrix; (c) standardized path coefficients in a path or structural equation model including the correlations among exogenous variables.
5. *Context*—the TAM was studied for a digital device, technology, software, or system.

Studies were excluded if less than three correlations were reported; however, we contacted the authors before excluding these studies and specifically asked for the correlation matrices their study was based upon. We contacted 19 authors to provide the correlation matrices for their studies; seven authors responded to our query and provided nine correlation matrices. For 25 studies that reported only standardized path coefficients without providing the correlation matrices, it was possible to retrieve the correlation matrix by applying Wright's tracing rules for path coefficients (Kline, 2016; Wright, 1934). A worked example illustrating this procedure can be found in the Supplementary Material S1. Moreover, for two studies that did not report correlation matrices, the authors provided either the raw data (Yusop, 2015) or item-item correlations (Luan & Teo, 2009), so that correlations could be estimated. The performance of the inclusion and exclusion criteria resulted in 134 studies reporting 146 correlation matrices. After removing four duplicate studies, the screening phase resulted in $n = 130$ studies reporting $k = 142$ correlation matrices and $m = 1223$ correlations between TAM constructs. In a final step, the extracted correlation matrices were subjected to testing for positive definiteness—a prerequisite for meta-analytic structural equation modeling which will be described later. References to the papers included in this meta-analysis can be found in Supplementary Material S6.

2.3. Measures of association

Overall, we extracted correlations among variables as the measures of associations (Borenstein, Hedges, Higgins, & Rothstein, 2009). Variables could be specified either as latent or manifest variables. In the case of manifest variables, we also extracted the reliability coefficients to correct for unreliability. We did not use regression or path coefficients extracted from the papers directly or along with the correlations. Although path coefficients and correlations are related, and several authors have proposed ways to approximate correlations with regression coefficients (Peterson & Brown, 2005), using both types of measures of association can lead to severe inaccuracies in both the pooled correlation matrix and standard errors (Aloe, 2015).

2.4. TAM variables

This meta-analysis considered the TAM core variables (i.e., perceived usefulness, perceived ease of use, and attitudes toward technology), along with relevant outcome variables (i.e., behavioral intention and technology use). Besides, external factors that

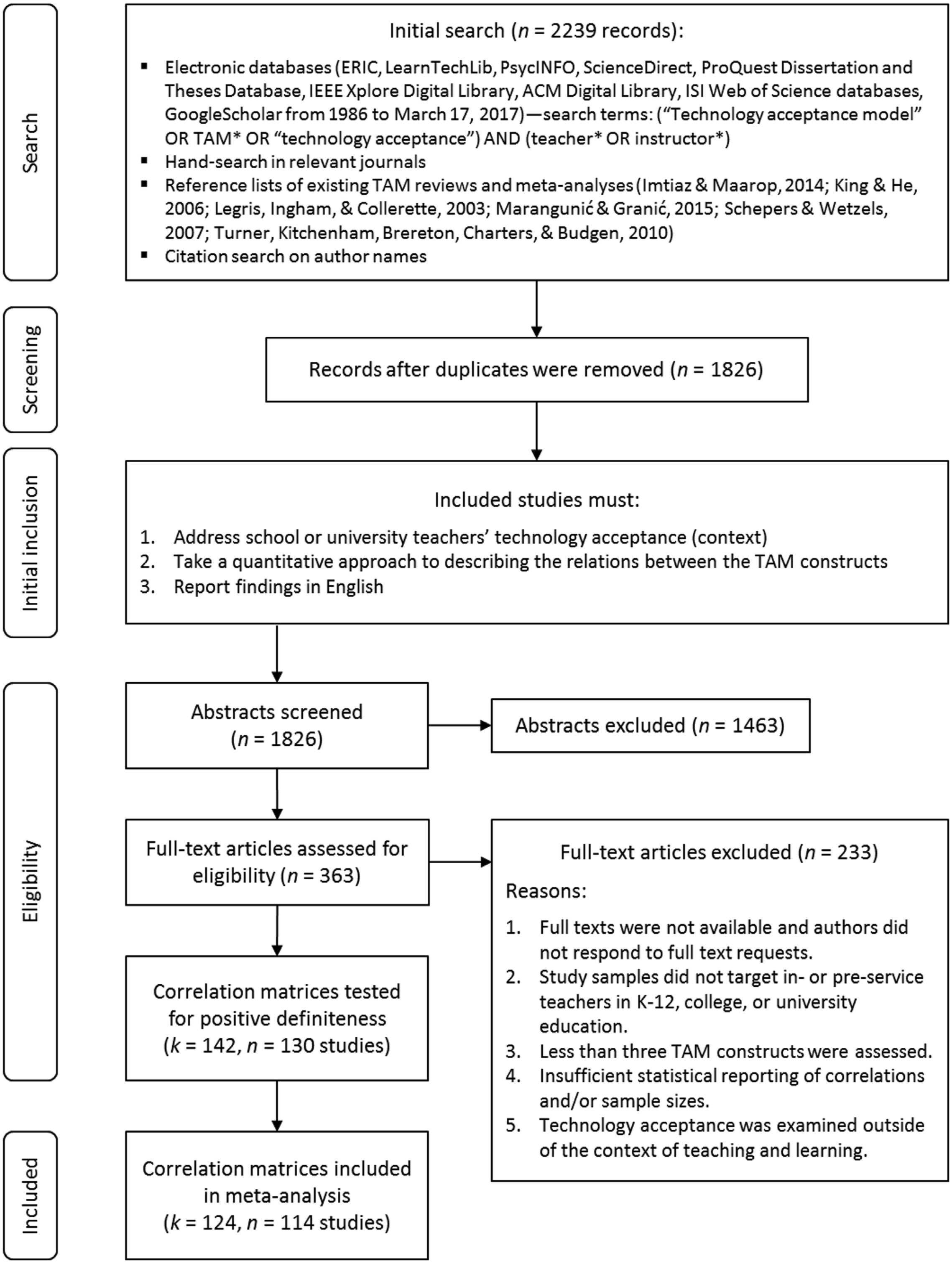

Fig. 2. Flow diagram describing the literature search and the selection of eligible studies for this meta-analysis (adapted from the PRISMA Statement; Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group e. a, 2009). *Note.* n = number of studies, k = number of correlation matrices (study samples).

might explain variation in PU and PEU are considered, including subjective norms, technology self-efficacy (often conceptualized as computer self-efficacy), and facilitating conditions (King & He, 2006; Marangunić & Granić, 2015). Despite the inclusion of technological complexity as another external variable in some TAM studies (e.g., Teo, 2009, 2015), we did not include it in the present meta-analysis for two reasons: First, very few studies reported the correlations between the TAM variables and technological complexity (TC). Second, technological complexity has often been operationalized as an element of facilitating conditions (Smarkola, 2011), creating confounding and multicollinearity issues.

Some of the papers focusing on teachers' technology integration used the Unified Theory of Acceptance and Use of Technology (UTAUT) as their conceptual framework (Venkatesh et al., 2003). These papers were also included if sufficient statistical information about the association among constructs was provided. Although UTAUT labels some of the technology acceptance variables differently, there is a clear correspondence with the TAM constructs (Nistor & Heymann, 2010; Pynoo et al., 2011): While performance expectancy often corresponds to perceived usefulness and effort expectancy to perceived ease of use, attitudes toward technology use, behavioral intentions, and use behavior are labelled the same in the TAM.

2.5. Publication bias

To test the robustness of aggregated correlations between the TAM constructs, we conducted several analyses of publication bias and sensitivity. These analyses were, however, performed on single correlations rather than correlation matrices. To our best knowledge, the assessment of publication bias of correlation matrices—matrices that contain several dependent correlations—is still in its infancy (M. W.-L. Cheung, 2015). Correlations were therefore aggregated under random-effects models, and the resultant average correlations were subjected to the analysis of publication bias. Correlations were transformed into Fisher's *Z*, aggregated, and then retransformed for reporting (Borenstein et al., 2009).

First, we examined the extent to which correlations were influenced by publication bias using funnel plots in conjunction with trim-and-fill-analyses (Duval & Tweedie, 2000). Second, we performed a fail-safe *N* analysis, following Rosenberg's (2005) weighted approach. Third, we analyzed the *p*-curves derived from the aggregated correlations (Simonsohn, Nelson, & Simmons, 2014). Studies have evidential value if the corresponding *p*-curve is right-skewed—however, they do not have evidential value if the corresponding *p*-curve is left-skewed. The *p*-curve analyses only included significant *p*-values ($ps < .05$) and were based on the reported correlations and sample sizes. *P*-curves were obtained from the *P*-curve Online App (Simonsohn, Nelson, & Simmons, 2017).

2.6. Statistical approaches

Correlation-based meta-analytic structural equation modeling (MASEM). To synthesize the extracted TAM correlation matrices, we applied correlation-based meta-analytic structural equation modeling via Two-Stage Structural Equation Modeling (TSSEM; M. W.-L. Cheung & Chan, 2005): In the first stage, the correlation matrices are combined, usually based on a random-effects model (M. W.-L. Cheung, 2014). In the second stage, the resultant correlation matrix is used to specify the hypothesized structural equation models. As noted earlier, in contrast to pooling correlations separately (e.g., via the univariate-*r* approach), pooling entire correlation matrices with the help of multi-group modeling accounts for the nesting of correlations in correlation matrices and thus provides less biased estimates than univariate approaches (M. W.-L. Cheung & Chan, 2005; Jak, 2015). Moreover, this meta-analytic structural equation modeling approach addresses critical data-analytic issues, including the use of the correct overall sample size for structural equation modeling, the handling of missing correlations in correlation matrices of individual studies, and the adequate use of correlation matrices for covariance-based modeling approaches (M. W.-L. Cheung & Chan, 2005; Hong & Cheung, 2015). Another advantage of the two-stage approach is that the stage of pooling correlation matrices can be based on a random-effects model (M. W.-L. Cheung & Cheung, 2016). This improves the estimates of the relations among variables and helps to avoid otherwise conflicting research results.

Whenever possible, the likelihood-based confidence intervals (LBCIs) were estimated because they overcome some of the challenges associated with the alternative Wald confidence intervals. For instance, LBCIs perform better in models targeted at categorical data, random effects, and nonlinear or logistic regression (M. W.-L. Cheung, 2009, 2015). At the same time, LBCIs have limitations as well, such as the fact that they might be out of reasonable boundaries if the distributional assumptions on the data are severely violated (M. W.-L. Cheung, 2015). The correlation matrices extracted from the studies were pooled with the help of the R package *metaSEM* (version 0.9.8), and further used for structural equation modeling (M. W.-L. Cheung, 2015).

Corrections for unreliability. The correlations extracted from the pool of eligible TAM studies were sometimes based on manifest variables which are subject to measurement bias due to unreliability (Schmidt & Hunter, 2014). To account for this source of bias, reported reliability coefficients of the TAM variables might be used to correct these correlations. In studies where reliability coefficients were not available, the average reliabilities obtained from the total sample of TAM studies can be used to perform this correction (Hong & Cheung, 2015). For the studies that reported correlations based on latent variables, there is no need for unreliability corrections, because factor correlations are free from measurement error (Card, 2015). Specifically, if the correlation r_{XY} between two TAM constructs X and Y was reported along with the scale reliabilities r_{XX} and r_{YY}, the corrected correlation can be determined as $\rho_{XY} = r_{XY}/\sqrt{r_{XX}\cdot r_{YY}}$ (Schmidt & Hunter, 2014). Michel, Viswesvaran, and Thomas (2011) recently claimed that this correction neither leads to more accurate results in meta-analyses nor provides different substantive conclusions—in fact, little consensus exists about the extent to which unreliability corrections affect the outcomes of the MASEM approach (M. W.-L. Cheung, 2015). Moreover, the use of attenuated correlations often leads to non-positive definite correlation matrices, thus limiting the applicability of structural equation modeling approaches (Kline, 2016). Studies exhibiting non-positive definite matrices must be excluded from the meta-analytic data set (M. W.-L. Cheung & Cheung, 2016). Considering these issues, we performed MASEM on uncorrected correlations and correlation matrices, yet compared the resultant model parameters with those obtained from the corrected correlations and correlation matrices to test the sensitivity of our findings to unreliability corrections.

Positive definiteness check and final sample size. Correlation matrices with missing correlations might not be positive definite, thus challenging the assumptions of structural equation modeling (M. W.-L. Cheung, 2015). To keep this limitation and the possible exclusion of studies as limited as possible, only studies were considered for inclusion that contained the correlations among at least three TAM constructs. Pooling correlation matrices from a set of correlation matrices that contain missing values is, however, likely to result in non-positive definite matrices (Naragon-Gainey, McMahon, & Chacko, 2017). Testing the correlation matrices underlying all models in this meta-analysis for positive definiteness, indeed, flagged several correlation matrices non-positive definite, particularly those containing both positive and negative correlations. For instance, studies exhibiting non-positive definite correlation matrices for the simplest model (Model 1) also exhibited non-positive definite correlation matrices for more extended versions of the TAM. Overall, we excluded 18 correlation matrices after performing the positive definiteness check, so that the current meta-analysis is based on $n = 114$ studies, $k = 124$ correlation matrices, and $m = 1098$ correlations with an overall sample of $N = 34357$ pre- and in-service teachers (see Fig. 2).

Independence of correlation matrices. Eleven studies reported more than one correlation matrix so that our data follow a nested structure (i.e., correlation matrices nested in studies)—this data structure might call for the application of hierarchical MASEM (Borenstein et al., 2009). Yet, at the same time, the correlation matrices reported in these studies derived from groups of teachers than could be treated independently (i.e., female vs. male teachers, in-service vs. pre-service teachers, teacher samples of different countries). We therefore assumed that all extracted possible correlation matrices from the study reports to be independent. This decision was also based on the very limited number of studies that contributed multiple correlation matrices.

Evaluation of model fit. We evaluated the fit of structural equation models on the basis of the common guidelines for an acceptable model fit (i.e., CFI ≥ 0.95, RMSEA ≤ 0.08, and SRMR ≤ 0.10; Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005). We compared competing models with respect to their information criteria (Akaike's Information Criterion [AIC], Bayesian Information Criterion [BIC])—the model with smaller values is preferred—and the results of the Likelihood-ratio test (LRT). Nevertheless, we note that these guidelines do not represent “golden rules” (Marsh, Hau, & Wen, 2004). For instance, they do not fully apply to structural equation models with complex factor structures (Khojasteh & Lo, 2015).

Subgroup analysis. To examine possible subgroup differences, we clustered the structural equation models (M. W.-L. Cheung, 2015). Clustering variables included the level of teaching experience (coded as *1 = In-service teachers, 0 = Pre-service teachers*), the specificity of the technology the TAM refers to (coded as *1 = Reference to specific technologies, 0 = Reference to technology or computers in general*), and the sample origin (*1 = Asian teacher sample, 0 = Teacher sample outside of Asia*). In the correlation-based MASEM approach, the dataset is then clustered, and the proposed structural equation models are specified within each cluster. This approach allows researchers to compare model parameters and fit indices across clusters. It is important to note that these subgroup analyses are limited to categorical grouping variables (M. W.-L. Cheung & Cheung, 2016). In the current meta-analysis, random-effects models were specified to the data of each subgroup, and the resultant model parameters were compared (Jak, 2015).

We chose to examine the above-mentioned subgroups for the following reasons: (1) Several primary studies indicated that not only the level of the TAM variables but also their relations may differ between pre- and in-service teachers (see Supplementary Material S2). These differences may be due to the variation in teaching experience and the professional knowledge needed to integrate technology in teaching (e.g., Teo, 2015). Although this dichotomous categorization of subgroups of teachers was clear-cut, a more precise indicator of teaching experience would have been desirable, such as the number of years of experience. However, the reports of teaching experience in the body of primary studies was too diverse to develop a common indicator or metric (e.g., years reported as general teaching experience vs. teaching with technology, years reported categorically vs. continuously). (2) As noted earlier, teachers' acceptance of technology can vary by the type of technology. Given the vast amount of different technologies reported in the primary studies on the one hand and the substantial number of studies reporting technology acceptance in general on the other hand, we coded this variable dichotomously. (3) In the body of primary studies, the dominance of studies in Asian countries was apparent. This observation, however, does not necessarily imply that Asian countries, such as Singapore and China, are at the forefront of using educational technology or technologically more developed—instead, this observation only indicates that most studies on the TAM were published for Asian samples of teachers. Given this dominance, which was also observed in a recent systematic review (Al-Emran, Mezhuyev, & Kamaludin, 2018), we tested whether Asian and non-Asian samples may differ in the relations between the TAM variables.

3. Results

3.1. Description of studies

Table 3 presents the discrete characteristics of teacher samples, study methods, and characteristics for the $n = 114$ eligible TAM studies which provided $k = 124$ samples (i.e., 124 correlation matrices). For a more detailed presentation of these characteristics per study, we kindly refer the reader to the Supplementary Material S2. Overall, the samples described in these studies included pre- and in-service teachers, almost to the same extent. Moreover, the educational level teachers were engaged in comprised not only primary and secondary schools, but also tertiary and special education. Ultimately, there was a clear dominance of Asian teacher samples ($k = 79$), followed by a considerable number of US-American samples ($k = 20$). Generally, a great spread of teacher samples across continents can be documented for the meta-analytic sample. Sample sizes varied considerably around an average of 277 teachers, 64.7% of which were female teachers (see Table 4). Teachers' age ranged between 19 and 47 years with an average of 30.5 years—hence, a tendency toward younger teachers existed. Only a limited number of papers specified certain technologies (e.g.,

Table 3
Discrete characteristics of study samples included in the meta-analysis.

Discrete variable	k	% of study samples
Teacher sample characteristics		
Context of teaching		
Primary school	26	20.97%
Special education	2	1.61%
Early childhood education	7	5.65%
Secondary school	19	15.32%
College	4	3.23%
University	18	14.52%
Not specified	48	38.71%
Teacher level		
Pre-service teachers	64	51.61%
In-service teachers	60	48.39%
Location of the study sample		
Abu Dhabi (UAE)	1	0.81%
Australia	4	3.23%
Belgium	3	2.42%
Brazil	1	0.81%
Cyprus	1	0.81%
Ghana	1	0.81%
Greece	2	1.61%
Hong Kong (China)	7	5.65%
India	2	1.61%
Iran	1	0.81%
Japan	2	1.61%
Lebanon	1	0.81%
Macau (China)	1	0.81%
Malaysia	11	8.87%
New Zealand	1	0.81%
Norway	1	0.81%
Pakistan	1	0.81%
Saudi Arabia	1	0.81%
Serbia	3	2.42%
Shanghai (China)	1	0.81%
Singapore	20	16.13%
Slovenia	2	1.61%
South Africa	1	0.81%
South Korea, Republic of Korea	1	0.81%
Spain	4	3.23%
Sweden	1	0.81%
Taiwan	11	8.87%
Thailand	1	0.81%
Turkey	10	8.06%
United Kingdom	1	0.81%
United States of America	20	16.13%
Mixed (Asian)	6	4.84%
Study methods		
Representation of TAM variables		
Manifest variables	52	41.94%
Latent variables	72	58.06%
Manifest and latent variables	0	0.00%
Model fit evaluation		
Model fit was evaluated	73	58.87%
Model fit was not evaluated	51	41.13%
If model fit was evaluated, the fit was … [a]		
Poor	2	1.61%
Mediocre	5	4.03%
Acceptable	24	19.35%
Close	42	33.87%
Type technology in the TAM		
Technology in general	70	56.45%
Specific technologies	54	43.55%
Study characteristics		
Publication status		
Published	107	86.29%
Grey literature	17	13.71%
Publication year		
2002	1	0.81%

(*continued on next page*)

Table 3 (*continued*)

Discrete variable	k	% of study samples
2003	0	0.00%
2004	1	0.81%
2005	1	0.81%
2006	2	1.61%
2007	4	3.23%
2008	4	3.23%
2009	7	5.65%
2010	10	8.06%
2011	9	7.26%
2012	14	11.29%
2013	13	10.48%
2014	16	12.90%
2015	20	16.13%
2016	21	16.94%
2017	1	0.81%

Note. k = Number of study samples (and correlation matrices). a: The following guidelines have been used to categorize model fit (e.g., Little, 2013): Poor (RMSEA > 0.10, CFI < 0.85), mediocre (0.08 < RMSEA ≤ 0.10, 0.85 ≤ CFI < 0.90), acceptable (0.05 < RMSEA ≤ 0.08, 0.90 ≤ CFI < 0.95), and close (RMSEA ≤ 0.05, CFI ≥ 0.95).

Table 4
Continuous characteristics of the study samples included in the meta-analysis.

Variable	*M*	*SD*[a]	% missing	*Min*	*Max*
Teacher sample					
Sample size	277.1	198.8	0.0%	29	1075
Average age [years]	30.5	8.4	29.0%	19.4	47.0
Proportion of female teachers	64.7%	19.6%	16.1%	0.0%	100.0%
Reliability coefficients[b]					
PU	.888	.058	18.6%	.720	.990
PEU	.869	.066	25.0%	.729	.990
ATT	.850	.076	46.8%	.620	.985
BI	.840	.114	36.3%	.517	.979
USE	.830	.070	88.7%	.668	.918
SN	.825	.101	69.4%	.610	.960
CSE	.857	.085	63.7%	.561	.982
FC	.828	.104	62.9%	.540	.990

Note. All statistics are based on k = 124 study samples (correlation matrices).
[a] Only the between-sample standard deviation is reported without considering within-sample variation.
[b] Reliability coefficients were mostly reported as Cronbach's α or McDonald's ω.

mobile phones, tablets, educational apps, learning management systems, virtual environments), encouraging teachers to think about the use of technology or computers for educational purposes in general (k = 70).

Considering the representation of constructs in the TAM and its versions, researchers created manifest and latent variables, with a clear focus on latent variables (k = 72; see Table 3). More than half of these studies reported model fit indices (k = 73), most of which exhibited acceptable and close fit (k = 66). At the same time, for more than 40% of the study samples and correlation matrices, information about model fit was not made available in the primary research papers. On average, reliability coefficients of the TAM variables were acceptable—however, for some variables, more than 80% of the studies did not report reliability coefficients (Table 4). Given this considerable amount for missing data, corrections for unreliability in manifest variables might result in biased overall correlations.

3.2. *Publication bias of correlations*

As noted earlier, publication bias was evaluated for single correlations. Supplementary Material S3 presents the resultant funnel plots (with trim-and-fill), fail-safe *N* values, and *p*-curves. Overall, the funnel plots indicated a reasonable degree of symmetry for all correlations, yet a slight overrepresentation of moderate to high correlations between the TAM core constructs (i.e., PEU, PU, and ATT). These constructs are generally highly correlated, as existing meta-analyses from other domains suggest (e.g., King & He, 2006). Furthermore, the fail-safe *N*s indicated that a considerable amount of studies would have been necessary to nullify the TAM correlations. Finally, all *p*-curves suggested the dominance of small *p*-values, indicated by right-skewed distributions. These findings suggest only a limited degree of publication bias in the extracted correlations.

Table 5
Meta-analytically pooled correlation matrices for Models 1 and 2 under a random-effects model (TSSEM-Stage 1).

	PU	PEU	ATT	BI
PEU				
r	.48*			
95% CI	[.45, .51]			
ρ	.50*			
τ^2	0.027*			
$SE(\tau^2)$	0.004			
I^2	93.5%			
ATT				
r	.59*	.53*		
95% CI	[.55, .62]	[.49, .56]		
ρ	.62*	.54*		
τ^2	0.020*	0.024*		
$SE(\tau^2)$	0.004	0.004		
I^2	92.8%	94.8%		
BI				
r	.55*	.42*	.52*	
95% CI	[.52, .59]	[.39, .46]	[.48, .57]	
ρ	.58*	.44*	.55*	
τ^2	0.027*	0.021*	0.028*	
$SE(\tau^2)$	0.004	0.004	0.006	
I^2	94.9%	89.3%	93.4%	
USE				
r	.42*	.33*	.42*	.46*
95% CI	[.34, .49]	[.25, .41]	[.40, .53]	[.39, .54]
ρ	.46*	.36*	.46*	.48*
τ^2	0.026*	0.029*	0.039*	0.018*
$SE(\tau^2)$	0.008	0.010	0.016	0.008
I^2	89.2%	89.7%	92.8%	84.4%

Note. The correlation matrices are based on the unattenuated correlations and a random-effects model ($k = 124$, $N = 34{,}357$). The correlation matrix above the dashed line is that of Model 1; the entire correlation matrix is that of Model 2. *r*: aggregated correlation (unattenuated), ρ: aggregated correlation (attenuated), τ^2: variance between correlation matrices (i.e., study samples), I^2: heterogeneity coefficient based on the *Q* statistic (Higgins & Green, 2011). *$p < .01$.

3.3. Aggregation of TAM correlations

To address Research Question 1, which is concerned with the aggregation of correlation matrices and the associated variation across samples, we performed the first stage of the TSSEM approach and pooled correlation matrices under the assumption of fixed or random effects. Given that each of the four TAM versions comprised a different set of variables (see Fig. 1), we performed this procedure for each of these models.

For Models 1 and 2, the assumption of fixed effects resulted in poor goodness-of fit (Model 1: $\chi^2(470) = 7201.4$, $p < .001$, CFI = 0.825, RMSEA = 0.227, SRMR = 0.155; Model 2: $\chi^2(535) = 8136.0$, $p < .001$, CFI = 0.815, RMSEA = 0.226, SRMR = 0.155); the same result was obtained from Models 3 and 4 which further contained external variables (Model 3: $\chi^2(984) = 13{,}066.7$, $p < .001$, CFI = 0.780, RMSEA = 0.211, SRMR = 0.161; Model 4: $\chi^2(1098) = 14{,}170.5$, $p < .001$, CFI = 0.774, RMSEA = 0.210, SRMR = 0.161). Given that the assumption of fixed effects did not hold for Model 1–4, we consequently introduced random effects and examined the extent to which between-study variance existed.

Models 1 and 2. The random-effects models for Models 1 and 2 exhibited overall heterogeneity between study samples (Model 1: $Q[470] = 12{,}806.1$, $p < .001$; Model 2: $Q[535] = 14{,}440.1$, $p < .001$). Moreover, each of the correlation coefficients in the correlation matrices varied significantly, $I^2 = 84.4$–94.9% (see Table 5).

Models 3 and 4. Similar to Models 1 and 2, random-effects models for Models 3 and 4 indicated between-study sample heterogeneity (Model 3: $Q[984] = 23{,}740.8$, $p < .001$; Model 4: $Q[1070] = 25{,}605.4$, $p < .001$). As Table 6 shows, the between-study sample variation of individual correlation coefficients was significant, except for three out of 28 correlation coefficients, and the variance explained by between-study sample differences was substantial, $I^2 = 75.3$–94.7%.

Overall, the evidence provided in the first stage of the TSSEM approach suggests that the assumption of fixed effects—that is, perfect homogeneity of correlation matrices between study samples—does not hold. Random-effects models capture the heterogeneity across samples and form the basis for all subsequent structural equation models. Our response to the first research question we raised is that the TAM relations can be aggregated in an overall correlation matrix, yet with significant variation of correlations between studies.

Table 6
Meta-analytically pooled correlation matrices for Models 3 and 4 under a random-effects model (TSSEM stage 1).

	PU	PEU	ATT	BI	SN	CSE	FC
PEU							
r	.48*						
95% CI	[.45, .51]						
ρ	.50*						
τ^2	0.025*						
$SE(\tau^2)$	0.004						
I^2	93.1%						
ATT							
r	.59*	.52*					
95% CI	[.55, .62]	[.49, .56]					
ρ	.62*	.54*					
τ^2	0.020*	0.024*					
$SE(\tau^2)$	0.004	0.004					
I^2	92.8%	94.7%					
BI							
r	.55*	.42*	.52*				
95% CI	[.52, .58]	[.39, .45]	[.48, .57]				
ρ	.58*	.44*	.55*				
τ^2	0.025*	0.019*	0.027*				
$SE(\tau^2)$	0.004	0.004	0.006				
I^2	94.6%	88.3%	93.7%				
SN							
r	.39*	.27*	.32*	.36*			
95% CI	[.34, .44]	[.22, .31]	[.27, .38]	[.30, .41]			
ρ	.40*	.26*	.33*	.35*			
τ^2	0.024*	0.016*	0.016*	0.022*			
$SE(\tau^2)$	0.006	0.004	0.005	0.006			
I^2	88.8%	82.8%	82.0%	84.0%			
CSE							
r	.41*	.46*	.40*	.40*	.28*		
95% CI	[.36, .46]	[.41, .52]	[.32, .47]	[.35, .45]	[.20, .37]		
ρ	.43	.47	.42	.42	.24		
τ^2	0.027*	0.032*	0.030*	0.028*	0.027*		
$SE(\tau^2)$	0.006	0.007	0.009	0.007	0.010		
I^2	91.7%	93.0%	90.7%	91.0%	88.8%		
FC							
r	.31*	.40*	.37*	.36*	.27*	.28*	
95% CI	[.27, .35]	[.35, .45]	[.31, .42]	[.31, .41]	[.22, .32]	[.21, .35]	
ρ	.33	.40	.37	.39	.27	.28	
τ^2	0.018*	0.030*	0.020*	0.022*	0.016*	0.028*	
$SE(\tau^2)$	0.004	0.007	0.006	0.005	0.005	0.008	
I^2	85.6%	91.8%	86.7%	88.0%	82.5%	89.4%	
USE							
r	.41*	.33*	.41*	.46*	.31*	.42*	.34*
95% CI	[.34, .48]	[.25, .41]	[.30, .52]	[.38, .53]	[.22, .39]	[.35, .50]	[.18, .51]
ρ	.46	.36	.45	.48	.34	.48	.37
τ^2	0.025*	0.029*	0.038*	0.017*	0.011	0.012	0.041
$SE(\tau^2)$	0.008	0.010	0.016	0.007	0.007	0.007	0.025
I^2	88.8%	89.5%	92.7%	84.0%	75.3%	78.1%	92.4%

Note. The correlation matrices are based on the unattenuated correlations and a random-effects model (k = 124, N = 34,357). The correlation matrix above the dashed line is that of Model 3; the entire correlation matrix is that of Model 4. r: aggregated correlation (unattenuated), ρ: aggregated correlation (attenuated), τ^2: variance between correlation matrices (i.e., study samples), I^2: heterogeneity coefficient based on the Q statistic (Higgins & Green, 2011). *$p < .01$.

3.4. Meta-analytic structural equation modeling of the core TAM (models 1 and 2)

On the basis of the pooled correlation matrices (see Table 5), we specified Models 1 and 2 to (a) examine whether these models represent the data well, and (b) test whether the direct effects of perceived usefulness on behavioral intention and attitudes on technology use existed (Research Question 2). To facilitate (b), we compared models with and without these direct effects in terms of model fit.

Model 1. The structural equation model without the direct path PU → BI had a good fit to the data, $\chi^2(2) = 104.9$, $p < .001$, CFI = 0.975, RMSEA = 0.039, SRMR = 0.085, AIC = 100.9, BIC = 84.0. Nevertheless, after introducing the direct effect, the overall goodness-of-fit improved significantly, $\Delta(\text{-2LL})$ [1] = 90.9, $p < .001$ (see Fig. 3, Model 1). These findings suggest that a direct effect between PU and BI exists—in the current model, this effect amounts to $b = 0.366$, 95% LBCI = [0.299, 0.432]; the indirect effect via

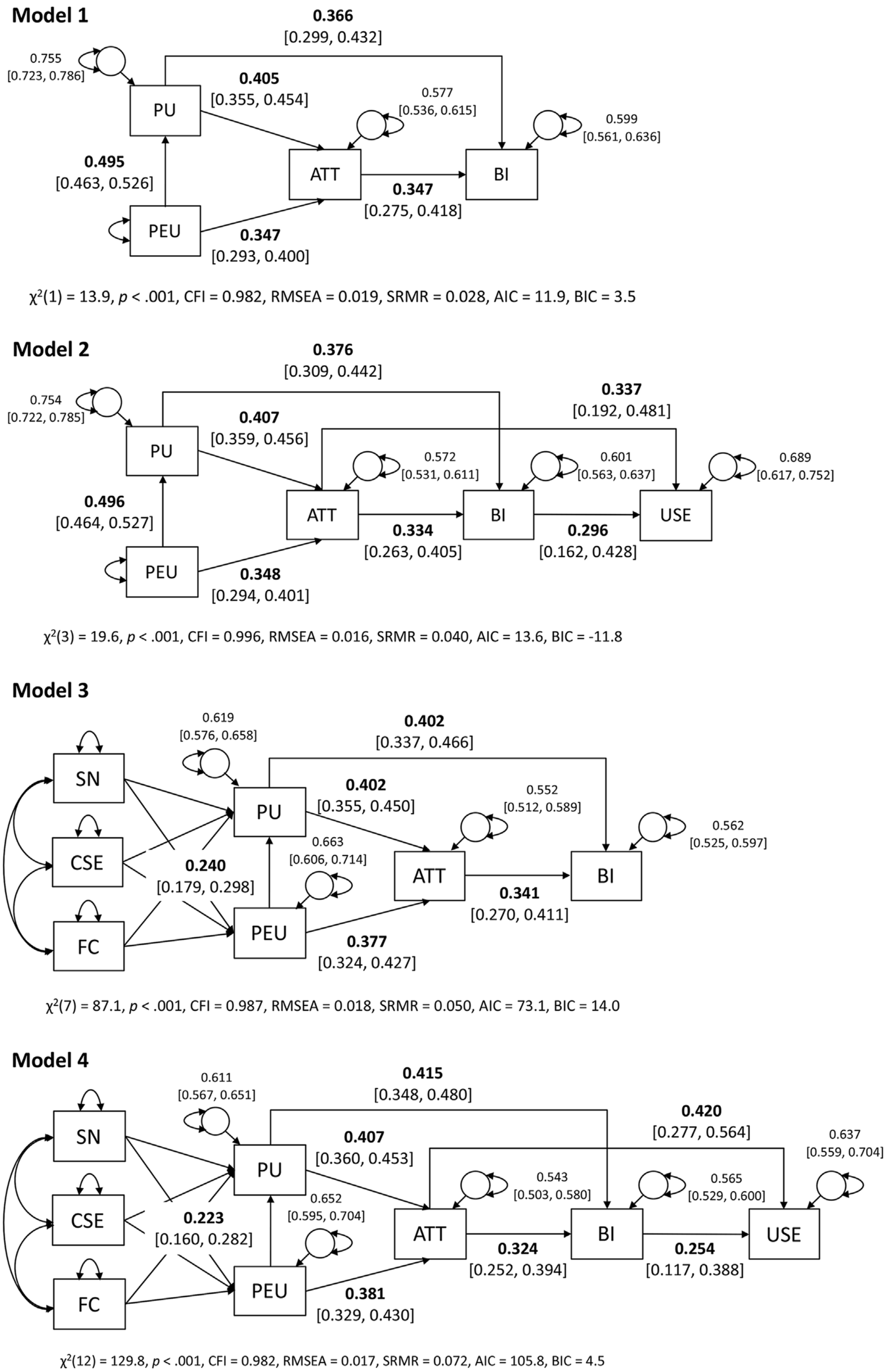

Fig. 3. Meta-analytic structural equation models 1 to 4 (TSSEM-Stage 2). *Note.* The 95% likelihood-based confidence intervals are shown in brackets. Path coefficients are highlighted in bold, residual variances in normal font.

ATT was weak but significant, $b = 0.140$, 95% LBCI = [0.109, 0.176]. Concerning the association between PEU and ATT ($b = 0.347$, 95% LBCI = [0.293, 0.400]), as well as PU and ATT ($b = 0.405$, 95% LBCI = [0.355, 0.454]), Model 1 showed positive and significant path coefficients with stronger effects of PU on ATT. All other hypothesized TAM relations could be established and were significantly positive. Fig. 3 shows the entire set of parameters in Model 1 along with their 95% likelihood-based confidence intervals. Overall, about 24.5% of variance in PU, 42.3% of variance in ATT, and 40.1% of BI variance was explained within the model.

Model 2. Following the same procedure as for Model 1, we first specified Model 2 without the direct effect ATT→USE. This model contained the direct effect PU→BI, given the prior evidence on its existence. The overall fit of the model was good, $\chi^2(4) = 39.7$, $p < .001$, CFI = 0.992, RMSEA = 0.013, SRMR = 0.068, AIC = 31.7, BIC = −2.1. Introducing the proposed direct effect, however, improved the model fit, Δ(-2LL) [1] = 20.2, $p < .001$ (see Fig. 3, Model 2). The direct effect ATT→USE was positive and significant, $b = 0.337$, 95% LBCI = [0.192, 0.481] (see Fig. 3). Moreover, the BI-USE link was significant, $b = 0.296$, 95% LBCI = [0.162, 0.428]. In total, 31.1% of variance in technology use could be explained. All other paths exhibited positive and significant relations.

Overall, Models 1 and 2 represented the data (i.e., the pooled correlation matrices derived from random-effects models in the first TSSEM stage) well and provided evidence for the existence of the hypothesized direct effects, PU→BI and ATT→USE. The variance explanations of behavioral intention and technology use were 40.1% and 31.1%. Hence, our response to our second research question is that the TAM with direct effects represents the data, and the hypothesized direct effects could be established empirically.

3.5. Subgroup analyses

As noted earlier, subgroup analyses were aimed at examining the generalizability of the findings surrounding the fit and parameters of the TAM (Research Question 3). For each of the subgroups examined in this meta-analysis, random-effects models were specified to aggregate correlation matrices. Supplementary Material S4 shows the results of the heterogeneity tests for each subgroup (TSSEM-Stage 1). The resultant tests indicated significant overall variation of correlation matrices across study samples; the corresponding estimates of I^2 supported the heterogeneity of single correlations within matrices. For all subgroups, Models 1 and 2 showed a good fit to the data.

Sample origin. Despite the large number of studies originating from Asian teacher samples, the differences in model parameters between Asian and non-Asian samples were marginal (see Fig. 4). This observation particularly applied to Model 1; for Model 2, however, differences in the variance explanation of technology use existed (Asian samples: $R^2 = 36.2\%$; non-Asian samples: $R^2 = 28.8\%$), primarily due to larger indirect effects of ATT on USE.

Teaching experience. Fig. 5 shows Models 1 and 2 specified for pre- and in-service teachers. Overall, only small differences in model parameters between these two groups of teachers existed. Some of these differences, however, resulted in larger variance explanations of behavioral intentions (pre-service teachers: $R^2 = 36.7\%$; in-service teachers: $R^2 = 44.3\%$) and technology use for in-service teachers (pre-service teachers: $R^2 = 21.7\%$; in-service teachers: $R^2 = 35.4\%$).

Specificity of technologies. Finally, we compared Models 1 and 2 between studies focusing on technology or computers in general and studies focusing on specific technologies (see Fig. 6). These comparisons revealed differences in the direct effects PU→BI and ATT→USE with larger effects for specific technologies. In fact, the ATT→USE relation was insignificant for studies referring to

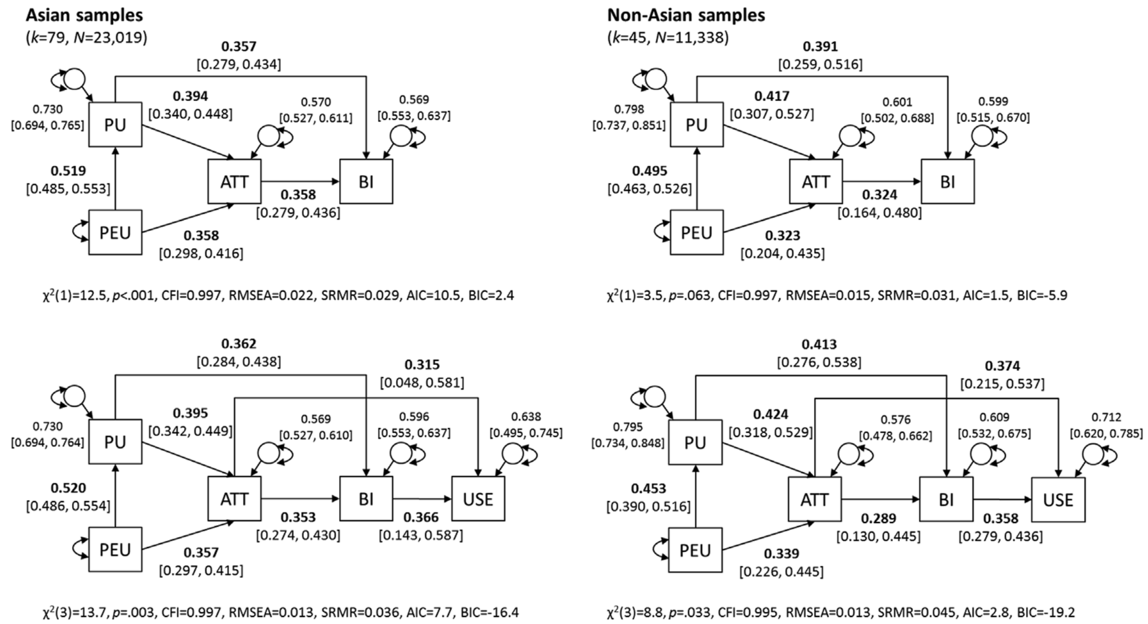

Fig. 4. Meta-analytic structural equation models 1 and 2 for Asian and non-Asian teacher samples (TSSEM-Stage 2). *Note.* The 95% likelihood-based confidence intervals are shown in brackets. Path coefficients are highlighted in bold, residual variances in normal font.

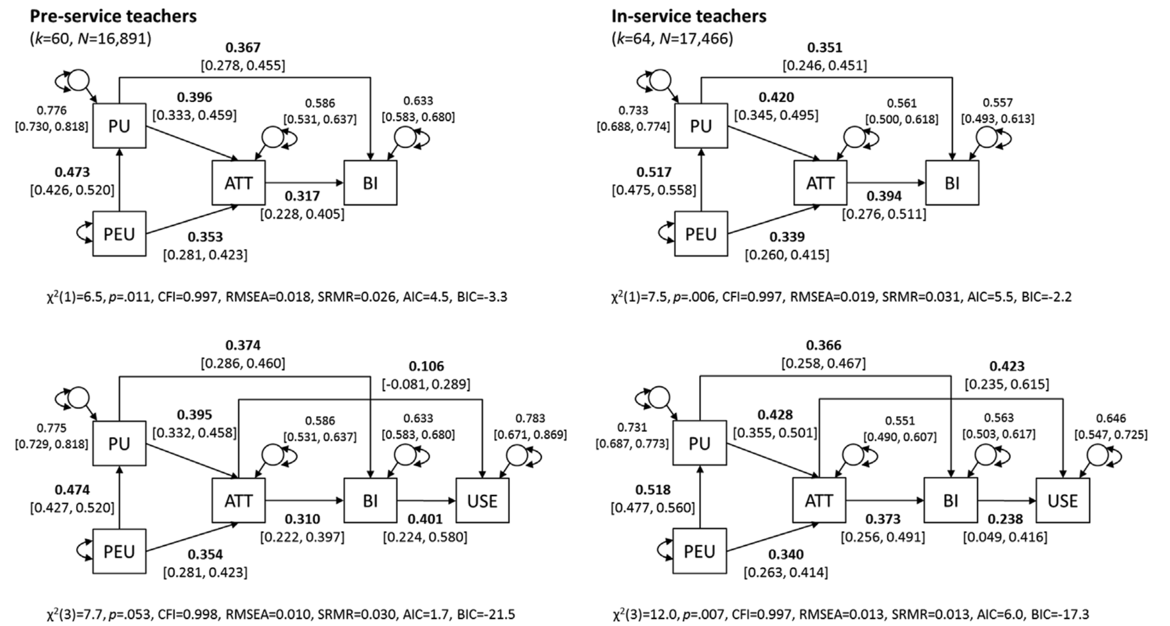

Fig. 5. Meta-analytic structural equation models 1 and 2 for pre- and in-service teacher samples (TSSEM-Stage 2). *Note.* The 95% likelihood-based confidence intervals are shown in brackets. Path coefficients are highlighted in bold, residual variances in normal font.

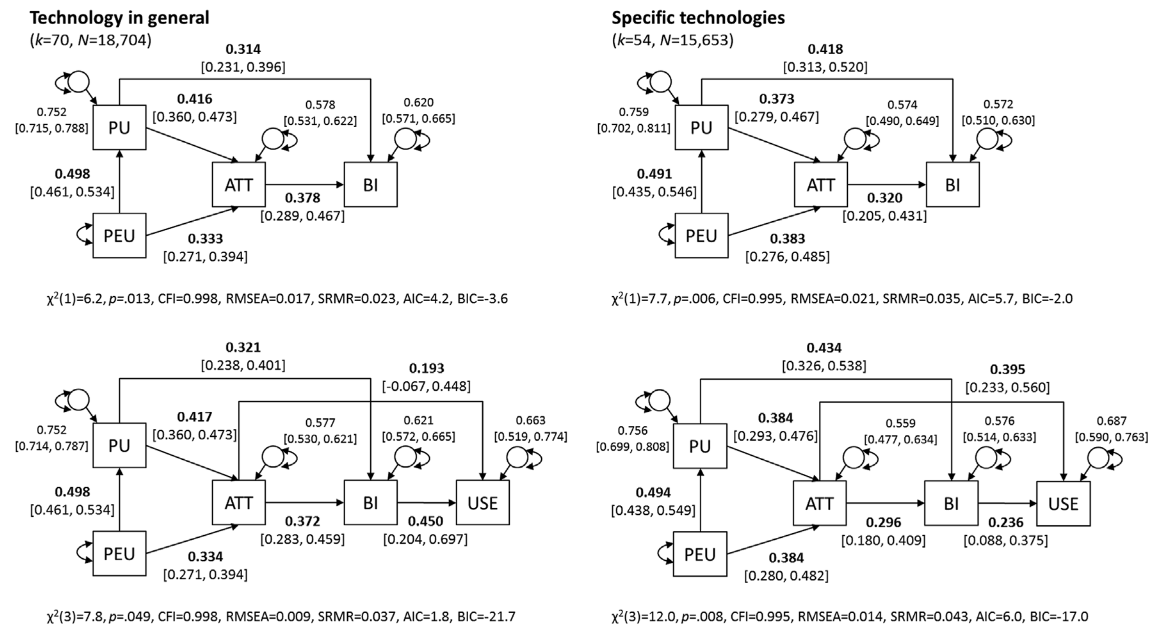

Fig. 6. Meta-analytic structural equation models 1 and 2 for studies using specific technologies and technology in general (TSSEM-Stage 2). *Note.* The 95% likelihood-based confidence intervals are shown in brackets. Path coefficients are highlighted in bold, residual variances in normal font.

technology in general. Moreover, larger variance explanations of behavioral intention in Model 1 (technology in general: R^2 = 38.0%; specific technologies: R^2 = 42.8%) occurred—however, variance explanations of technology use in Model 2 were comparable (technology in general: R^2 = 33.7%; specific technologies: R^2 = 31.3%).

Comparing the effects of PEU and PU on ATT across subgroups indicates that stronger effects of PU appeared for non-Asian samples, in-service teachers, and studies referring to technology in general—all other subgroups exhibited almost equal effects. Overall, the subgroup analyses suggested that the parameters in Models 1 and 2 were, by and large, similar between subgroups of TAM studies—however, some differences surfaced, exhibiting moderation effects on model parameters. In light of these findings, our response to Research Question 3 is that especially teacher experience and the specificity of technology affected the parameters in the TAM.

Table 7
Effects of external variables on perceived usefulness and ease of use (Models 3 and 4).

External variables	Perceived usefulness	Perceived ease of use
	b [95% LBCI]	
Model 3		
Subjective norm	0.276 [0.217, 0.333]	0.093 [0.027, 0.155]
Computer self-efficacy	0.225 [0.153, 0.293]	0.373 [0.306, 0.439]
Facilitating conditions	0.120 [0.061, 0.175]	0.303 [0.239, 0.365]
R^2	38.1%	33.8%
Model 4		
Subjective norm	0.280 [0.222, 0.337]	0.094 [0.026, 0.156]
Computer self-efficacy	0.244 [0.172, 0.312]	0.386 [0.319, 0.451]
Facilitating conditions	0.122 [0.063, 0.177]	0.300 [0.235, 0.362]
R^2	38.9%	34.8%

Note. The variance explanations (R^2) are that of perceived usefulness and perceived ease of use.

3.6. Effects of external variables

To address Research Question 4, we extended Models 1 and 2 by three external variables, namely subjective norms, computer self-efficacy, and facilitating conditions. These variables served as predictors of perceived usefulness and ease of use (see Fig. 1, Models 3 and 4). Based on the stage 1 pooling of correlation matrices under random-effects models (see Table 6), Models 3 and 4 provided meta-analytic path coefficients describing the effects of the external variables. These path coefficients are shown in Table 7.

Both Models 3 and 4 showed good model fit (see Fig. 3, Models 3 and 4). Furthermore, both models exhibited the following patterns of relations between external variables, PU, and PEU: Whereas subjective norm and computer self-efficacy were the most important predictors of perceived usefulness explaining 38–39% of variance, computer self-efficacy and facilitating conditions dominated the prediction of perceived ease of use and explained 34–35% of variance. The inclusion of external variables consequently reduced the path coefficient connecting PU and PEU (Model 3: $b = 0.240$, 95% LBCI = [0.179, 0.298]; Model 4: $b = 0.223$, 95% LBCI = [0.160, 0.282]). Fig. 3 depicts the remaining path coefficients and residual variances in Models 3 and 4. Overall, as a response to our fourth research question, we point out that all three external variables explained variance in PU and PEU, yet to varying degrees.

3.7. Sensitivity analysis

To test the sensitivity of our findings, we specified Models 1–4 for the corrected correlation matrices. The corrections for unreliability, however, led to the exclusion of 23 study samples due to non-positive definite correlation matrices. Supplementary Material S5 provides a more detailed description of these analyses. Overall, pooling the correlation matrices for Models 1–4 was best achieved under random-effects models. Indeed, the overall heterogeneity tests indicated substantial variation between study samples. All models specified with corrected correlations showed a good fit to the data—this could also be observed for the uncorrected correlations. By and large, structural parameters within Models 1–4 did not differ substantially between corrected and uncorrected matrices. However, due to stronger effects of the external variables, the variance explanations in PU and PEU were slightly higher in the corrected versions of Models 3 and 4, $R^2 = 42.4$–43.5%. Despite these differences, our findings were robust against the correction of individual correlations for unreliability.

4. Discussion

4.1. Model fit and relations within the TAM

Overall, our meta-analysis of the relations within the TAM has shown that considerable variation in correlation matrices across study samples exists. This finding has at least two consequences: First, synthesizing correlation matrices should be based on random-effects models rather than fixed-effects models—this conclusion has been drawn in other domains as well (M. W.-L. Cheung & Cheung, 2016). Second, it implies heterogeneity in TAM relations which can potentially be explained by further variables. In fact, considering the existing body of empirical TAM studies and meta-analyses, variation in TAM relations was expected (e.g., Ritter, 2017; Schepers & Wetzels, 2007). This variation, as current research suggests, may be due to sample, measurement, and study characteristics (Šumak et al., 2011; L.; Zhang et al., 2012). Next to this heterogeneity stands the overall good fit of the TAM, as it was exhibited in the second step of correlation-based MASEM for Models 1 and 2. The assumptions underlying the relations within the TAM thus represent the nature of the empirical data well. This observation could be explained as evidence supporting the validity, or more precisely the applicability of the TAM to the overall teacher sample.

Considering the relations within the TAM, perceived usefulness, next to the perceived ease of use, significantly predicted behavioral intentions via attitudes toward technology. In light of the original hypotheses associated with the TAM, this finding confirms the importance of teachers' perceptions (PEU and PU) and attitudes for user intentions (Venkatesh et al., 2003). The role of attitudes in the TAM is comparable to that of a mediator (Taylor & Todd, 1995). Moreover, the effects on BI were much more profound for PU than for PEU, because a direct effect existed next to the indirect effect—this was confirmed by the significantly better model fit of Model 2 as compared to Model 1 and the significant PU→BI effect. Hence, perceived usefulness of technology seems to be a critical factor of user intentions (Scherer et al., 2015). We therefore propose that teacher education and professional development practices consider strengthening PU next to PEU.

Extending Model 1 by the reported use of technology provided insights into the role of attitudes. Specifically, next to the indirect effect of attitudes on technology use via behavioral intentions, evidence for a direct effect could be obtained. Although such an effect has hardly been considered in previous empirical studies or meta-analysis, Šumak et al. (2011) could also identify it in the context of e-learning. Once again, this finding supports the relevance of attitudes toward technology for use behavior (Nistor & Heymann, 2010; Scherer, Tondeur, Siddiq, & Baran, 2018). In addition to this relevance, we encourage researchers to not only consider behavioral intentions as outcome variables in the TAM but also the reported or actual use of technology. In fact, Nistor (2014) criticized that the BI–USE link is often not examined in TAM studies, primarily due to the limitations associated with the self-reported rather than actual use of technology. Bringing back the USE variable to the TAM extends the inferences drawn from the TAM—these refer to the prediction of use beyond use intentions.

4.2. Generalizability of the TAM

Our results further testify the generalizability of the TAM, specified as Models 1 and 2, across study samples. More precisely, these models showed a good fit to the data of the subgroups of study samples, including pre- and in-service teachers, Asian and non-Asian teacher samples, specific technologies and technology in general. At the same time, some relations differed between subsamples, suggesting moderation effects (e.g., larger effects of BI on USE for pre-service teachers compared to in-service teachers; see Fig. 5). Such effects were also hypothesized and identified in previous meta-analyses (Hsiao & Yang, 2011; King & He, 2006; Schepers & Wetzels, 2007). They also show the relevance and applicability of the TAM for both teacher education (pre-service teachers) and professional development (in-service teachers). Nevertheless, the existence of moderation effects indicates that the TAM is, to some extent, specific to the study context in terms of sample and technology. It is therefore a model that might exhibit differential variance explanation of both the BI and USE variables. In addition to the substantive moderators examined in this meta-analysis, sensitivity against unreliability corrections of correlations was explored. The fact that the results obtained from corrected and uncorrected correlation matrices agree supports our overall findings.

At the same time, our study cannot provide evidence for an overall generalizability of the TAM for several reasons: First, the primary studies were almost exclusively based on cross-sectional data and did not manipulate certain variables within the TAM to test possible causal relations. The TAM versions examined in these studies did not incorporate the possibility of reciprocal relationships among variables, although these kinds of relations may seem likely. For instance, both PEU and PU may not only predict teachers' behavioral intentions to use technology but, in turn, they may be predicted by teachers' past experiences and use of technology as well (Scherer et al., 2015). Second, as mentioned earlier, the link between the TAM and teachers' professional knowledge was missing in the primary studies, thus limiting its implications for teacher training.

4.3. Effects of external variables

Besides testing the fit of the TAM for the entire sample and subsamples of teachers, we further examined the extent to which external variables explained variance in PEU and PU. The selection of external variables comprised subjective norms, computer self-efficacy, and facilitating conditions—three of the most prominent predictors of PEU and PU (Abdullah & Ward, 2016; Baydas & Goktas, 2017). Considering *subjective norms*, Abdullah and Ward (2016) found positive effects on both PEU and PU with stronger effects on PEU ($\beta_{SN\text{-}PEU} = .20$, $\beta_{SN\text{-}PU} = .30$). This finding was confirmed in our meta-analysis for teacher samples, yet with smaller effects on PEU (Model 3: $\beta_{SN\text{-}PEU} = .09$, $\beta_{SN\text{-}PU} = .28$). Moreover, the effects varied across studies, indicating possible context- or sample-specificity. Hence, subjective norms played a larger role of teachers' perceptions of the usefulness of technology in educational contexts. From our perspective, this finding needs further attention and substantive backing, because subjective norm—that is, teachers' perceptions that most people think they should use technology—refers to a different belief system than perceived usefulness—that is, teachers' perceptions of the usefulness of technology for teaching and learning (Antonietti & Giorgetti, 2006; Schepers & Wetzels, 2007). Whereas the former takes other people, for instance, teacher colleagues, supervisors, or fellow students, as the frame of reference, the latter uses the technology itself as a static entity to frame a reference. Along the same lines, the connection between SN and PEU should be weak, as PEU indicates teachers' perceptions of the ease of using technology—another belief with a reference to technology rather than people. Nevertheless, PEU—as it is defined here—may well be explained by teachers' *self-efficacy*, because it interferes with beliefs about the extent to which a person can perform tasks with technology (Scherer & Siddiq, 2015). Indeed, our meta-analysis confirms this expectation (Model 3: $\beta_{CSE\text{-}PEU} = .37$, $\beta_{CSE\text{-}PU} = .23$), and is in line with the results reported by Abdullah and Ward (2016) ($\beta_{CSE\text{-}PEU} = .35$, $\beta_{CSE\text{-}PU} = .17$) and Scherer et al. (2015) ($\beta_{CSE\text{-}PEU}$'s = 0.22–0.31). As competence perceptions that are based on prior experience of mastery facilitate the future engagement or anticipation of engagement in certain activities, they also determine perceptions of task difficulty and possible mastery (Bandura, 1977; Tschannen-Moran & Hoy, 2007). To conclude, self-efficacy in using technology is linked to the TAM-core variables and may therefore represent a possible barrier or enabler for technology use or use intention in education—yet, the direct or indirect mechanisms leading up to this importance are still to be examined in greater detail.

Facilitating conditions were positively related to both PEU (Model 3: $\beta_{FC\text{-}PEU} = .30$) and PU (Model 3: $\beta_{FC\text{-}PU} = .12$), with stronger effects on PEU. Once again, perceptions of possible barriers that are related to school or classroom resources are linked to perceptions of how easy the use of technology may be. This finding brings into play the responsibilities schools have to create conditions that allow teachers to use technology for teaching and learning (Fraillon et al., 2014).

Overall, the conditions facilitating technology adoption are multifaceted as they relate to school resources (FC), peer influences (SN), and personal competence beliefs (CSE). The integration of technology therefore requires a multidimensional approach which goes beyond strengthening teachers' competences and competence beliefs (Straub, 2009). Our meta-analysis shed light on the effects external variables can have on PEU and PU—two of the TAM-core variables—and provide insights into the differential effects of antecedents. It also contributes to the field by meta-analyzing the TAM extended by external variables instead of analyzing the effects of external variables solely (Abdullah & Ward, 2016) or considering only one external variable (Schepers & Wetzels, 2007).

4.4. Methodological issues in TAM studies

By and large, the TAM studies reviewed in this meta-analysis provided evidence for both the reliability and validity of measures of TAM variables and their resultant scores. This evidence surfaced in high average reliabilities, acceptable and close model fit for most of the studies that evaluated model fit ($k = 66$), and the replicability of the TAM for different teacher samples. At the same time, more than 40% of the studies did not evaluate model fit. Considering that a sufficient fit between the data collected and the theoretical model specified is critical to drawing valid inferences from structural equation models (e.g., Kline, 2016; West, Taylor, & Wu, 2012), this finding encourages researchers in the field to examine the fit of their empirical models and explore possible causes for deviations to back the inferences drawn from the resultant model parameters. We believe that a thorough investigation of model fit—for both teacher samples and other subsamples—is a critical step towards creating a validity argument (Kane, 2013). These investigations may also include continuous factors, such as the proportion of female teachers or teachers' age.

Besides, this meta-analysis further revealed that empirical TAM studies made use of both manifest and latent variable models, and this differed in their approaches to represent the TAM constructs. This observation might be problematic from a statistical point of view: Whereas latent variable models explicitly account for measurement error, manifest variable scores such as sum or mean scale scores do not (Kline, 2016). Consequently, the latter necessitate corrections for unreliability; the former do not. To our best knowledge, it is currently unclear as to whether the differential handling of measurement error in the studies used to synthesize research findings affects both the pooled correlation parameters and their variances. Consequently, the mixed treatment of variables results in differential treatments of unreliability corrections.

Finally, the empirical studies reviewed in this meta-analysis did not allow for any causal claim on the relations among TAM variables. Although some authors engaged in causal interpretations of effects, the cross-sectional data used to specify the TAM with the help of structural equation models cannot deliver evidence for causality (Kline, 2012)—instead, longitudinal designs accounting for possible confounders and experimental studies are needed to substantiate causality (Venkatesh & Bala, 2008).

4.5. Practical implications of the TAM

The results of this meta-analysis confirm that the TAM successfully predicts user behavior and can thus be of interest to all potential users of a new technology (Pynoo et al., 2011; Šumak et al., 2011). Our meta-analysis further highlights that the TAM is equally relevant for several sub-groups, including pre- and in-service teachers, teachers teaching at different educational levels, and various countries. Clearly, education can benefit by knowing the potential determinants, but one of the most common criticisms of TAM has been the lack of actionable guidance to practitioners, including educational stakeholders (Lee, Kozar, & Larsen, 2003). Venkatesh and Bala (2008), therefore, classified the possible relevance of the TAM model into two categories: pre-implementation and post-implementation phases. According to these authors, the pre-implementation phase is characterized by stages leading to the actual roll-out of technology while the post-implementation phase entails stages that follow the actual deployment of technology in educational practice. Both stages are relevant for the implementation of technology in education.

The pre-implementation phase stresses the need for a set of organizational activities that take place before the introduction of technology in education and can potentially lead to greater acceptance. To illustrate, the Shroff, Deneen, and Ng (2011) study analyzed the Technology Acceptance Model to examine university students' behavioral intention to use an electronic portfolio system, meaning how students use and appropriate it within the specific framework of a course. The proactive phase of interventions is in this case necessary to minimize resistance towards the integration of an e-portfolio system in educational processes. The post-implementation phase, on the other hand, refers to informal or formal activities or functions to assist educational stakeholders in using new technologies effectively (Venkatesh & Bala, 2008). Training has been suggested as one of the most important post-implementation phase that leads to greater user acceptance and system success. To illustrate, Baturay, Gökçearslan, and Ke (2017) explored 476 pre-service teachers' acceptance of digital technologies in Turkey. Their findings supported the idea that pre-service teachers need to be trained about technological innovations and that they need to learn how to use these technologies for education and their individual development.

As our findings on the relevance of external variables suggest, training approaches targeted at improving perceived usefulness and perceived ease of use may also focus on enhancing teachers' self-efficacy in using technology. In fact, cross-sectional studies indicated a link between teachers' self-efficacy in technological and pedagogical content knowledge, PEU, and PU (e.g., Mei et al., 2017). For a training approach to be successful, teacher attitudes, knowledge, and instructional practices concerning technology must be considered (Lawless & Pellegrino, 2007). Overall, insights into the TAM can guide teachers and schools in the development of educational technology use.

4.6. Limitations and future directions

The present meta-analytic review has some limitations worth noting. First, except for variance in reliabilities, full comparability of the TAM measures across studies was assumed. Whereas this is an assumption in almost any meta-analysis, it implies that the measurement models of the TAM constructs are assumed to be invariant (M. W.-L. Cheung, 2015). This is in fact a strong assumption in the context of TAM, since a considerable number of studies uncovered that full measurement invariance might not hold even across smaller sets of study samples or countries (e.g., Teo, 2015; Teo et al., 2009). Therefore, the model parameters and their standard errors in the aggregated structural equation model might change slightly if the assumption of comparability is relaxed. Yet, in the current model, variance in the structural parameters was captured and described as a random variance component. Moreover, to the best of our knowledge, we (a) corrected the reported correlations for unreliability and (b) investigated the extent to which differences in the aggregated TAM existed between different modeling approaches. We note that this poses a methodological challenge, particularly because model parameters and scale reliabilities are oftentimes based on different modeling approaches and research designs (Churchill & Peter, 1984; Raykov & Marcoulides, 2013).

Second, the meta-analytic structural equation approach was based on a small sample of indicators of each TAM variable—the diversity in items measuring TAM variables only allowed for the inclusion of an overall score for each construct. The TAM was therefore tested as a path-analytic model containing manifest variables rather than latent variables. This approach was chosen due to the enormous diversity of modeling approaches and items in the TAM literature. Hence, the aggregated model parameters and their standard errors in our meta-analysis contain the variation between different modeling approaches. In the most ideal scenario, all studies would have taken the same approach and would have used the same set of items to indicate the TAM constructs.

Third, we did not consider further variables that may predict either PEU and PU or the TAM outcome variables (BI and USE). We believe that linking the TAM with teachers' professional knowledge could shed more light on the processes of technology acceptance and extend the current perspective of the TAM as a model merely predicting user intentions or the use of technology to the meaningful integration of technology in teaching and learning.

5. Conclusions

The current meta-analysis synthesized the existing body of research on pre- and in-service teachers' technology adoption based on the Technology Acceptance Model using random-effects, correlation-based MASEM under M. W.-L. Cheung and Chan's (2005) two-step modeling approach. This study has two main contributions: First, from a substantive perspective, the meta-analytic findings support the applicability of the TAM to teacher samples and clarify some inconsistencies of certain relations within the model, including the existence of direct effects of TAM core variables on technology use and use intentions. Second, from a methodological point of view, this meta-analysis synthesizes correlation matrices rather than single correlations, showcasing how M. W.-L. Cheung and Chan's (2005) two-stage modeling approach can be applied to test theory-driven models. Despite its superiority over univariate meta-analysis, this approach has rarely been taken in meta-analyzing the TAM in educational contexts. Overall, the TAM is a powerful model that hypothesizes direct and indirect mechanisms leading up to teachers' technology use. The fact that this model fits for both pre- and in-service teachers suggests its generalizability across these sub-samples and, thus, points to its relevance for both teacher education and professional development.

Acknowledgement

This research was partly supported by the FINNUT Young Research Talent Project Grant (NFR-254744 "ADAPT21") awarded to Ronny Scherer by The Research Council of Norway. We are grateful for the comments and suggestions from three anonymous reviewers—these reviews have greatly improved the clarity of presentation and reasoning.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2018.09.009.

References

References marked with an asterisk indicate studies included in the meta-analysis.

Abdullah, F., & Ward, R. (2016). Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior, 56*, 238–256. https://doi.org/10.1016/j.chb.2015.11.036.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in M-learning context: A systematic review. *Computers & Education, 125*, 389–412. https://doi.org/10.1016/j.compedu.2018.06.008.

Aloe, A. M. (2015). Inaccuracy of regression results in replacing bivariate correlations. *Research Synthesis Methods, 6*(1), 21–27. https://doi.org/10.1002/jrsm.1126.

Antonietti, A., & Giorgetti, M. (2006). Teachers' beliefs about learning from multimedia. *Computers in Human Behavior, 22*(2), 267–282. https://doi.org/10.1016/j.chb.2004.06.002.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191.

Baturay, M. H., Gökçearslan, Ş., & Ke, F. (2017). The relationship among pre-service teachers computer competence, attitude towards computer-assisted education, and intention of technology acceptance. *International Journal of Technology Enhanced Learning, 9*(1), 1–13. https://doi.org/10.1504/IJTEL.2017.10003119.

Baydas, O., & Goktas, Y. (2017). A model for preservice teachers' intentions to use ICT in future lessons. *Interactive Learning Environments, 25*(7), 930–945. https://doi.org/10.1080/10494820.2016.1232277.

Beller, M. (2013). Technologies in large-scale assessments: New directions, challenges, and opportunities. In M. v. Davier, E. Gonzalez, I. Kirsch, & K. Yamamoto (Eds.). *The role of international large-scale assessments: Perspectives from technology, economy, and educational research* (pp. 25–45). Dordrecht: Springer Science + Business Media. https://doi.org/10.1007/978-94-007-4629-9_3.

Berrett, B., Murphy, J., & Sullivan, J. (2012). Administrator insights and reflections: Technology integration in schools. *The Qualitative Report, 17*(1), 200–221.

Bishop, M. J., & Spector, J. M. (2014). Technology integration. In J. M. Spector, D. Merrill, J. Elen, & M. J. Bishop (Eds.). *Handbook of research on educational communications and technology* (pp. 817–818). (4 ed.). New York, NY: Springer Science + Business Media.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2009). *Introduction to meta-analysis.* Chichester, West Sussex: John Wiley & Sons, Ltd.

Burton-Jones, A., & Hubona, G. S. (2006). The mediation of external variables in the technology acceptance model. *Information & Management, 43*(6), 706–717. https://doi.org/10.1016/j.im.2006.03.007.

Card, N. A. (2015). *Applied meta-analysis for social science research.* New York, NY: Guilford Press.

Cheung, M. W.-L. (2009). Constructing approximate confidence intervals for parameters with structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(2), 267–294. https://doi.org/10.1080/10705510902751291.

Cheung, M. W.-L. (2014). Fixed- and random-effects meta-analytic structural equation modeling: Examples and analyses in R. *Behavior Research Methods, 46*(1), 29–40. https://doi.org/10.3758/s13428-013-0361-y.

Cheung, M. W.-L. (2015). *Meta-analysis: A structural equation modeling approach.* Chichester, West Sussex: John Wiley & Sons, Ltd.

Cheung, M. W.-L., & Chan, W. (2005). Meta-analytic structural equation modeling: A two-stage approach. *Psychological Methods, 10*(1), 40–64. https://doi.org/10.1037/1082-989X.10.1.40.

Cheung, M. W.-L., & Cheung, S. F. (2016). Random-effects models for meta-analytic structural equation modeling: Review, issues, and illustrations. *Research Synthesis Methods, 7*(2), 140–155. https://doi.org/10.1002/jrsm.1166.

*Cheung, E. Y. M., & Sachs, J. (2006). Test of the technology acceptance model for a web-based information system in a Hong Kong Chinese sample. *Psychological Reports, 99*(3), 691–703. https://doi.org/10.2466/PR0.99.3.691-703.

Churchill, G. A., & Peter, J. P. (1984). Research design effects on the reliability of rating scales: A meta-analysis. *Journal of Marketing Research, 21*(4), 360–375. https://doi.org/10.2307/3151463.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189–211. https://doi.org/10.2307/249688.

von Davier, A. A., Hao, J., Liu, L., & Kyllonen, P. (2017). Interdisciplinary research agenda in support of assessment of collaborative problem solving: Lessons learned from developing a collaborative science assessment prototype. *Computers in Human Behavior, 76*, 631–640. https://doi.org/10.1016/j.chb.2017.04.059.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results. (PhD).* Cambridge, MA: Massachusetts Institute of Technology. Retrieved from https://dspace.mit.edu/bitstream/handle/1721.1/15192/14927137-MIT.pdf?sequence = 2.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008.

Duval, S., & Tweedie, R. (2000). Trim and fill: A simple funnel-plot–based method of testing and adjusting for publication bias in meta-analysis. *Biometrics, 56*(2), 455–463. https://doi.org/10.1111/j.0006-341X.2000.00455.x.

Fishbein, M. (1979). A theory of reasoned action: Some applications and implications. *Nebraska Symposium on Motivation, 27*, 65–116.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research.* Reading, MA: Addison-Wesley.

Flórez, F. B., Casallas, R., Hernández, M., Reyes, A., Restrepo, S., & Danies, G. (2017). Changing a generation's way of thinking: Teaching computational thinking through programming. *Review of Educational Research, 87*(4), 834–860. https://doi.org/10.3102/0034654317710096.

Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Gebhardt, E. (2014). *Preparing for life in a digital age - the IEA international computer and information literacy study international report*Heidelberg, New York, Dordrecht, London: Springer International Publishinghttps://doi.org/10.1007/978-3-319-14222-7.

Higgins, J. P. T., & Green, S. (2011). *Cochrane handbook for systematic reviews of interventions*, *Vol. 4*. Chichester, West Sussex: John Wiley & Sons.

Hong, R. Y., & Cheung, M. W.-L. (2015). The structure of cognitive vulnerabilities to depression and anxiety: Evidence for a common core etiologic process based on a meta-analytic review. *Clinical Psychological Science, 3*(6), 892–912. https://doi.org/10.1177/2167702614553789.

Hsiao, C. H., & Yang, C. (2011). The intellectual development of the technology acceptance model: A co-citation analysis. *International Journal of Information Management, 31*(2), 128–136. https://doi.org/10.1016/j.ijinfomgt.2010.07.003.

Hsu, L. (2016). Examining EFL teachers' technological pedagogical content knowledge and the adoption of mobile-assisted language learning: A partial least square approach. *Computer Assisted Language Learning, 29*(8), 1287–1297. https://doi.org/10.1080/09588221.2016.1278024.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118.

Imtiaz, M. A., & Maarop, N. (2014). A review of technology acceptance studies in the field of education. *Jurnal Teknologi, 69*(2), 27–32. https://doi.org/10.1109/CTIT.2013.6749472.

Jak, S. (2015). *Meta-analytic structural equation modelling.* Utrecht, The Netherlands: Springerhttps://doi.org/10.1007/978-3-319-27174-3.

Kane, M. T. (2013). Validating the interpretations and uses of test scores. *Journal of Educational Measurement, 50*(1), 1–73. https://doi.org/10.1111/jedm.12000.

Khojasteh, J., & Lo, W.-J. (2015). Investigating the sensitivity of goodness-of-fit indices to detect measurement invariance in a bifactor model. *Structural Equation Modeling: A Multidisciplinary Journal, 22*(4), 531–541. https://doi.org/10.1080/10705511.2014.937791.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003.

*Kirmizi, Ö. (2014). Measuring technology acceptance level of Turkish pre-service English teachers by using technology acceptance model. *Educational Research and Reviews, 9*(23), 1323–1333.

Kline, R. B. (2012). Assumptions in structural equation modeling. In R. H. Hoyle (Ed.). *Handbook of structural equation modeling* (pp. 111–125). New York, London: Guilford Press.

Kline, R. B. (2016). *Principles and practice of structural equation modeling.* New York, NY: The Guilford Press.

Koehler, M. J., & Mishra, P. (2009). What Is technological pedagogical content knowledge? *Contemporary Issues in Technology and Teacher Education (CITE), 9*(1), 60–70.

Koehler, M. J., Mishra, P., Kereluik, K., Shin, T. S., & Graham, C. R. (2014). The technological pedagogical content knowledge framework. In M. J. Spector, D. M. Merrill, J. Elen, & J. M. Bishop (Eds.). *Handbook of research on educational communications and technology* (pp. 101–111). New York, NY: Springer.

Lawless, K. A., & Pellegrino, J. W. (2007). Professional development in integrating technology into teaching and learning: Knowns, unknowns, and ways to pursue better questions and answers. *Review of Educational Research, 77*(4), 575–614. https://doi.org/10.3102/0034654307309921.

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems, 12*, 752–780.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*, 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4.

Little, T. D. (2013). *Longitudinal structural equation modeling.* New York, NY: Guilford Press.

*Luan, W. S., & Teo, T. (2009). Investigating the technology acceptance among student teachers in Malaysia: An application of the Technology Acceptance Model (TAM). *Asia-Pacific Education Researcher, 18*(2), 261–272.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1.

Marsh, H. W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit evaluation in structural equation modeling. In A. Maydeu-Olivares, & J. J. McArdle (Vol. Eds.), Contemporary psychometrics: Vols. 275–340. Mahwah, NJ: Lawrence Erlbaum.

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and bentler's (1999) findings. *Structural Equation Modeling: A Multidisciplinary Journal, 11*(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2.

Mei, B., Brown, G. T. L., & Teo, T. (2017). Toward an understanding of preservice English as a foreign language teachers' acceptance of computer-assisted language learning 2.0 in the people's republic of China. *Journal of Educational Computing Research*. https://doi.org/10.1177/0735633117700144.

Michel, J. S., Viswesvaran, C., & Thomas, J. (2011). Conclusions from meta-analytic structural equation models generally do not change due to corrections for study artifacts. *Research Synthesis Methods, 2*(3), 174–187. https://doi.org/10.1002/jrsm.47.

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record, 108*(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x.

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. The PRISMA Group, e. a. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine, 6*(7), 1–6. https://doi.org/10.1371/journal.pmed.1000097.

*Nam, C. S., Bahn, S., & Lee, R. (2013). Acceptance of assistive technology by special education teachers: A structural equation model approach. *International Journal of Human-Computer Interaction, 29*(5), 365–377. https://doi.org/10.1080/10447318.2012.711990.

Naragon-Gainey, K., McMahon, T. P., & Chacko, T. P. (2017). The structure of common emotion regulation strategies: A meta-analytic examination. *Psychological Bulletin, 143*(4), 384–427. https://doi.org/10.1037/bul0000093.

Nistor, N. (2014). When technology acceptance models won't work: Non-significant intention-behavior effects. *Computers in Human Behavior, 34*(Supplement C), 299–300. https://doi.org/10.1016/j.chb.2014.02.052.

Nistor, N., & Heymann, J. O. (2010). Reconsidering the role of attitude in the TAM: An answer to Teo (2009). *British Journal of Educational Technology, 41*(6), E142–E145. https://doi.org/10.1111/j.1467-8535.2010.01109.x.

OECD (2015). *Students, computers and learning: Making the connection.* Paris: OECD Publishinghttps://doi.org/10.1787/9789264239555-en.

Peterson, R. A., & Brown, S. P. (2005). On the use of beta coefficients in meta-analysis. *Journal of Applied Psychology, 90*(1), 175–181. https://doi.org/10.1037/0021-9010.90.1.175.

Pynoo, B., Devolder, P., Tondeur, J., van Braak, J., Duyck, W., & Duyck, P. (2011). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human Behavior, 27*(1), 568–575. https://doi.org/10.1016/j.chb.2010.10.005.

*Pynoo, B., Tondeur, J., van Braak, J., Duyck, W., Sijnave, B., & Duyck, P. (2012). Teachers' acceptance and use of an educational portal. *Computers & Education, 58*(4), 1308–1317. https://doi.org/10.1016/j.compedu.2011.12.026.

Raykov, T., & Marcoulides, G. A. (2013). Meta-analysis of scale reliability using latent variable modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(2), 338–353. https://doi.org/10.1080/10705511.2013.769396.

Ritter, N. L. (2017). Technology acceptance model of online learning management systems in higher education: A meta-analytic structural equation model. *International Journal of Learning Management Systems, 5*(1), 1–15. https://doi.org/10.18576/ijlms/050101.

Romeo, G., Lloyd, M., & Downes, T. (2013). Teaching teachers for the future: How, what, why, and what next? *Australian Educational Computing, 27*(3), 3–12.

Rosenberg, M. S. (2005). The file-drawer problem revisited: A general weighted method for calculating fail-safe numbers in meta-analysis. *Evolution, 59*(2), 464–468. https://doi.org/10.1111/j.0014-3820.2005.tb01004.x.

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007.

Scherer, R., & Siddiq, F. (2015). Revisiting teachers' computer self-efficacy: A differentiated view on gender differences. *Computers in Human Behavior, 53*, 48–57. https://doi.org/10.1016/j.chb.2015.06.038.

Scherer, R., Siddiq, F., & Teo, T. (2015). Becoming more specific: Measuring and modeling teachers' perceived usefulness of ICT in the context of teaching and learning. *Computers & Education, 88*, 202–214. https://doi.org/10.1016/j.compedu.2015.05.005.

Scherer, R., Tondeur, J., Siddiq, F., & Baran, E. (2018). The importance of attitudes toward technology for pre-service teachers' technological, pedagogical, and content knowledge: Comparing structural equation modeling approaches. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2017.11.003.

Schmidt, F. L., & Hunter, J. E. (2014). *Methods of meta-analysis: Correcting error and bias in research findings* (3 ed.). Thousand Oaks, CA: Sage.

Shroff, R. H., Deneen, C. C., & Ng, E. M. (2011). Analysis of the technology acceptance model in examining students' behavioural intention to use an e-portfolio system. *Australasian Journal of Educational Technology, 27*(4), 600–618. https://doi.org/10.14742/ajet.940.

Shute, V. J., & Rahimi, S. (2017). Review of computer-based assessment for learning in elementary and secondary education. *Journal of Computer Assisted Learning, 33*(1), 1–19. https://doi.org/10.1111/jcal.12172.

Siddiq, F., Hatlevik, O. E., Olsen, R. V., Throndsen, I., & Scherer, R. (2016). Taking a future perspective by learning from the past – a systematic review of assessment instruments that aim to measure primary and secondary school students' ICT literacy. *Educational Research Review, 19*, 58–84. https://doi.org/10.1016/j.edurev.2016.05.002.

Siddiq, F., Scherer, R., & Tondeur, J. (2016). Teachers' emphasis on developing students' digital information and communication skills (TEDDICS): A new construct in 21st century education. *Computers & Education, 92–93*, 1–14. https://doi.org/10.1016/j.compedu.2015.10.006.

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). P-curve: A key to the file-drawer. *Journal of Experimental Psychology: General, 143*(2), 534–547. https://doi.org/10.1037/a0033242.

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2017). *P-curve online app version 4.0*.

Smarkola, C. (2011). A mixed-methodological technology adoption study. In T. Teo (Ed.). *Technology acceptance in education* (pp. 9–41). Rotterdam, The Netherlands: Sense Publishers. https://doi.org/10.1007/978-94-6091-487-4_2.

Spector, J. M. (2008). Cognition and learning in the digital age: Promising research and practice. *Computers in Human Behavior, 24*(2), 249–262. https://doi.org/10.1016/j.chb.2007.01.016.

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research, 79*(2), 625–649. https://doi.org/10.3102/0034654308325896.

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in Human Behavior, 27*(6), 2067–2077. https://doi.org/10.1016/j.chb.2011.08.005.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing, 22*, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137.

Tang, R. W., & Cheung, M. W.-L. (2016). Testing IB theories with meta-analytic structural equation modeling: The TSSEM approach and the Univariate-r approach. *Review of International Business and Strategy, 26*(4), 472–492. https://doi.org/10.1108/RIBS-04-2016-0022.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144.

*Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education, 52*(2), 302–312. https://doi.org/10.1016/j.compedu.2008.08.006.

Teo, T. (2015). Comparing pre-service and in-service teachers' acceptance of technology: Assessment of measurement invariance and latent mean differences. *Computers & Education, 83*, 22–31. https://doi.org/10.1016/j.compedu.2014.11.015.

*Teo, T., Lee, C. B., Chai, C. S., & Wong, S. L. (2009). Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the technology acceptance model (TAM). *Computers & Education, 53*(3), 1000–1009. https://doi.org/10.1016/j.compedu.2009.05.017.

*Teo, T., & Milutinovic, V. (2015). Modelling the intention to use technology for teaching mathematics among pre-service teachers in Serbia. *Australasian Journal of Educational Technology, 31*(4), 363–380. https://doi.org/10.14742/ajet.1668.

*Teo, T., & van Schaik, P. (2012). Understanding the intention to use technology by preservice teachers: An empirical test of competing theoretical models. *International Journal of Human-Computer Interaction, 28*(3), 178–188. https://doi.org/10.1080/10447318.2011.581892.

Tschannen-Moran, M., & Hoy, A. W. (2007). The differential antecedents of self-efficacy beliefs of novice and experienced teachers. *Teaching and Teacher Education, 23*(6), 944–956. https://doi.org/10.1016/j.tate.2006.05.003.

Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology, 52*(5), 463–479. https://doi.org/10.1016/j.infsof.2009.11.005.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540.

West, S., Taylor, A., & Wu, W. (2012). Model fit and model selection in structural equation modeling. In R. H. Hoyle (Ed.). *Handbook of structural equation modeling* (pp. 209–231). New York, NY: Guilford Press.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management, 28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088.

Wright, S. (1934). The method of path coefficients. *The Annals of Mathematical Statistics, 5*(3), 161–215. https://doi.org/10.1214/aoms/1177732676.

*Yusop, F. D. (2015). A dataset of factors that influence preservice teachers' intentions to use Web 2.0 technologies in future teaching practices. *British Journal of Educational Technology, 46*(5), 1075–1080. https://doi.org/10.1111/bjet.12330.

Zhang, P., Aikman, S. N., & Sun, H. (2008). Two types of attitudes in ICT acceptance and use. *International Journal of Human-Computer Interaction, 24*(7), 628–648. https://doi.org/10.1080/10447310802335482.

Zhang, L., Zhu, J., & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. *Computers in Human Behavior, 28*(5), 1902–1911. https://doi.org/10.1016/j.chb.2012.05.008.