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Review

Unpacking teachers' intentions to integrate technology: A meta-analysis

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ABSTRACT

The Technology Acceptance Model (TAM) is a key model describing teachers' intentions to use technology. This meta-analysis clarifies some of the contradictory findings surrounding the relations within the TAM for a sample of 45 studies comprising 300 correlations. We evaluate the overall fit of the TAM and its structural parameters, and quantify the between-sample variation through meta-analytic structural equation modeling. The TAM fitted the data well, and all structural parameters were statistically significant. On average, the TAM variables explained 39.2% of the variance in teachers' intentions to use technology. Several sample, measurement, and publication characteristics, including teachers' experience and the representation of the TAM variables, moderated the relations within the TAM. Overall, the TAM represents a valid model explaining technology acceptance—however, the degree of explanation and the relative importance of predictors vary across samples. Implications for further research, in particular the generalizability of the TAM, are discussed.

1. Introduction

Research on the integration of technology and the factors determining teachers' acceptance and adoption of technology in classrooms has a long tradition in education, as numerous empirical studies testify (e.g., Ritter, 2017; Scherer, Siddiq, & Tondeur, 2019; Straub, 2009; Teo, 2015). Teachers' technology acceptance can be considered a complex construct as it is determined not only by the conditions schools provide to help teachers use technology but also motivational traits, self-beliefs, and beliefs about technology and its use (e.g., Scherer & Siddiq, 2015; Teo, 2009a, b). Based on social cognitive theory, these factors have been organized in several conceptual models one of which has dominated the existing body of research (Marangunić & Granić, 2015; Schepers & Wetzels, 2007)—the Technology Acceptance Model (TAM). The TAM, in its simplest form, explains teachers' intentions to use technology, often labelled as "behavioral intentions (BI)", by their attitudes toward technology (ATT), which are in turn predicted by their beliefs about technology. The latter include the perceived usefulness (PU) and the perceived ease of technology use (PEOU). It is further hypothesized that the pereceived ease of use informs teachers' perceptions of the overall usefulness of technology for teaching and learning (Davis, 1986). Researchers have often tested whether and to what extent the relations within the TAM exist, performing structural equation and path modeling (Marangunić & Granić, 2015) and evaluating model fit (Teo, 2011, 2015). The existing meta-analyses and systematic reviews of technology acceptance models indicate the dominance and popularity of the TAM as a simplistic model that explains the intentions to use technology and technology use (e.g., Hsiao & Yang, 2011; Marangunić & Granić, 2015;

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Mortensen & Vidgen, 2016). Nevertheless, the TAM has experienced multiple updates, resulting in several technology acceptance models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003). These models contain an extended list of variables and perhaps slightly different assumptions on the structural relations among constructs—however, although sometimes labelled differently, many constructs in these newer models correspond to the variables included in the TAM (Nistor & Heymann, 2010). In this sense, the TAM can be considered a core model common to almost all technology acceptance models (Venkatesh, Thong, & Xu, 2016). Ultimately, the goal of any technology acceptance model is to predict and explain use intentions and technology use. Concerning the latter, several large-scale studies in education showed that teachers have generally good digital skills and make use of technology frequently (OECD, 2016). However, this use is mainly limited to the preparation of lessons and to word processing, presentation, and information tools (European Commission, 2013). The meaningful integration of technology as a tool to facilitate teaching and learning has been a challenge to many teachers around the world (Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014).

Despite the popularity of the TAM and the large body of empirical studies testing its validity for different teacher samples, some of the findings surrounding the TAM were contradictory: (a) While some studies identified a significant and positive effect of perceived usefulness on behavioral intentions, others could not find any evidence for it (e.g., Luan & Teo, 2011; Mac Callum, Jeffrey, & Kinshuk, 2014); (b) The strengths of associations within the TAM varied considerably between studies and teacher samples, thus yielding a broad range of variance explanations in behavioral intentions (e.g., Teo, 2015); (c) Different sets of variables moderated the TAM relations, including teachers' age and experience as well as the type of technology (e.g., Siddiq & Scherer, 2016). These diverse findings challenge the overall validity of the TAM for teacher samples and may lead to diverging inferences drawn from them. Moreover, several methodological challenges are associated with synthesizing these findings in meta-analyses, one of which concerns the dependencies between multiple correlations that were extracted from primary studies (Cheung, 2015). The insufficient addressing of this challenge in previous meta-analyses of the TAM warrants the application of alternative modeling approaches, such as meta-analytic structural equation modeling. Addressing the challenges associated with the diverse findings on the TAM and the methodological approaches, we aimed at synthesizing the existing body of research on the TAM for teacher samples by (a) evaluating the overall fit of the TAM to the data; (b) quantifying the degree to which the relations within the TAM varied across teacher samples; (c) explaining this variation by sample, measurement, and publication characteristics, using the novel parameter-based meta-analytic structural equation modeling approach. The findings of our meta-analysis clarify some of the controversies surrounding the TAM and, at the same time, point to future research directions.

1.1. The technology acceptance model (TAM)

Rooted in the Theory of Reasoned Action (Fishbein, 1979) and the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (TAM) describes the factors determining the use and the intentions to use technology. These factors comprise external, mediating, and outcome variables, some of which evolved as the TAM has been developed further (e.g., Šumak, Hericko, & Pušnik, 2011). Despite the existence of different TAM versions—sometimes with or without external variables, sometimes with or without the actual technology use as an outcome variable—the core variables in the TAM comprise the perceived ease of use, perceived usefulness, attitudes toward technology, and the intentions to use technology (e.g., Davis, 1986; Marangunić & Granić, 2015; Venkatesh & Bala, 2008). The perceived ease of use describes the degree to which a person believes that using technology would be free of effort or, in other words, easy to use (Davis, 1986). Similarly, the perceived usefulness of technology refers to the degree to which a person believes that the use of technology would enhance his or her job performance (Davis, 1986). A person's overall evaluation of technology represents a key component of his or her attitudes toward technology (Zhang, Aikman, & Sun, 2008), which determine a person's intentions to use technology. The TAM organizes these variables in the following way (Davis, 1986; see Fig. 1a): Both the perceptions of the usefulness and the ease of using technology predict ATT. ATT, as a motivational variable, in turn predicts the distal outcome BI—in this sense, ATT has a mediating role between PU and PEOU on the one hand and BI on the other hand. Finally, PEOU may explain variation in PU. This setup of the core variables in the TAM links the more cognition-lean perceptions (PEOU, PU) with a behavioral outcome (BI) via the attitudes toward technology (ATT). This simple version of the TAM has been studied extensively in the extant literature on teachers' technology integration (Teo, 2009b), and the measurement and empirical distinction between the core variables was evident for diverse teacher samples, including pre- and in-service teachers (Teo, 2015).

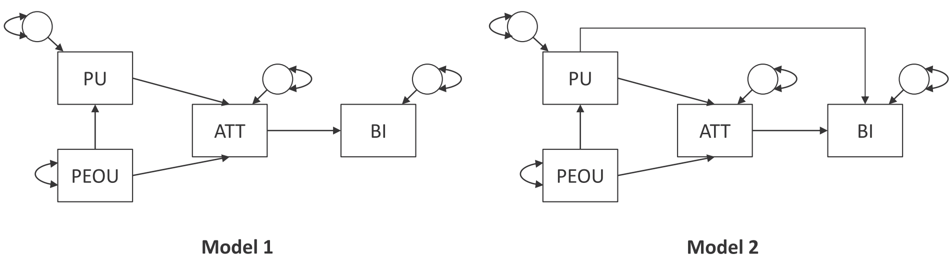

Fig. 1. Two versions of the Technology Acceptance Model. *Note.* ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness.

1.2. Some divergent findings surrounding the TAM

Given the popularity of the TAM to describe technology integration for various samples, the number of empirical studies testing this model is still growing, and researchers are applying the TAM in several contexts and for several samples (Marangunić & Granić, 2015; Schepers & Wetzels, 2007). This, however, has led to a great diversity in the resultant findings and has necessitated a constant validation of the model (King & He, 2006). In this section, we review some of these findings and possible causes and variables that may explain their diversity. First, we highlight the variation of path coefficients within the TAM and the resultant variation ofn the variance explained in technology use intentions—this perspective concerns the "internal" relations among the TAM core variables. Second, we highlight the variation of moderation effects, that is, the effects of variables explaining the between-study variation—this perspective concerns the "external" relations of the TAM core variables to study, sample, or measurement characteristics.

Path coefficients and variance explanations. Concerning the path coefficients within the TAM and, ultimately, the variance explanations of both ATT and BI, considerable variation between teacher samples exists. For instance, some studies supported the statistical significance of the PEOU→PU structural parameter (e.g., Atif, Richards, Busch, & Bilgin, 2015; Luan & Teo, 2011), whereas others did not (Koutromanos, Styliaras, & Christodoulou, 2015; Mac Callum et al., 2014). Furthermore, several reviews showed that the strengths of the effects of PU and PEOU on technology acceptance outcomes vary across studies: In some studies, PU was a stronger predictor than PEOU; in other studies, these effects were reversed and PEOU was the stronger predictor (e.g., Scherer et al., 2019; Sharp, 2006; Šumak et al., 2011; Zhang, Zhu, & Liu, 2012). Similarly, some TAM studies resulted in a positive and significant relation between PU and BI (Cheung & Sachs, 2006; Pynoo et al., 2012), whereas others could not find support for the significance of this relation (Kirmizi, 2014; Teo & Milutinović, 2015). Furthermore, meta-analyses of the TAM focusing on a broad range of samples have questioned the existence of the PU→BI effect, primarily due to its significant moderation by the type of technology and the experience of technology users (King & He, 2006; Schepers & Wetzels, 2007; Šumak et al., 2011). As a consequence, different versions of the TAM exist, with or without the PU→BI effect (see Fig. 1a and b). The list of variation in structural parameters can easily be extended—Table 1 provides some more examples of primary studies supporting the diversity of structural parameters in the TAM. Finally, the structural parameters within the TAM may vary between studies or samples to different degrees, as indicated by different heterogeneity parameters in previous meta-analyses (e.g., King & He, 2006).

Effects of moderator variables. The between-sample or between-study variation of structural parameters within the TAM may be explained by several variables. In their studies of technology acceptance including teachers and other groups of technology users, Yousafzai, Foxall, and Pallister (2007a) and Sun and Zhang (2006) proposed three categories of moderators at different levels: (1) *Organizational factors*, such as participants' voluntariness to use technology, the nature of the tasks and professions in which technology is sought to be integrated; (2) *Technological factors*, such as the complexity of technology, the purpose of the technology use, and the type of the technology specified as individual or group technologies; (3) *Individual factors*, such as participants' gender, age, cultural background, intellectual capabilities, experience with technology, and their perceptions about whether or not people who are important to them think that one should use technology for teaching and learning purposes (i.e., the subjective norm). Whereas the existing body of research agrees that these factors can moderate the relations within the TAM, the degree to which they actually affect the structural parameters varies across structural parameters and study samples (Schepers & Wetzels, 2007). For example, King and He (2006) found differences in the PU→BI parameter between job-office and e-commerce or Internet applications for samples of teachers and other technology users alike. Schepers and Wetzels (2007) also studied the moderation by technology types and identified significant differences in the structural parameters PU→BI and PU→ATT between studies using microcomputers and those using other technology devices. Šumak et al. (2011) found significantly smaller PEOU→ATT effects for e-learning systems than for other applications. Besides these differences in the moderation effects of technological features, differences in the types of technology users existed in these studies: Whereas King and He (2006) could hardly identify any moderation by user type, Schepers and Wetzels (2007) found significant moderation effects of user types (e.g., student vs. non-student) for almost all relations in the TAM. Šumak et al.'s (2011) meta-analysis confirmed the significant moderation of the ATT→BI, PEOU→PU, and PU→BI effects by user type (e.g., students vs. teachers/professors). Once again, the list of divergent findings could be extended, yet this selection already shows that

Table 1
Selected studies exhibiting divergent findings on the TAM structural parameters.

Structural parameter	Supporting statistical significance	Undermining statistical significance
PEOU→PU	Atif et al. (2015)	Koutromanos et al. (2015)
	Luan and Teo (2011)	Mac Callum et al. (2014)
	Teo (2012)	Wu, Hu, Gu, and Lim (2016)
PEOU→ATT	Cheung and Sachs (2006)	Koutromanos et al. (2015)
	Luan and Teo (2011)	Wu et al. (2016)
PU→ATT	Atif et al. (2015)	–[a]
	Pynoo et al. (2012)	
ATT→BI	Shiue (2007)	Mac Callum et al. (2014)
	Teo (2013)	Park, Lee, and Cheong (2007)
PU→BI	Lai, Chang, Wen-Shiane, Fan, and Wu (2013)	Kirmizi (2014)
	Wong (2016)	Teo et al. (2009)

Note. ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness.
[a] All primary TAM studies that were selected for this meta-analysis exhibited a statistically significant path coefficient PU→ATT.

moderation effects on the structural parameters in the TAM may vary between studies.

1.3. The present meta-analysis

Our initial review of TAM studies and existing research syntheses uncovered several issues that motivate the present meta-analysis: First, the TAM relations or, more precisely, the structural parameters describing the effects within the TAM are diverse and vary between studies, necessitating quantifying the extent to which these relations vary and explaining this variation. Second, despite the claims that the TAM represents a robust model that can be applied to any context of technology adoption (Marangunić & Granić, 2015), the variation across studies challenges these claims and ultimately the validity of the model. The wide application of the TAM to teacher samples is still to be confirmed. Third, existing meta-analyses focused on diverse samples of technology users and contexts, thus causing considerable variation in the findings on the TAM (Šumak et al., 2011). This observation motivates the clear focus of TAM studies on teacher samples and educational contexts in the present meta-analysis. Fourth, to out best knowledge, some characteristics of the sample and the measurement of the TAM core constructs have not yet been explicitly considered as moderators of the TAM structural parameters. These characteristics include the teachers' experience and certain psychometric features of the assessments, such as the reported reliability and the representation of constructs as latent or manifest variables. In the context of the former, only few studies directly compared the structural relations among the TAM core variables between pre- and in-service teachers (Teo, 2015). Fifth, although previous meta-analyses synthesized some of the TAM relations, only until recently, it has become possible to address several data issues and potential causes for severe bias in the meta-analytic parameters. For instance, the newly developed approaches of correlation- and parameter-based meta-analytic structural equation modeling allow researchers to address the dependencies between multiple correlations that were extracted from the same study (Cheung, 2015)—in this sense, the present meta-analysis illustrates a synergism between methodological advancements and substantive research on the TAM. In sum, the main goal of this meta-analysis is to synthesize the existing body of empirical research.

Specifically, we synthesize the structural relations between the core constructs in the TAM—including PU, PEOU, ATT, and BI—and quantify possible variation in these relations between study samples. These relations are synthesized using the relatively novel approach of parameter-based MASEM (Cheung & Cheung, 2016). Possible variation between study samples may be explained by sample, measurement, and publication characteristics. Our meta-analysis addresses the following research questions:

1. To what extent do the hypothesized structural relations between the TAM core constructs represent the data? (*Model fit evaluation*)
2. To what extent do the structural parameters in the TAM vary across study samples? (*Fixed-vs. random-effects models*)?
3. Which sample, measurement, and publication characteristics explain the possible variation of the structural parameters? (*Moderator analysis*)

Our first research question is aimed at establishing the fit of the TAM. Given the conflicting evidence on the existence of the direct PU→BI effect, we compare the models with and without it and examine which of them represents the data better. This step provides information on the baseline model which will then be subjected to further analyses. To retrieve this information, we compare the two TAM versions with respect to their model fit for each primary study. Moreover, we perform correlation-based MASEM to combine all correlation matrices to an overall correlation matrix which is subsequently used to perform the model fit comparison at an aggregated level (i.e., one matrix resulting from all studies). This step may further substantiate the decision for a baseline model. Our second research question quantifies the structural parameters in the TAM. Although alternative MASEM approaches exist, we chose parameter-based MASEM for the following reason: The key advantage of parameter-based over, for example, correlation-based MASEM is that variation in structural parameters can be quantified and further explained by categorical and continuous moderators (Cheung & Cheung, 2016). Finally, our third research question addresses the possible moderator effects on the structural parameters in the TAM.

Overall, this meta-analysis contributes to the extant literature by (a) synthesizing the TAM for teacher samples—this includes in- and pre-service teachers, (b) clarifying some of the inconsistent findings surrounding the existence of certain effects within the TAM, (c) quantifying and explaining variation in the TAM structural parameters to identify possible determinants that might be subject to further, perhaps experimental studies, (d) identifying moderating variables of the TAM relations that have not yet been examined in detail (e.g., pre-vs. in-service teachers, psychometric variables) and, ultimately, pointing to future directions of research. Despite the variety of the TAM versions presented in the extant literature, we focused on the common set of core variables, independent of whether the studies included more variables. Our main goal was to synthesize the evidence surrounding the structural relations among the core variables.

2. Method

2.1. Literature search

To identify the published and unpublished literature relevant to this meta-analysis, we conducted searches in four main sources: literature databases, academic journals in the field, publication lists of scholars, and reference lists of existing reviews and meta-analyses. We restricted our search to the following literature databases: ACM Digital Library, ERIC, IEEE Xplore Digital Library, Google Scholar (only entries 1–100; March 17, 2017),[1] LearnTechLib, ProQuest Dissertation and Theses Database, PsycINFO, and ScienceDirect. All searches in these databases focused on titles, abstracts, and keywords for the following reason: Without this restriction, publications that may have only mentioned the TAM or one of the search terms once in the full text, yet did not present an empirical investigation of the TAM, would have been included otherwise (see also Scherer et al., 2019). To back this argument, we ran searches in these databases with and without this restriction and found a nearly perfect match between the resultant entries. We used the search terms "technology acceptance model" and "teacher". For databases that allowed us to specify Boolean terms (e.g., ERIC, PsycINFO, ScienceDirect), we adapted these search terms to ("Technology acceptance model" OR TAM* OR "technology acceptance") AND (teacher* OR instructor*). Concerning the academic journals in the field, we conducted hand-searches in all volumes of the following journals and extracted the resultant entries: 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. We chose these journals because they have been labelled as designated journals in the field of educational technology by their publishers and relevant associations in this field (e.g., Society for Information Technology & Teacher Education). Concerning the academic works published by scholars in the field, we focused on some scholars who have published key empirical articles about the technology acceptance model: Fred D. Davis, Timothy Teo, Viswanath Venkatesh, and Gary Wong. We reviewed their publication lists via Google Scholar and extracted the relevant entries. Finally, we extracted cited papers about the TAM from the reference lists of the extant body of reviews and meta-analyses—these included: Imtiaz and Maarop (2014), King and He (2006), Legris, Ingham, and Collerette (2003), Marangunić and Granić (2015), Schepers and Wetzels (2007), Turner, Kitchenham, Brereton, Charters, and Budgen (2010).

Overall, we retrieved 2,239 entries (March 2017), which were further checked for duplicates. After removing all duplicates and limiting the publication years to 1986–2017,[2] a total of 1,826 publications were submitted to further screening. Fig. 2 summarizes the search and subsequent screening processes.

2.2. Screening and coding

Initially, we screened publications according to (a) the study context—studies were included if they measured pre- or in-service teachers' technology acceptance in school, college, or university; (b) the reporting of quantitative measures—studies were included if they administered quantitative measures of the TAM core constructs; (c) the language of reporting—studies were included if the results were reported in English. This initial screening resulted in 363 publications, which were further screened based on the following inclusion and exclusion criteria:

1. *Accessibility of study results*: Full texts or secondary resources that describe the study results and characteristics in sufficient detail must have been available.
2. *Teacher sample*: The study targeted a sample of in- or pre-service teachers in primary, secondary, or tertiary education.
3. *TAM constructs:* The study assessed all four core constructs in the TAM (perceived usefulness, perceived ease of use, attitudes toward ICT use, and behavioral intentions.
4. *Reporting of correlations:* The study reported all correlations among the four TAM constructs and reported the corresponding sample sizes.
5. *Technological context:* The acceptance of a digital device, technology, software, or system was examined.

One paper reported item-item correlations instead of correlations at the level of latent variables or scale scores (Luan & Teo, 2009). For this study, we estimated the correlations among the TAM variables directly; the item-item correlation matrix served as input for the structural equation modeling software M*plus* (Muthen & Muthen, 1998-2015), in which PU, PEOU, ATT, and BI were specified as correlated, latent variables. Several authors did not report the correlations among the TAM constructs, yet they provided the standardized path coefficients within the TAM. Using Wright's tracing rules (Kline, 2016), we retrieved the underlying correlation matrices and verified their accuracy using M*plus* (i.e., by feeding the correlation matrices back into the structural equation modeling software and checking whether the reported path coefficients could be replicated).

Two additional issues surfaced during the screening: (1) Studies that presented the TAM in a structural equation modeling framework yet failed to report goodness-of-fit indices were not excluded per se. Instead, we extracted the model-implied correlation matrices and examined the goodness-of-fit subsequently (please refer to section 3.2 in the paper). We argue that the lack of reporting fit indices cannot be directly linked to the quality of the structural equation modeling—it is rather an issue of the reporting of findings in a scientific paper. (2) Although the authors of the primary studies may have presented different versions of the TAM—for instance, sometimes comprising all TAM core constructs (PU, PEOU, ATT, and BI) and sometimes comprising only subsets of them—, this variety did not affect the inclusion of primary studies, because we extracted only the correlations among the constructs relevant for this meta-analysis. The performance of the inclusion and exclusion criteria resulted in 46 studies reporting $k = 51$ independent correlation matrices.

[1] The search in Google Scholar was limited to the first 100 entries due to the substantial overlap (> 99%) between these entries and those identified in scientific databases, such as PsycINFO. In this sense, the Google Scholar search was aimed at validating the entries from other databases and identifying possible, additional resources. Nevertheless, most of the resultant entries were duplicates. For a detailed discussion of limiting the search entries in Google Scholar, we kindly refer the reader to Haddaway, Collins, Coughlin, and Kirk (2015).

[2] In line with Marangunić and Granić (2015), we chose 1986 as the starting point—in this year an initial version of the technology acceptance model was published under this label (Davies, 1986).

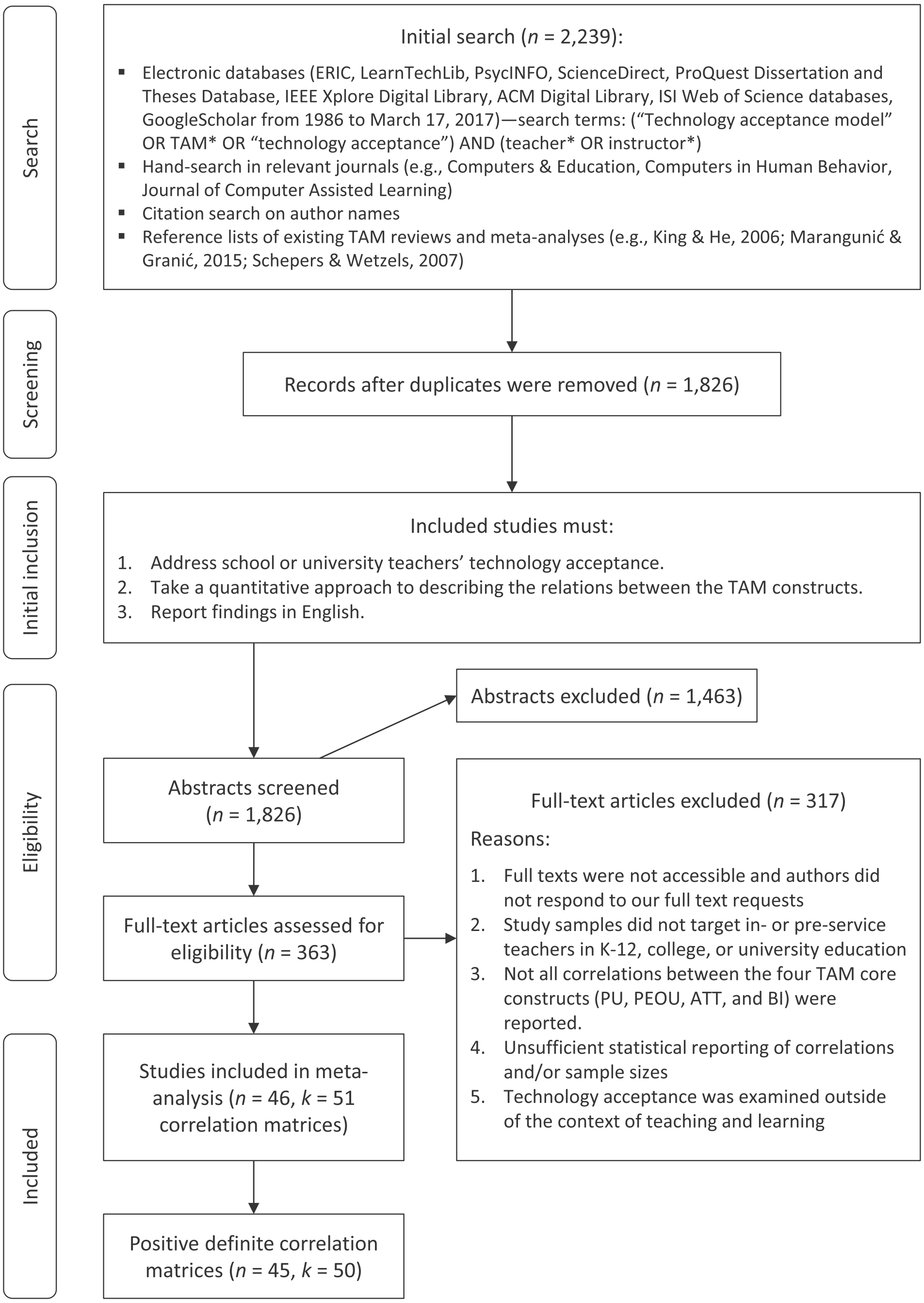

Fig. 2. Flow diagram describing the literature search and the selection of eligible TAM studies (adapted from the PRISMA Statement; Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009).

Both the screening and the coding of studies were mainly conducted by the first author. To ensure the quality of these two key steps in our meta-analysis, we performed a double screening of 80% of all studies in each step using the artificial intelligence toolkit in the software *DistillerSR* (Evidence Partners, 2018a, b). This toolkit allows researchers to double-screen publications without the involvement of a second screener. The artificial intelligence machine performed natural language processing, trained itself based on 20% of the data that were coded by the first author, and subsequently applied the extracted screening patterns and criteria to 80% of the publications. Using both probabilistic and a non-probabilistic classifiers resulted in an agreement of 94.1% for the screening and 93.1% for all the processes up to the data extraction. Disagreements were reviewed, and the screening or coding of studies were adjusted if needed.

2.3. Effect sizes and corrections for unreliability

As noted earlier, we retrieved the correlations between the four TAM variables that were stored in correlation matrices containing six correlations, reported as Pearson correlations. As we will describe later on, although we retrieved correlation matrices, the measures we synthesized meta-analytically were the path coefficients within the TAM that resulted from the correlation matrices. We refrained from synthesizing directly the reported path coefficients for the following reasons: (a) The setup of the TAM varied between study samples so that some models deviated from those we focused on (see Fig. 1); (b) The reporting of the relations within the TAM differed across study samples—some authors reported only correlations, others reported only path coefficients. Only a few studies reported both and made their findings completely reproducible; (c) The reporting of path coefficients differed across samples—some authors reported them as fully standardized coefficients, others did not and therefore compromised their comparability; (d) The reporting of model fit and its evaluation varied considerably across samples—some authors did not report any model fit statistic so that we could not determine the validity of the TAM for their study sample. Hence, using correlation matrices as the starting point for our meta-analysis ensured the comparability of the measures of association between the four TAM variables in light of the diversity of reporting.

One of the sources of bias in correlation coefficients is the unreliability of the scores used to estimate them. Some authors argued for the correction of possible measurement bias in correlations r_{XY} and suggested weighting them by the reliability coefficients α_X and α_Y, $r_c = r_{XY}/\sqrt{\alpha_X \alpha_Y}$ (Schmidt & Hunter, 2015). Although this correction may handle measurement error, its use is problematic, especially in situations where correlation matrices instead of single correlations are synthesized meta-analytically: Cheung (2015) notices that such corrections may lead to non-positive definite correlation matrices or Heywood cases (e.g., correlation coefficients larger than 1). These issues, however, compromise the application of structural equation modeling and may ultimately result in the exclusion of primary studies. Besides, the impact of corrections for unreliability on the final structural equation models is still unclear (Cheung, 2015). Acknowledging that corrections for unreliability may or may not influence the structural parameters within the TAM, we compared them for correlation matrices with and without these corrections (sensitivity analyses). Some practical issues are worth noting here: (a) If authors reported correlations among latent variables, we did not correct them for unreliability, because latent variables separate measurement error from the true scores directly (Kline, 2016); (b) If authors reported correlations among manifest variables but did not provide reliability coefficients, we used the average reliability obtained from all TAM studies in our sample (Hong & Cheung, 2015). Supplementary Material S1 contains all correlations and their corrections.

2.4. Coding of possible moderators and publication status

The possible moderators examined in our meta-analysis referred to the study context including sample characteristics, the measurement of constructs, and the publication features—aspects that might affect the fit and parameters of the meta-analytic structural equation models. Teachers' level of *educational experience* (i.e., pre-service vs. in-service teachers), the *percentage of female teachers* in the sample, and *teachers' age* were used as important sample characteristics. Further study features were the *type of technology* which referred to in the assessments of the TAM variables (i.e., technology in general vs. specific technological devices, platforms, or tools) and the *country* in which the study was conducted. The measurement of constructs was approached in two ways: First, we differentiated the studies by the *type variables* specified in the TAM (i.e., manifest vs. latent variables). Second, we compared the overall results before and after a *correction for unreliability* within our sensitivity analyses. Supplementary Material S1 contains all moderator variables.

Drawing from previous reviews, meta-analyses, and correlational studies of technology acceptance (e.g., Ritter, 2017; Schepers & Wetzels, 2007; Scherer et al., 2019), we identified three main characteristics of the teacher samples that may influence the relations between the TAM core variables and explain between-study variation: teaching experience, gender, and age. This selection is, however, by no means complete; yet, several findings on the TAM differed across these sample characteristics. For instance, Teo (2015) found that pre- and in-service teachers may differ significantly in the TAM core variables, and technology acceptance models that were developed out of the TAM, such as the UTAUT, include explicitly moderator variables that represent users' experience assuming that the relations among variables may be subject to differences across experience levels (e.g., Imtiaz & Maarop, 2014). In the following, we describe the coding of these possible moderators and some findings surrounding them.

Experience. We assessed teachers' experience indirectly, distinguishing between pre-service (code: 0) and in-service teachers (code: 1). The use of this dichotomous coding was motivated by the clear distinction between these two levels of experience in all TAM studies and the lack of information on the specific years of teaching experience in most studies. Straub (2009) pointed out that pre- and in-service teachers' experience with technology may further moderate the relations within the TAM—indeed, some studies identified some moderation effects, possibly due to the different environments and conditions pre-service teachers are experiencing in teacher education (Teo, 2015). In the current meta-analysis, however, we did not include technological experience as a moderating variable for three reasons: First, only about 20% of the studies screened for coding contained information on this variable. Second, for the studies that reported on technological experience, a great variety of the conceptualization and operationalization existed. Specifically, some studies reported teachers' overall computer experience in years (Ball, 2008; McGill, Klobas, & Renzi, 2011); some studies reported teachers' experience with the use of technology for teaching and learning using a single categorical variable with arbitrary levels of experience (Wong, 2015). Overall, this coding represents teachers' experience with teaching in general, yet not necessarily their teaching experience with technology. In this regard, it is not possible to draw direct inferences on the effect of teaching experience with technology.

Gender. The percentage of female teachers was coded and derived from a large body of research that identified substantial gender differences in both the levels and correlations of attitudes toward technology and other relevant TAM constructs (Cai, Fan, & Du, 2017; Scherer & Siddiq, 2015; Shashaani, 1993; Siddiq, Scherer, & Tondeur, 2016).

Age. Teachers' age was coded in years and reported as an average for each study. Teachers' age moderated several relations in the TAM and cognate models of technology acceptance (e.g., Teo & Noyes, 2014; Venkatesh & Bala, 2008). Furthermore, Hauk, Hu¨ffmeier, and Krumm (2018) brought to attention recently that age matters for the TAM core variables.

Type of technology. The TAM studies considered in this meta-analysis differed in the degree of specificity regarding technology: Whereas many studies referred to technology in general (code: 0), some studies explored the TAM with reference to specific technologies, such as software, whiteboards, mobile phones, and online platforms (code: 1).

Country. Given the dominance of Asian studies and samples in the primary studies (Teo, 2009b), we simplified the coding of the countries by dichotomizing the country variable into Asian vs. non-Asian countries. Hence, the effects of the country the sample was derived from indicate possible moderation effects of Asian country origin (*1 = Asian country, 0 = Non-Asian country*). Among others, Asian countries included Singapore, Malaysia, Taiwan, and China; non-Asian countries included Serbia, the United States of America, Greece, New Zealand, and others.

Type of variables. TAM constructs were represented either by manifest scores (e.g., average scores for scales) or latent variables. These approaches may result in considerable variation of the model parameters within the TAM (Davis & Venkatesh, 1996)—hence, we explored possible differences between the two approaches (*0 = Manifest variables used in the TAM, 1 = Latent variables used in the TAM*).

Publication status. To address possible publication bias, we examined the moderating effects of publication status. Publication status was coded as 1 if the study was published in a scholarly journal followed by peer-review, and 0 else. The latter coding included dissertations, conference abstracts, book chapters, and working papers and thus indicated “grey literature” (see Adams, Smart, & Huff, 2017).

2.5. Statistical approaches

One of the key issues compromising the validity of meta-analytic results is the dependence between effect sizes in primary studies (Borenstein, Hedges, Higgins, & Rothstein, 2009). This issue is especially relevant when multiple correlations are nested in studies or, as it is the case in our meta-analysis, in entire correlation matrices that form the basis for further structural equation modeling. Researchers tended to synthesize single correlations across study samples using univariate meta-analytic approaches and submit them subsequently to structural equation modeling (Sheng, Kong, Cortina, & Hou, 2016). However, this approach may lead to severe bias in the resultant model parameters or even misleading conclusions (Cheung & Hong, 2017). In contrast, a multivariate approach to meta-analytic structural equation modeling that accounts for the dependencies between correlations within correlation matrices circumvents these challenges (Cheung, 2015). This approach is the method of choice in our meta-analysis.

Meta-analytic structural equation modeling (MASEM). From our review of the extant literature on MASEM approaches, we conclude that at least two alternatives to aggregating single correlations exist: correlation-based and parameter-based MASEM. Whereas correlation-based MASEM—often applied as Two-Stage Structural Equation Modeling (Cheung & Chan, 2005)—synthesizes the correlation matrices of the primary studies in the first stage and performs structural equation modeling on the resultant, overall correlation matrix, parameter-based MASEM performs structural equation modeling on the correlation matrices first and aggregates the resultant model parameters using multivariate meta-analysis (Cheung, 2015). Both approaches can include random effects, either in correlations or in model parameters (Cheung & Cheung, 2016). Researchers that are primarily interested in comparing structural equation models to examine which might best represent the data and thus support certain theories and assumptions, may want to perform correlation-based MASEM. However, if the focus of the research lies in questions which variables might explain certain structural parameters in a structural equation model (i.e., moderating effects), parameter-based MASEM may be more suitable, especially when explanatory variables are continuous. Another feature in which the two appraoches deviate is the handling of missing data: Whereas the former can rely on well-established procedures to deal with missing correlations in primary correlation matrices (e.g., full-information-maximum-likelihood procedure; Cheung, 2015), the latter relies complete correlation matrices (Cheung & Cheung, 2016). Cheung and Cheung (2016) provide a detailed comparison of the two approaches.

In light of our research questions, our main approach to the data is that of parameter-based MASEM, because we were mainly interested in the variation of the structural parameters within the TAM across study samples (i.e., not the variation of the underlying correlations or correlation matrices) and we aimed at explaining this variation by a set of categorical and continuous variables. However, we draw from correlation-based MASEM to gather more evidence on the fit of different TAM versions to the data. We performed all analyses with the R packages metaSEM (Cheung, 2018) and lavaan (Rosseel, 2018) using maximum-likelihood estimation. Supplementary Material S3 contains the sample R code.

Model fit evaluation. To evaluate the fit of the TAM to the primary study data in the first step of our meta-analysis, we applied the common guidelines for an acceptable model fit (i.e., RMSEA $\leq$ .08, CFI $\geq$ 0.95, TLI $\geq$ 0.95, and SRMR $\leq$ 0.10; see Marsh, Hau, & Grayson, 2005). However, these guidelines do not represent strict rules, and possible deviations from them may still indicate a reasonable model fit. Besides, we estimated the χ^2 statistic as an indicator of the fit between the hypothesized and the empirical structural equation models (Kline, 2016). To compare the two versions of the TAM (see Fig. 1a and b), we conducted χ^2 difference testing and evaluated the differences in all other fit statistics, including Akaike's Information Criterion (AIC).

Publication bias. To examine the extent to which publication bias was present in the data set, we conducted several analyses: First, for single correlations, we performed trim-and-fill analyses to identify correlations we may have missed in order to achieve symmetry in the funnel plots. Second, we conducted Egger's regression test with standard errors as predictors to test the symmetry of the funnel plots. Third, we calculated Rosenberg's fail-safe *N*s—the number of studies that would be needed to turn the overall correlation to insignificant—for each correlation. Fourth, we inspected the *p*-curves for each correlation to rule out a possible file-drawer issue. If studies have evidential value, the *p*-curve should be right-skewed; a left-skewed curve indicates publication bias (Simonsohn, Nelson, & Simmons, 2014). These analyses, however, are based on single, aggregated correlations rather than correlation matrices, thus limiting their evidential value.

Sensitivity analyses. We further tested the sensitivity of our findings to two factors: the correction of correlations for unreliability and the removal of influential correlations from the data set. We identified influential correlation using Viechtbauer and Cheung's (2010) procedure, as implemented in the R package 'metafor'.

3. Results

3.1. Descriptive results

The overall sample of primary studies yielded $k = 51$ correlation matrices that were obtained from $N = 15{,}189$ participating teachers. Table 2 shows the teacher, model, and study characteristics. The overall sample mainly contained participants who taught in primary schools (35.29%). However, many articles did not contain any information on the educational level teachers were focusing on in their daily work (41.18%). The sample was comprised of pre- and in-service teachers to almost the same extent (56.86% vs. 43.14%). These teachers' technology acceptance was studied mainly in Asian countries. Once the data had been gathered, two thirds of the authors represented the TAM variables as latent instead of manifest variables and provided information on certain model fit statistics. To report reliability, authors primarily presented Cronbach's α as a measure of internal consistency (56.86%). The TAM was specified for technology in general (60.78%) and was hardly tied to specific types of technology (39.22%). Concerning the publication status, more than 90% of the studies included in this meta-analysis were published in peer-reviewed journals from 2006 on. These studies reported the correlations between the TAM variables ATT, BI, PEOU, and PU (see Supplementary Materials S1 [raw data] and S2 [forest plots]), which formed the basis for our meta-analytic structural equation modeling approach. Table 3 further shows the summary statistics of teachers' age, the average sample sizes in primary studies, and the proportion of women participating in the studies. Besides, the reliability coefficients of the TAM variables are summarized, each of which exceeded 0.80. We note that all subsequent analyses, except for the sensitivity analyses, were based on the uncorrected correlations.

3.2. Model fit evaluation (RQ 1)

Initial check of correlation matrices. In order to perform meta-analytic structural equation modeling, the correlation matrices obtained from the primary studies must be positive definite (Cheung, 2015; see also; Wothke, 1993). After checking this prerequisite for the 51 correlation matrices, we identified one matrix that was non-positive definite (Ibili & Sahin, 2016). This matrix was consequently excluded from the data set, reducing the data set to $k = 50$ available correlation matrices from 45 studies (Fig. 2).

Parameter-based MASEM. To address our first research question, we specified Models 1 and 2 to the correlation matrices of the primary studies (see Fig. 1) and compared their fit (see Table 4). For 40 of the 50 correlation matrices, Model 2 fitted the data significantly better than Model 1, supporting the existence and relevance of the direct PU→BI effect in the TAM. For the remaining ten correlation matrices, Models 1 and 2 did not differ significantly in their overall fit; nevertheless, when including the PU→BI effect, the chi-square statistic was still reduced. Moreover, $k = 29$ correlation matrices indicated an almost perfect fit of Model 2 to the data, with *p*-values based on the chi-square statistics larger than .05. For Model 1, however, only eight correlation matrices exhibited almost perfect model fit. A model detailed account of all fit statistics is given in Supplementary Material S2. Concerning alternative fit statistics, Model 2 fitted better than Model 1 and exhibited an acceptable overall fit. However, for 19 correlation matrices, the RMSEA values exceeded 0.10, possibly due to the small sizes of teacher samples available in these primary studies. All other fit indices were within the range of acceptable fit. Overall, these findings suggested the superiority of Model 2 over Model 1 in terms of model fit.

Correlation-based MASEM. To further substantiate the superior fit of the model with the direct PU→BI effect, we also performed correlation-based MASEM. In correlation-based MASEM, the correlation matrices obtained from the primary studies are pooled in a first stage using a multivariate random-effects model (Cheung, 2015; Cheung & Cheung, 2016). For the 50 included TAM studies, this stage resulted in the overall correlation matrix that is shown in Table 5. All correlations in this matrix exhibited statistical significance, and the largest correlation occurred between PU and ATT. On the basis of this pooled correlation matrix, we specified the two versions of the TAM in the second stage. Model 1 exhibited an acceptable fit to the data, $\chi^2(2) = 53.43$, $p < .001$, RMSEA = 0.042, CFI = 0.985, SRMR = 0.070. Adding the direct PU→BI effect to this model resulted in an improvement of the overall model fit, $\chi^2(1) = 10.52$, $p = .0012$, RMSEA = 0.025, CFI = 0.997, SRMR = 0.029. This model (i.e., Model 2) outperformed Model 1 in terms of fit significantly, $\Delta\chi^2(1, N = 14{,}918) = 42.91$, $p < .001$. The correlation-based MASEM approach supported the superior fit of Model 2 and the existence of the direct effect of PU on BI. Overall, the TAM with the PU→BI effect (Model 2) exhibited a good fit to the data.

3.3. Fixed-vs. random-effects modeling (RQ 2)

Our second research question addressed the variation of the structural parameters across study samples. The TAM was best represented by Model 2 (see RQ 1), and thus this model formed the basis for quantifying the between-sample variation of effects. As

Table 2
Categorical features of the primary TAM studies.

Study feature	Number of study samples	Relative frequency
Teacher characteristics		
Context of teaching		
Early childhood education	1	1.96%
Primary school	18	35.29%
Secondary school	4	7.84%
University or college	7	13.73%
Not reported	21	41.18%
Teacher level		
Pre-service teachers	29	56.86%
In-service teachers	22	43.14%
Subject domain		
Science, technology, engineering, and mathematics	8	15.69%
Language learning	2	3.92%
Mixed	3	5.88%
Not reported	38	74.51%
Location of the study sample		
Abu Dhabi (UAE)	1	1.96%
Australia	1	1.96%
Belgium	1	1.96%
Brazil	1	1.96%
Cyprus	1	1.96%
Greece	2	3.92%
Hong Kong (China)	4	7.84%
Iran	1	1.96%
Japan	1	1.96%
Malaysia	5	9.80%
New Zealand	1	1.96%
Serbia	3	5.88%
Shanghai (China)	1	1.96%
Singapore	10	19.61%
Slovenia	2	3.92%
Taiwan	4	7.84%
Turkey	7	13.73%
United States of America	2	3.92%
Mixed (Asian countries)	3	5.88%
Model characteristics		
Representation of TAM variables		
Manifest variables	17	33.33%
Latent variables	34	66.67%
Model fit evaluation		
Model fit was not evaluated	13	25.49%
Model fit was evaluated	38	74.51%
Reliability coefficient		
Cronbach's α	29	56.86%
McDonald's ω	15	29.41%
Not reported	7	13.73%
Specification of the technology in the TAM		
Technology in general	31	60.78%
Specific technologies	20	39.22%
Study characteristics		
Publication status		
Published	48	94.12%
Grey literature	3	5.88%
Publication year		
2006	1	1.96%
2007	2	3.92%
2008	2	3.92%
2009	4	7.84%
2010	1	1.96%
2011	4	7.84%
2012	8	15.69%
2013	3	5.88%
2014	5	9.80%
2015	12	23.53%
2016	8	15.69%
2017	1	1.96%

Table 3
Continuous features of the primary TAM studies.

Study feature	*M*	*SD*	*Missing*	*Mdn*	*Min*	*Max*
Teacher sample						
Age [years]	28.63	7.87	25.49%	25.20	19.40	45.70
Sample size	297.82	184.17	0.00%	245.00	29.00	919.00
Female teachers [%]	66.18%	17.72%	17.65%	69.85%	0.00%	100.00%
Reliability coefficients[a]						
PU	0.88	0.07	13.73%	0.88	0.66	0.96
PEOU	0.87	0.08	13.73%	0.89	0.61	0.98
ATT	0.85	0.07	13.73%	0.85	0.71	0.97
BI	0.85	0.09	15.69%	0.86	0.67	0.98

Note. All statistics are based on the $k = 51$ teacher samples. ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness.

[a] Reliability coefficients were mostly reported as Cronbach's α or McDonald's ω (see Table 2).

mentioned earlier, parameter-based MASEM was the approach we chose to quantify this variation. We extracted the structural parameters from Model 2 as it was specified for each and every correlation matrix and synthesized them using multivariate meta-analysis (Cheung & Cheung, 2016). To decide whether between-samples variances in these parameters existed, we specified both a fixed- and a random-effects model and compared their fit. Transferring these multivariate models into the context of structural equation modeling, Cheung (2015) indicated the vector of multiple effect sizes (i.e., correlations in our case) for the *i*th study by θ. The multivariate fixed-effects model consequently results in the following vector of conditional means and variance-covariance matrix (p. 137):

$$\mu_i(\theta) = \beta_F \text{ and } \sum_i (\theta) = \boldsymbol{V}_i \tag{1}$$

In this model, β_F represents the vector of true effects, and $\boldsymbol{V}_i$ represents the sampling variance-covariance matrix. This model does not assume between-study heterogeneity. Extending this model by accounting for between-study variation, Cheung (2015) specified the multivariate random-effects model as follows (p. 137):

$$\mu_i(\theta) = \beta_R \text{ and } \sum_i (\theta) = \boldsymbol{T}^2 + \boldsymbol{V}_i \tag{2}$$

In this model, β_R represents the vector of true effects, and $\boldsymbol{T}^2$ the matrix of random effects quantifying the heterogeneity of the multiple effects between studies.

The fixed-effects model exhibited the following fit statistics: 2LL = 2,352.07, Npar = 5, AIC = 1,862.07; the random-effects model assuming variation of structural parameters across study samples exhibited the following fit statistics: 2LL = −158.66, Npar = 10, AIC = −638.66. Comparing these two models using a likelihood-ratio test indicated that the random-effects model was statistically preferred over the fixed-effects model, Δ(-2LL) [5] = 2,510.73, $p < .001$. Akaike's information criterion was smaller for the random-effects model, supporting this preference as well. Moreover, a global heterogeneity test of the structural parameters showed significant heterogeneity across study samples, $Q(245) = 3{,}368.51$, $p < .001$. The I^2-statistics ranged between 88% (PU→ATT) and 93% (PU→BI), and suggested considerable heterogeneity in the TAM effects between samples. Although these statistics cannot be interpreted using their absolute values, they still indicate that the proportion of the observed variance that reflects variance in true effect sizes rather than sampling error varies between effects, yet only marginally (Borenstein, Higgins, Hedges, & Rothstein, 2017). These findings suggested statistically significant variation in the structural parameters of the TAM across samples.

The multivariate random-effects model resulted in positive and significant structural parameters within the TAM that ranged from β = 0.303 to 0.487 (see Table 6). The fact that the direct PU→BI effect was significant as well (β = 0.303, 95% CI = [0.245, 0.362]) testified, once again, to the relevance of it. The strongest relation was identified between the variables PEOU and PU (β = 0.487, 95% CI = [0.442, 0.532]). On average, the variance explained in teachers' behavioral intention to use technology was 39.22% (*SD* = 20.80%, *Mdn* = 38.13%) and ranged between 2.78% and 89.84%.

Overall, all relations within the TAM exhibited statistical significance. Furthermore, all of the structural parameters showed significant variation across study samples (Table 6). Explaining this variation was the main focus of our third research question.

3.4. Moderator analysis (RQ 3)

On the basis of the multivariate random-effects model, we used the study, measurement, and publication characteristics as possible moderator variables of the structural parameters in the TAM. Instead of including all moderator variables at the same time, we specified separate mixed-effects models to examine these effects for the following reasons: (1) The size of our meta-analytic sample ($k = 50$ correlation matrices) limited the number of parameters than can be estimated in mixed-effects models without a major loss in statistical power (Hedges & Pigott, 2004); (2) Some of the moderator variables were substantially correlated, as shown in the Supplementary Material S2 (section E). To circumvent issues associated with the multicollinearity of predictor variables

Table 4
Chi-square statistics for the TAM versions (models 1 and 2) and model comparisons.

Study sample	Model 1		Model 2			Comparison	
	$\chi^2(2)$	p	$\chi^2(1)$	p	N	$\Delta\chi^2(1)$	p
Okazaki & Renda dos Santos (2012)	0.836	0.658	0.000	1.000	446	0.836	0.360
Parkman (2015)	54.928	0.000	17.562	0.000	88	37.366	0.000
Wong (2015)	26.353	0.000	7.547	0.006	234	18.806	0.000
Cote & Miliner (2015)	5.554	0.062	5.092	0.024	29	0.462	0.497
Teo and Milutinović (2015)	0.002	0.999	0.001	0.975	313	0.001	0.982
Teo, Fan, and Du (2015)-1	7.084	0.029	0.571	0.450	169	6.513	0.011
Teo et al. (2015)-2	6.673	0.036	6.444	0.011	170	0.230	0.632
Koutromanos et al. (2015)-1	24.167	0.000	3.457	0.063	151	20.710	0.000
Koutromanos et al. (2015)-2	3.342	0.188	0.183	0.669	106	3.160	0.075
Wu et al. (2015)	22.554	0.000	4.076	0.044	340	18.478	0.000
Kabakci-Yurdakul, Ursavaş, and Becit-Isciturk (2014)	177.530	0.000	3.823	0.051	579	173.707	0.000
Kirmizi (2014)	18.839	0.000	1.453	0.228	213	17.386	0.000
Mac Callum et al. (2014)	9.696	0.008	1.519	0.218	196	8.177	0.004
Wong, Osman, Goh, and Rahmat (2013)	52.075	0.000	2.243	0.134	302	49.831	0.000
Teo, Ursavas et al. (2011a)	28.956	0.000	0.141	0.707	197	28.815	0.000
Teo, Luan et al. (2008)	44.819	0.000	3.644	0.056	495	41.174	0.000
Šumak and Sorgo (2016)-1	1.847	0.397	0.006	0.940	438	1.841	0.175
Šumak and Sorgo (2016)-2	0.828	0.661	0.129	0.719	460	0.699	0.403
Wu et al. (2016)	12.521	0.002	4.030	0.045	144	8.491	0.004
Wong (2016)	11.231	0.004	6.848	0.009	185	4.383	0.036
Atif et al. (2015)	45.929	0.000	8.355	0.004	184	37.574	0.000
Tokel and Isler (2015)	22.062	0.000	0.192	0.662	46	21.870	0.000
Sadeghi et al. (2014)	23.483	0.000	0.110	0.740	275	23.373	0.000
Pynoo et al. (2012)	290.995	0.000	0.536	0.464	919	290.459	0.000
Aypay, Celik, Aypay, and Sever (2012)	214.044	0.000	17.743	0.000	754	196.301	0.000
Chen and Tseng (2012)	233.086	0.000	35.847	0.000	402	197.239	0.000
Teo (2012)	9.801	0.007	0.025	0.876	157	9.776	0.002
Teo and van Schaik (2012)	27.474	0.000	1.870	0.172	429	25.604	0.000
Teo and Noyes (2011)	13.722	0.001	0.096	0.756	153	13.625	0.000
Teo, Lee et al. (2009a)-1	5.979	0.050	3.184	0.074	250	2.795	0.095
Teo, Lee et al. (2009a)-2	43.480	0.000	2.400	0.121	245	41.080	0.000
Teo (2009a)	29.147	0.000	3.659	0.056	475	25.488	0.000
Park et al. (2007)	87.508	0.000	7.436	0.006	191	80.072	0.000
Cheung and Sachs (2006)	13.736	0.001	7.061	0.008	57	6.675	0.010
Teo (2011)	86.789	0.000	12.063	0.001	592	74.726	0.000
Shiue (2007)	13.617	0.001	6.817	0.009	242	6.800	0.009
Chiu (2017)	9.747	0.008	0.656	0.418	306	9.091	0.003
Lai et al. (2013)	205.060	0.000	14.400	0.000	160	190.661	0.000
Teo, Zhou, and Noyes (2016)	70.399	0.000	3.846	0.050	592	66.553	0.000
Teo (2008)	16.316	0.000	11.118	0.001	139	5.197	0.023
Wong et al. (2012)	48.301	0.000	4.838	0.028	302	43.463	0.000
Luan and Teo (2009)	32.468	0.000	0.000	0.998	245	32.468	0.000
Teo, Ursavas et al. (2012)	108.601	0.000	4.625	0.032	487	103.976	0.000
Teo and Zhou (2014)	17.621	0.000	0.000	0.992	314	17.621	0.000
Teo (2013)	50.024	0.000	26.450	0.000	385	23.574	0.000
Teo et al., 2017-1	7.661	0.022	6.604	0.010	226	1.057	0.304
Teo et al., 2017-2	0.674	0.714	0.263	0.608	226	0.411	0.521
Pittalis & Christou (2010)	125.310	0.000	0.001	0.973	105	125.309	0.000
Fathema, Shannon, and Ross (2015)	30.666	0.000	1.680	0.195	560	28.986	0.000
Luan and Teo (2011)	44.446	0.000	3.366	0.067	245	41.080	0.000

Note. All models were specified using maximum likelihood estimation. The degrees of freedom are shown in brackets.

Table 5
Aggregated correlation matrix.

TAM variables	PU	PEOU	ATT	BI
Perceived usefulness (PU)	1.000			
Perceived ease of use (PEOU)	.497	1.000		
Attitudes toward technology (ATT)	.619	.542	1.000	
Behavioral intention (BI)	.528	.426	.533	1.000

Note. This matrix is based on $k = 50$ positive definite correlation matrices and the assumption of random effects across study samples. $N = 14,918$.

Table 6
Meta-analysis of the structural parameters in the TAM.

Estimate	ATT→BI	PU→BI	PU→ATT	PEOU→ATT	PEOU→PU
Parameter β	0.338	0.303	0.465	0.304	0.487
95% CI [β]	[0.283, 0.394]	[0.245, 0.362]	[0.428, 0.502]	[0.258, 0.349]	[0.442, 0.532]
z	11.96*	10.21*	24.56*	13.09*	21.10*
τ^2	0.035	0.039	0.015	0.024	0.023
95% CI [τ^2]	[0.020, 0.051]	[0.022, 0.057]	[0.007, 0.022]	[0.013, 0.034]	[0.012, 0.033]
I^2	92.23%	92.97%	87.82%	92.09%	90.69%

Note. The table shows the 95% Wald confidence intervals. τ^2 represents the estimate of the between-samples variation (i.e., random effects). I^2 represents the heterogeneity index (based on τ^2). ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness. *$p < .001$.

(Cohen, Cohen, West, & Aiken, 2015), we took a "divide-and-conquer approach" and refrained from including multiple moderators. At the same time, we notice that this decision has several limitations, especially because it does not allow for examining interactions between moderator variables (Aguinis, Gottfredson, & Wright, 2011). Nevertheless, both the issues of power and multicollinearity may bias mixed-effects parameters significantly.

Table 7 shows the resultant moderator effects along with the tests of statistical significance and the corresponding between-samples variance explanations. Neither the type technology nor the publication year affected the structural parameters. Moreover, there was no difference in structural parameters between Asian and non-Asian teacher samples, neither did teachers' age moderate the TAM relations. Nevertheless, some moderation effects surfaced:

Table 7
Moderator analysis of the structural parameters in the TAM.

Moderator variables	ATT→BI	PU→BI	PU→ATT	PEOU→ATT	PEOU→PU
Teacher experience (*0 = pre-service, 1 = in-service*)					
Parameter β	0.059	0.003	0.044	**−0.110**	0.013
95% CI [β]	[-0.052, 0.170]	[-0.114, 0.121]	[-0.029, 0.118]	[-0.197, −0.023]	[-0.079, 0.104]
z	1.04	0.06	1.18	−2.49*	0.27
R^2	6.99%	6.60%	14.90%	24.22%	0.00%
Type of technology (*0 = technology in general, 1 = specific technology*)					
Parameter β	−0.056	0.090	0.046	−0.041	−0.012
95% CI [β]	[-0.170, 0.058]	[-0.028, 0.209]	[-0.030, 0.121]	[-0.135, 0.053]	[-0.105, 0.082]
z	−0.97	1.50	1.19	−0.86	−0.25
R^2	6.62%	10.20%	14.45%	14.30%	0.00%
Type of variables (*0 = manifest, 1 = latent*)					
Parameter β	0.083	**−0.124**	−0.033	**0.120**	0.060
95% CI [β]	[-0.033, 0.198]	[-0.244, −0.005]	[-0.111, 0.049]	[0.028, 0.213]	[-0.036, 0.155]
z	1.40	−2.04*	−0.77	2.56*	1.22
R^2	9.75%	14.27%	12.65%	24.70%	0.86%
Country category (*0 = Non-Asian country, 1 = Asian country*)					
Parameter β	0.037	0.023	−0.063	0.028	0.071
95% CI [β]	[-0.089, 0.162]	[-0.109, 0.156]	[-0.144, 0.018]	[-0.074, 0.131]	[-0.030, 0.172]
z	0.57	0.35	−1.53	0.54	1.37
R^2	5.25%	6.74%	16.92%	13.80%	1.76%
Publication year (*centered to 2006*)					
Parameter β	0.047	−0.145	0.056	−0.001	−0.068
95% CI [β]	[-0.100, 0.194]	[-0.296, 0.005]	[-0.042, 0.153]	[-0.121, 0.120]	[-0.187, 0.052]
z	0.62	−1.90	1.12	−0.01	−1.11
R^2	5.89%	13.21%	13.62%	13.97%	0.04%
Teachers' age (*years*)					
Parameter β	0.003	−0.003	0.002	−0.002	0.001
95% CI [β]	[-0.004, 0.011]	[-0.010, 0.003]	[-0.003, 0.006]	[-0.007, 0.004]	[-0.005, 0.008]
z	0.94	−1.04	0.74	−0.64	0.39
R^2	27.38%	51.88%	36.33%	47.03%	6.93%
Proportion of female teachers in the sample (%)					
Parameter β	0.003	**−0.005**	0.001	0.000	−0.002
95% CI [β]	[0.000, 0.006]	[-0.008, −0.002]	[-0.002, 0.003]	[-0.003, 0.003]	[-0.005, 0.001]
z	1.73	−2.85**	0.45	−0.06	−1.45
R^2	34.40%	35.98%	9.18%	25.46%	8.77%

Note. The table shows the 95% Wald confidence intervals. R^2 represents the relative reduction of the between-samples variation (i.e., random effects) when comparing the baseline model (without moderators) and the model with the moderator (Snijders & Bosker, 2012). ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness. Significant moderator effects are highlighted in bold. *$p < .05$, **$p < .01$.

Table 8
Assessment of publication bias in reported correlations.

Correlation	Trim-and-fill analyses			Fail-safe N	Egger's regression test
	r	95% CI	k		
ATT–BI	0.634	[0.578, 0.684]	65	59,076	$t(49) = -9.47, p < .001$
PEOU–ATT	0.674	[0.638, 0.708]	66	76,963	$t(49) = -9.38, p < .001$
PEOU–BI	0.465	[0.410, 0.516]	56	36,224	$t(49) = -6.03, p < .001$
PEOU–PU	0.574	[0.522, 0.621]	62	52,045	$t(49) = -8.54, p < .001$
PU–ATT	0.593	[0.545, 0.638]	61	58,308	$t(49) = -8.54, p < .001$
PU–BI	0.608	[0.552, 0.658]	62	57,191	$t(49) = -8.45, p < .001$

Note. Trim-and-fill analyses were based on random-effects models for each correlation. Fail-safe *N*s were obtained from Rosenberg's method (target *p*-value = .05). Egger's regression test was based on standard errors as predictors. ATT = Attitudes toward technology, BI = Behavioral intention to use technology, PEOU = Perceived ease of use, PU = Perceived usefulness.

(1) Teachers' experience explained between-samples variance in the PEOU→ATT effect and exhibited negative moderation ($\beta = -0.110$)—thus, the structural parameter is significantly larger for pre-service than for in-serivce teacher samples.
(2) The proportion of female teachers moderated the PU→BI effect negatively, that is, the fewer women in the teacher sample were, the larger the effect.
(3) Next to the sample characteristics, the type of TAM variables (latent vs. manifest) influenced the PU→BI effect ($\beta = -0.124$) and the PEOU→ATT effect ($\beta = 0.120$). Hence, studies using latent variables to represent the TAM variables exhibited a smaller PU→BI effect but a larger PEOU→ATT effect than studies using manifest variables that were not corrected for unreliability. The moderation effect on PU→BI remained even after correcting the correlations for unreliability, $\beta = -0.159$. However, the moderation of the PEOU→ATT effect became insignificant ($\beta = -0.024$), while the effect on PU→ATT was significant, $\beta = 0.093$ (see Supplementary Material S2, section D). These findings indicate the confounding of some moderation effects of the type of variables used in primary studies with unreliability.
(4) Finally, the publication status showed a negative moderation effect on the PEOU→ATT structural parameter and a positive effect on the PU→ATT parameter. Hence, the former suggests smaller effects for published studies; the latter suggests larger effects for published studies.

3.5. Publication bias

The trim-and-fill analyses for all correlations between the TAM variables suggested that several correlations should be added to adjust for possible publication bias (see Table 8). Inspecting the funnel plots' asymmetry (see Supplementary Material S2) via Egger's regression test suggested the existence of some publication bias (*ps* < .05). Rosenberg's fail-safe *N*s however were large in light of the overall sample size; it therefore seemed unlikely that many studies were missing in our meta-analysis. The *p*-curves were all left-skewed and, consequently, did not indicate any possible *p*-hacking (see Supplementary Material S2). Overall, the analysis of publication bias did not draw a clear picture of the extent to which such bias existed in our data set. We assume that its degree may not have affected the main outcomes of our study. Moreover, we note that all approaches were based on univariate meta-analyses of single correlations rather than multivariate analyses of structural parameters—hence, the information gained from these analyses is limited.

3.6. Sensitivity analysis

We tested the sensitivity of our findings to influential correlations and the correction of correlations for the unrelaibility of the TAM variables. Concerning the former, in only one study, one correlation (PU–ATT) was flagged as influential (see Supplementary Material S2); however, this possible outlier could not be explained by any study characteristic, and we decided to keep it in the data set. No further influential cases were flagged. Concerning the unreliability-corrected correlations, the structural parameters in the TAM, their between-samples variance estimates, and the moderator effects differed only to some extent from those obtained from the uncorrected correlations (see Supplementary Material S2). Due to the correction, three more correlation matrices were flagged as non-positive definite—these matrices were excluded, and the resultant, overall sample contained $k = 47$ correlation matrices. Clearly, the preference of Models 2 over Model 1 could be replicated by both the study-by-study model comparisons and the comparison based on a pooled correlation matrix. Moreover, the structural parameters were similar to those obtained from the uncorrected correlations, and the significant between-samples variation was significant. However, some of the moderator effects could not be replicated, possibly due to the exclusion of three more correlation matrices (see Supplementary Material S2).

4. Discussion

4.1. The overall fit and relations within the TAM

Overall, the TAM exhibited an acceptable to very good fit to the data provided by the primary studies and to the overall correlation matrix that was obtained by means of correlation-based MASEM. The comparison between the TAM with and without the direct PU→BI effect further suggested that this effect is, for most of the studies, needed to improve the model fit significantly. The fact that the TAM fitted the data well testifies to its validity in describing teachers' intentions to use and integrate technology in their teaching (e.g., Teo, 2011). The TAM seems to remain a powerful model that links the cognitive, affective, and behavioral responses to various types of technology (Davis, 1986) and that is broadly applicable to various technologies and contexts (Marangunić & Granić, 2015). In essence, teachers' intentions to use technology for teaching and learning are well-described by the TAM. All relations within the TAM exhibited statistical significance and thus pointed to the relevance of PU, PEOU, and ATT as predictors of BI. Given that this observation is in line with preceding meta-analyses that focused on other samples and technologies (e.g., King & He, 2006; Schepers & Wetzels, 2007; Tang & Chen, 2011; Šumak et al., 2011), we interpret this finding as support for the validity of the TAM for teacher samples.

Concerning the overall fit of the TAM, one finding is worth emphasizing: The inclusion of the effect of PU on BI was essential in all primary studies. For more than 80% of the primary studies, adding this path to the model improved the overall fit significantly. For some studies, the changes in the overall fit were dramatic—whereas the model without the PU→BI effect did not fit the data sufficiently, the model with this effect provided an acceptable to very good fit to the data (e.g., Pynoo et al., 2012; Sadeghi, Saribagloo, Aghdam, & Mahmoudi, 2014). Although the original version of the TAM did not contain a direct link between PU and BI (Davis, 1986), it seems necessary to include (Lee, Kozar, & Larsen, 2003).

Moving beyond the mere methodological perspective on including the PU→BI effect, we believe that PU does not only operate indirectly via ATT to predict BI, but also directly. Hence, teachers' perceptions of the usefulness of technology to support teaching and learning processes determine teachers' intentions to use it (Baydas & Goktas, 2017). Interventions that are aimed at improving pre- or in-service teachers' intentions to use technology may therefore pay special attention to helping teachers perceive technology as useful. In their systematic review of strategies to support teachers to integrate technology into classrooms, Gamage and Gamage, 2017 demanded that “more attention should be paid to teachers' perceptions of usefulness in introducing ICTs” (p. 25). Brenner and Brill (2016) suggested possible activities that may accomplish this, such as modeling the effective use of technology in content-specific areas, reflecting upon learning activities that utilize technology, and practicing the use of technology in authentic contexts. Next to institutional support, the role of teacher educators to implement and support these activities is critical to the improvement of teachers' PU (Tondeur et al., 2012). Overall, our findings establish the importance of PU for BI and highlight the existence of the direct PU→BI effect.

Although the TAM is a well-fitting model that describes teachers' behavioral intentions in many countries, for many samples, for different types of technology, and several subject domains, there is still some variation between study samples—not only in the model parameters but also in the degree to which the TAM fits the data. This variation suggests some degree of situation-, sample-, and context-specificity of the model (e.g., Howard, Chan, Mozejko, & Caputi, 2015; Nistor, 2014; Zhang et al., 2012; Šumak et al., 2011). Along these lines, we advise researchers to examine the fit of the TAM in their specific research context instead of taking for granted that the model will surely fit the data well. Moreover, any deviations from an acceptable model fit may be worthwhile explaining under the lenses of the cultural, technological, and sample contexts.

Next to the acceptable model fit, the TAM exhibited a moderate variance explanation of BI of 39% with a broad range between 3% and 90%. Once again, the substantial variance explanation testifies to the validity of TAM in general and the predictive potential of PU, PEOU, and ATT for BI specifically (e.g., Mathieson, 1991; Venkatesh & Bala, 2008). The amount of variance explained confirms those found in other meta-analyses (e.g., Tang & Chen, 2011)—again, testifying to the generalizability of the TAM. As the early works on the TAM hypothesized, these predictors represent relevant cognitive and affective factors explaining technology acceptance (Davis, 1985), even for diverse teacher samples. Nevertheless, the variance explanations vary considerably across study samples—hence, the TAM, despite its robustness in many contexts, does not provide evidence for its predictive validity to the same extent (Teo, Lee, Chai, & Wong, 2009; Wu & Du, 2012).

4.2. Explaining variation across samples

As we mentioned earlier, model fit statistics, variance explanations, and path coefficients within the TAM varied across study samples—a finding that indicates some degree of context- or, more precisely, sample-specificity in the model. In the following, we highlight several observations that accompany this between-sample variation.

(1) *The path coefficients varied across samples, yet not homogeneously.* The largest variances occurred for the PU→BI and ATT→BI effects; the smallest variance occurred for the PU→ATT effect. The latter suggests that the relation between PU and ATT is more homogeneous across samples than others. Some effects within the TAM may be more important than others for certain samples of pre- and in-service teachers. Several previous meta-analyses testified to similar findings: For instance, Schepers and Wetzels (2007) found that considerable between-sample variation existed in the TAM relations, some of which could be explained by the origin of the study samples (i.e., Eastern vs. Western cultures). Marangunić and Granić (2015) discovered that the TAM relations varied substantially between studies, yet not to the same extent. In sum, our study showed that the TAM relations are

heterogeneous to varying degrees.

(2) *The between-sample variance could be partly explained by sample, measurement, and publication characteristics.* More specifically, teachers' experience in their profession (i.e., pre-vs. in-service teachers), the proportion of female teachers in the sample, the treatment of TAM variables as either manifest or latent, and the publication status explained significant variance between samples. As for the overall between-sample variation, the moderators did not uniformly explain variance across the TAM relations—in fact, variance in the PEOU→ATT, PU→BI, and PU→ATT effects was explained, yet not in the other effects. Hence, in contrast to some expectations (e.g., Yousafzai et al., 2007a), the explanatory power of the selected moderators differed across TAM relations, again pointing to the fact that the variation in the TAM relations may have different causes. Hence, the different moderators may not be equally important to all TAM relations. In addition, the moderation effects of some variables, namely teacher experience and the publication status, differed in their direction between structural parameters. Once again, these differences support the observation that moderation effects can vary between structural parameters.

We would like to point out that the fact that sample, measurement, and publication characteristics explained between-sample variance is in line with previous meta-analyses of the TAM in other contexts and underlines the importance to consider this set of characteristics as potential moderators in future TAM studies (e.g., King & He, 2006; Marangunić & Granić, 2015; Schepers & Wetzels, 2007; Yousafzai, Foxall, & Pallister, 2007b). From a substantive point of view, some of these moderation effects are worth considering: For in-service teachers, the PEU→ATT effect was significantly smaller than that for pre-service teachers. This finding points to the higher relevance of the perceived ease of use for overall attitudes toward technology for pre-service teachers and may encourage teacher educators to consider improving the ease of technology use in their teaching (Teo, 2009b). The measurement moderation effect may have been partly caused by the differences in the correction for measurement error between models with manifest and latent variables. In fact, when correcting for unreliability in the manifest TAM variables, the moderation effects decreased to some extent. We therefore encourage TAM reseachers to consider comparing the path coefficients between models using manifest and models using latent variables. Recent psychometric research suggested that there may be differences between these two approaches in several model parameters (Savalei, 2018). Finally, the proportion of female teachers in the primary studies explained between-sample variance in the PU→ATT effect. One possible interpretation of this finding may be that the perceived usefulness of technology is more important to men than to women. We believe that further investigations are needed to substantiate and explain this finding, especially because some primary studies did not identify gender differences in the PU–ATT relation (e.g., Wong, Teo, & Russo, 2012).

(3) *The type of technology used as a reference in the TAM did not explain between-sample variance.* Although previous meta-analyses of the TAM identifed the type of technology as a moderator (e.g., King & He, 2006; Schepers & Wetzels, 2007), the between-sample variance could not be explained by this variable. For the sample of primary studies included in our meta-analysis, the effects were therefore not specific to the conceptualization of certain technologies, thus supporting their generalizability across technological contexts. At the same time, we note that our coding of the technologies was only dichotomous and differentiated between a reference to technology in general and more specific technologies, yet without considering any further classification of further technologies. This simplistic distinction may of course be less informative than a more fine-grained classification of technology. Nevertheless, considering the number of available studies, such a classification could have compromised the power to detect moderation effects.

4.3. Methodological reflections

In this meta-analysis, we took a multivariate rather than a univariate approach to aggregating the correlations between the TAM variables. Although aggregating single correlations using univariate random-effects models has been a common procedure in educational and psychological meta-analyses (Sheng et al., 2016), the multivariate alternatives provide more accurate model parameters, such as path coefficients (Cheung & Chan, 2005). In this sense, we would like to encourage researchers in the field who aim at replicating and extending our meta-analysis to consider multivariate meta-analytic models to synthesize model parameters or correlation matrices. Of course, these models might not be equally informative—for instance, whereas correlation-based MASEM is a powerful approach to testing alternative models that represent different theoretical assumptions on the structure of the data, parameter-based MASEM is more suitable in situations where a specific model and its parameters are tested for variation between samples and possible moderation by other variables (Cheung & Cheung, 2016). Albeit the differences between these two MASEM approaches, we believe that their synergism may strengthen the meta-analytic evidence on the fit of a certain models and the subsequent moderator analyses. Overall, we consider the current MASEM approaches the methods of choice when researchers are interesting in synthesizing correlations that are submitted to further structural equation modeling.

None of the primary TAM studies followed a longitudinal design and tested the causality of effects. This observation was surprising, in particular because the interpretation of the relations within the TAM were mostly causal. Venkatesh and Bala (2008) argued for the adoption of longitudinal and causal study designs in future studies of the TAM. Besides, such designs may also shed light on the effects of certain interventions that are aimed at improving teachers' technology acceptance (Hu, Clark, & Ma, 2003).

4.4. Limitations and future directions

Our meta-analysis has some limitations worth mentioning: First, we focused on four variables in the TAM, namely PEOU, PU, ATT, and BI, without considering additional variables, such as teachers' actual technology use or external variables (e.g., technology self-efficacy, facilitating conditions). This choice was mainly informed by existing reviews and meta-analyses which identified the four, above-mentioned variables as the core variables within the TAM (e.g., Marangunić & Granić, 2015). Moreover, if the list of variables was to be extended and if complete correlation matrices were needed to examine the moderating effects of continuous variables on the structural parameters, the number of available studies would decrease—this however could compromise the statistical power of the meta-analytic procedures and ultimately their credibility. Second, a larger sample of studies may have provided more insights into the cultural differences in the structural parameters and variance explanations within the TAM compared to our dichotomized comparison between Asian and non-Asian countries. Given the diversity of the countries within these categories, more fine-grained differences between them could be examined for larger samples of studies. We therefore encourage updates of our meta-analysis that explicitly test the cross-cultural differences in greater detail. Third, differentiating between pre- and in-service teachers as a measns to account for possible differences in teaching experience in general or with technology was simplistic and served only as a rough proxy of their exposure to technology in education. To draw valid inferences on the extent to which teaching experience in general and with technology may affect certain relations within the TAM, we encourage researchers in the field to measure these two variables explicitly.

4.5. Conclusion

With this meta-analysis, we synthesized the existing body of research on the Technology Acceptance Model for teacher samples, based on complete reports of correlations between the four core variables PU, PEOU, ATT, and BI. The resultant synthesis clarified some inconsistencies in primary TAM studies, including the (non-)existence of a direct effect of teachers' perceived usefulness on their intentions to use technology for teaching and learning and the variation of the relations between the TAM variables across study samples. We found support for the direct PU→BI effect, which was often neglected in primary studies, and argue that this effect should be added to the TAM to improve its model fit. Moreover, the TAM relations varied between samples to different degrees, and sample, measurement, and publication characteristics should be considered as explanatory variables. Overall, we conclude that the TAM is a powerful model that explains pre- and in-service teachers' intentions to use technology. Our meta-analysis provided evidence on its validity and generalizability across certain groups of teachers and types of studies. Nonetheless, the overall validity of the TAM and the measures of the TAM variables should always be considered and, more importantly, examined in primary studies of teacher samples.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.edurev.2019.03.001.

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Studies included in this meta-analysis are marked with an asterisk.

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