The Technology Acceptance Model (TAM): A Meta-Analytic Structural Equation

Modeling Approach to Explaining Teachers' Adoption of Digital Technology in Education

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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.

Keywords: Meta-analysis; Teacher education; Technology Acceptance Model (TAM); Technology adoption

Highlights

- The Technology Acceptance Model (TAM) explains teachers' technology adoption.
- Relations among variables in the TAM are synthesized meta-analytically.
- The TAM and its versions fit the data well—even for subsamples of teachers.
- Within the TAM, direct effects of PU on BI and ATT on USE exist.
- The TAM explains behavioral intentions and technology use significantly.

The Technology Acceptance Model (TAM): A Meta-Analytic Structural Equation Modeling

Approach to Explaining Teachers' Adoption of Digital Technology in Education

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; Siddig, 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; Siddig, 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, 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.

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

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 metaanalysis. 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 Figure 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).

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 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 preand 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; 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 metaanalyses, 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 ($\beta_{PEU-ATT} = .52$) and a weak positive effect of PU on ATT ($\beta_{PU-ATT} = .16$), Schepers and Wetzels (2007) found the opposite ($\beta_{PEU-ATT} = .26$, $\beta_{PU-ATT} = .46$)—so did L. Zhang, Zhu, and Liu (2012) in their meta-analysis ($\beta_{PEU-ATT} = .07$, $\beta_{PU-ATT} = .24$). 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).

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).

Method

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.

Screening, Inclusion and Exclusion Criteria

Figure 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*—full 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.

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).

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 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, Morris, Davis, & Davis, 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 labeled the same in the TAM.

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).

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 & M. W.-L. 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 & M. W.-L. 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 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 et al., 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 Figure 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., $CFI \ge .95$, $RMSEA \le .08$, and $SRMR \le .10$; 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 I = In-service teachers, 0 = Pre-service teachers), the specificity of the technology the TAM refers to (coded as I = 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.

Results

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., 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.

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 Ns 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.

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 Figure 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: $\chi^2(470) = 7,201.4$, p < .001, CFI = 0.825, RMSEA = 0.227, SRMR = 0.155; Model

2: $\chi^2(535) = 8,136.0$, 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: $\chi^2(1,098) = 14,170.5$, 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.

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, $\Delta(-2LL)$ [1] = 90.9, p < .001 (see Figure 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 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. Figure 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, $\Delta(-2LL)$ [1] = 20.2, p < .001 (see Figure 3, Model 2). The direct effect ATT→USE was positive and significant, b = 0.337, 95% LBCI = [0.192, 0.481] (see Figure 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.

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 I² 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 Figure 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. Figure 5 shows Models 1 and 2 specified for pre- and inservice 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 Figure 6). These comparisons revealed differences in the direct effects PU \rightarrow BI and ATT \rightarrow USE with larger effects for specific technologies. In fact, the ATT \rightarrow USE relation was insignificant for studies referring to 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.

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 Figure 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 Figure 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]). Figure 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.

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.

Discussion

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, Siddiq, & Teo, 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.

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 Figure 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, Siddiq, & Teo, 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.

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 (β_{SN}- $_{PEU}$ = .20, β_{SN-PU} = .30). This finding was confirmed in our meta-analysis for teacher samples, yet with smaller effects on PEU (Model 3: $\beta_{SN-PEU} = .09$, $\beta_{SN-PU} = .28$). 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: $\beta_{CSE-PEU} = .37$, $\beta_{CSE-PU} = .23$), and is in line with the results reported by Abdullah and Ward (2016) ($\beta_{CSE-PEU} = .35$, $\beta_{CSE-PU} = .17$) and Scherer et al. (2015) ($\beta_{CSE-PEU}$'s = .22–.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: β_{FC-PEU} = .30) and PU (Model 3: β_{FC-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).

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).

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, Brown, & Teo, 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.

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.

Conclusions

The current meta-analysis synthesized the existing body of research on pre- and inservice teachers' technology adoption based on the Technology Acceptance Model using random-effects, correlation-based MASEM under M. W.-L. Cheung's 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's 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.

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Tables

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	A person's evaluation of technology or specific
(ATT)	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)

Table 2

Overview of selected meta-analyses synthesizing TAM studies

Meta-analysis	TAM	k	Moderators	MASEM	Fixed Effec	ets (β)						
	core variables			approach	PEU→PU	PEU→ATT	PEU→BI	PU→ATT	PU→BI	ATT→BI	ATT→USE	BI→USE
Gerow et al. (2013)	PEU, PU, BI, USE	185	T	Univariate-	0.39*	-	0.16*	-	0.36*	-	-	0.48*
King & 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 & Wetzels (2007)	PEU, PU, ATT, BI, USE	63	U, T, C	Univariate-	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-	0.40*	0.29*	0.24*	0.51*	0.40*	0.33*	0.33*	0.44*
Wu & Du (2012)	PEU, PU, BI, USE	103	V	Univariate-	0.50*	-	-	-	-	-	-	-
Zhang et al. (2012)	PEU, PU, ATT, BI, USE	58	С	Univariate-	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, C = Culture, C = Culture,

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	20	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 %

52	41.94 %
72	58.06 %
0	0.00 %
73	58.87 %
51	41.13 %
2	1.61 %
5	4.03 %
24	19.35 %
42	33.87 %
70	56.45 %
54	43.55 %
107	86.29 %
17	13.71 %
1	0.81 %
0	0.00 %
1	0.81 %
1	0.81 %
	1.61 %
	3.23 %
	3.23 %
7	5.65 %
10	8.06 %
	7.26 %
	11.29 %
	10.48 %
	12.90 %
	16.13 %
	16.94 %
1	0.81 %
	72 0 73 51 2 5 24 42 70 54 107 17 1 0 1 1 2 4 4

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 > .10, CFI < .85), mediocre (.08 < RMSEA \le .10, .85 \le CFI < .90), acceptable (.05 < RMSEA \le .08,

 $.90 \le CFI \le .95$), and close (RMSEA $\le .05$, CFI $\ge .95$).

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	1,075
Average age [years]	30.5	8.4	29.0 %	19.4	47.0
Proportion of female	64.7 %	19.6 %	16.1 %	0.0 %	100.0 %
teachers					
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 $\omega.$

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*			
$\frac{\rho}{\tau^2}$	0.027*			
$SE(\tau^2)$	0.004			
I^2	93.5 %			
ATT				
r	.59*	.53*		
95% CI	[.55, .62]	[.49, .56]		
ρ	.62*	.54*		
$\begin{array}{c} \rho \\ \tau^2 \end{array}$	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]	
	.58*	.44*	.55*	
$\begin{matrix} \rho \\ \tau^2 \end{matrix}$	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*
$\begin{array}{c} \rho \\ \tau^2 \end{array}$	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 randomeffects 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), I²: heterogeneity coefficient based on the Q statistic (Higgins & Green, 2011). * *p* < .01

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*						
$\begin{array}{c} \rho \\ \tau^2 \end{array}$	0.025*						
$SE(\tau^2)$	0.004						
I^2	93.1 %						
ATT							
r	.59*	.52*					
95% CI	[.55, .62]	[.49, .56]					
$\begin{matrix} \rho \\ \tau^2 \end{matrix}$.62*	.54*					
	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]				
$\frac{\rho}{\tau^2}$.58*	.44*	.55*				
$ au^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*			
$\begin{matrix} \rho \\ \tau^2 \end{matrix}$	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		
$\begin{matrix} \rho \\ \tau^2 \end{matrix}$	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	
$\begin{array}{c} \rho \\ \tau^2 \end{array}$	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
$\begin{matrix} \rho \\ \tau^2 \end{matrix}$	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), τ^2 : heterogeneity coefficient based on the Q statistic (Higgins & Green, 2011). * p < .01

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
<i>b</i> [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.

Supplementary Material

The Technology Acceptance Model (TAM): A Meta-Analytic Structural Equation

Modeling Approach to Explaining Teachers' Adoption of Digital Technology in Education

Abbreviations

ATT	Attitudes toward technology	PEU	Perceived ease of
		use	
BI	Behavioral intention	PU	Perceived usefulness
CSE	Computer self-efficacy	SN	Subjective norms
FC	Facilitating conditions	USE	Technology use

S1. Worked example: Application of the tracing rules

For studies that did not provide correlation matrices in the published papers, yet the fully standardized structural parameters, we applied Wright's tracing rules to retrieve the correlation matrices (Wright, 1934). These rules specify how researchers can recreate correlations among variables whenever all necessary pathways in a structural equation model are provided (Kline, 2016; Loehlin, 2004). At this point, we note that several authors have warned against the use of path or regression coefficients as correlations in meta-analyses (Peterson & Brown, 2005). Furthermore, Cheung (2015) argued that the use of pooled correlation matrices in MASEM mainly serves the main purpose of comparing alternative structural equation models; alternatively, extracting model parameters directly extracted from studies (e.g., path coefficients) allows researchers to explore the variability of these parameters across groups or continuous variables, such as age or years of experience (Cheung & Hafdahl, 2016). As the current meta-analysis set out to compare alternative TAM versions, we refrained from using path coefficients and recreated correlation matrices. Hence, this meta-analysis takes a correlation-rather than parameter-based approach to MASEM.

Wright's tracing rules. The correlations between two variables can be decomposed into the sum of the coefficients of all possible paths connecting them (Kenny, 1979; Loehlin, 2004). The space of all possible paths is constrained by a set of rules:

- (1) Each variable can only be passed through once.
- (2) Tracing does not allow going forward and then backward.
- (3) Only a single correlation can be passed on a path.

Tracing rules can be applied to both manifest and latent variables. For instance, if research present a model of confirmatory factor analysis with two correlated latent variables, each of which is indicated by three manifest variables, the correlations between the manifest variables can be reconstructed by applying the tracing rules. In such a model, the paths

describing the correlation between two manifest variables that belong to the same latent variable pass through the latent variables—if manifest variables belong to different latent variables, paths pass through the latent variables and their correlation. Besides the examination of correlations between manifest variables, correlations between latent variables can be recreated if sufficient information about the structural parameters is accessible. The factor correlations are traced according to the same rules (1) to (3); their measurement models are, however, ignored. One might therefore consider the resultant factor correlations as already attenuated. We suspect that the recreating the correlation matrix from item indicators rather than latent variables only may provide more accurate results, because unreliability is directly accounted for.

Example. We consider the structural equation model in Figure S1 researchers have reported in their paper. This model contains core TAM variables and presents the fully standardized parameters as follows:

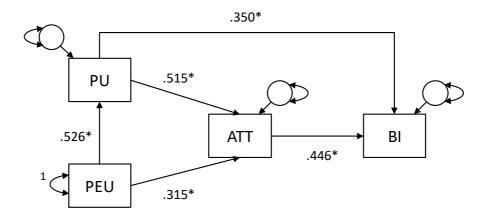


Figure S1. Original structural equation model describing technology acceptance.

Note. PU = Perceived usefulness, PEU = Perceived ease of use, ATT = Attitudes toward technology, BI = Behavioral intention to use technology. The path coefficients shown in the figure are those obtained from the fully standardized solution. All path coefficients are statistically significant. * p < .01.

Application of the tracing rules. The structural equation model contains four manifest variables, and we are interested in their correlations to retrieve a correlation matrix that can be

used for further pooling in MASEM. Given that four variables are of interest, six correlations are needed. For instance, the correlation between PU and BI is based on three possible paths adhering to Wright's rules: PU \rightarrow BI (i.e., direct effect), PU \rightarrow ATT \rightarrow BI (i.e., indirect effect), and PU \leftarrow PEU \rightarrow ATT \rightarrow BI (i.e., PEU is the "common cause" of PU and ATT). As coefficients along a path are multiplied, the elements used to calculate the correlation between PU and BI are: 0.350, 0.515 \times 0.446, and 0.526 \times 0.315 \times 0.446. The correlation is recreated as the sum of these elements: $r_{PU,BI} = 0.350 + 0.515 \times 0.446 + 0.526 \times 0.315 \times 0.446 = 0.654$. In the remainder, the rules are applied to all $\binom{4}{2} = 6$ correlations.

$$\begin{array}{lll} r_{PU,PEU} & = & 0.526 \\ \\ r_{PU,ATT} & = & 0.515 + 0.526 \times 0.315 = 0.681 \\ \\ r_{PU,BI} & = & 0.350 + 0.515 \times 0.446 + 0.526 \times 0.315 \times 0.446 = 0.654 \\ \\ r_{PEU,ATT} & = & 0.315 + 0.526 \times 0.515 = 0.586 \\ \\ r_{PEU,BI} & = & 0.315 \times 0.446 + 0.526 \times 0.515 \times 0.446 + 0.526 \times 0.350 = 0.445 \\ \\ r_{ATT,BI} & = & 0.446 + 0.515 \times 0.350 + 0.315 \times 0.526 \times 0.350 = 0.684 \end{array}$$

The resultant correlation matrix contains all information about the structural parameters describing the relations among the variables:

	PU	PEU	ATT	BI
PU	1			
PEU	.526	1		
ATT	.681	.585	1	
BI	.654	.445	.684	1

Along with the structural parameters, the authors of this study have also reported the size of the sample. In this example, the sample comprised N = 245 pre-service teachers. To test whether the retrieved correlation matrix is accurate, it can be used as input for structural equation modeling software such as Mplus (Muthén & Muthén, 1998-2015).

TITLE: Test of retrieved correlation matrix – Study number 2259

DATA: FILE IS tam-study-2215.dat;

TYPE = CORR;

! Correlation matrix as input

NOBSERVATIONS = 245;

! Sample size as reported in study 2259

VARIABLE: NAMES ARE PU PEU ATT BI;

USEVARIABLES ARE PU-BI;

ANALYSIS: ESTIMATOR = ML;

! Maximum likelihood estimation

MODEL: ! Specification of the structural part in the TAM

PU ON PEU;

ATT ON PU PEU;

BI ON PU ATT;

OUTPUT: CINTERVAL;

! Wald confidence intervals

The model fitted the data well ($\chi^2[1] = 0.00$, p = .998, RMSEA = .00, CFI = 1.00,

TLI = 1.01, SRMR = .00), and the resultant structural parameters matched the original structural parameters perfectly (Figure S2)—the tracing rules have been applied successfully.

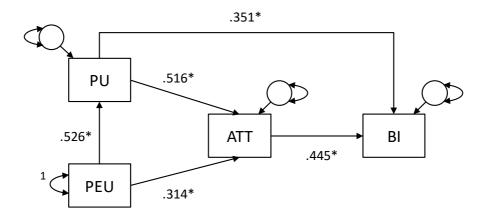


Figure S2. Recreated structural equation model describing technology acceptance.

Note. PU = Perceived usefulness, PEU = Perceived ease of use, ATT = Attitudes toward technology, BI = Behavioral intention to use technology. The path coefficients shown in the figure are those obtained from the fully standardized solution. All path coefficients are statistically significant. * p < .01.

S2. Studies contributing correlation matrices to the meta-analysis

The subsequent table provides an overview of the studies included in this meta-analysis. Along with the raw and corrected correlations, study characteristics are reported. These characteristics formed the basis for the subgroup analyses presented in the main text.

Abbreviations and coding

Teachers	Status of teachers ($0 = pre\text{-}service teachers$, $1 = in\text{-}service$
	teachers)
Level	Educational level ($\theta = early\ childhood,\ primary\ school,\ and\ special$
	education, $1 = secondary school$, $2 = college and university$)
Technology	Technology context ($0 = specific technologies, 1 = technology in$
	general)
Measure	Type of measurement ($0 = manifest \ variables$, $1 = latent \ variables$)
Status	Publication status ($0 = grey\ literature\ [dissertations,\ conference]$
	proceedings], $1 = published$ [journal article, peer-reviewed book
	chapter])
N	Sample size
r	Raw Pearson correlation
ρ	Corrected correlation (i.e., corrected for the unreliability of
	variables)

Reference	Teac	Country/R	I	M	F	Techn	Mea	S	N	Varia	r	ρ
	hers	egion	evel	ean age	emale	ology	sure	tatus		bles		
				[years]	[%]							
Ahmad et al. (2010)	1	Malaysia	2	2 39.	60	0	1	1	73	PU-BI		.5
				7	.0				1		560	60
										PU-		.3
										USE	380	80
										BI-		.5
										USE	510	10
										PU-		.5
										CSE	540	40
										BI-		.4
										CSE	450	50
										USE-		.5
										CSE	570	70
Ahmad et al. (2015) ^a	0	Nigeria	-	-	59	1	0	1	10	PEU-	•	.0
					.0				0	ATT	013	15

										PEU-		.0
										BI	012	14
										ATT-		-
										BI	025	.030
										PEU-		-
										USE	225	.264
										ATT-		.0
										USE	044	52
										BI-		.1
										USE	127	52
Alshahri (2015)	1	Saudi	2	31.	24	0	1	0	27	PU-		.5
		Arabia		7	.0				0	PEU	568	68
- Sample 1										PU-		.7
										ATT	739	39
										PEU-		.5
										ATT	531	31

Alshahri (2015) ^a	1	USA	2	47.	49	0	1	0	24	PU-		.5
				7	.0				5	PEU	564	64
- Sample 2										PU-		.4
										ATT	424	24
										PEU-		-
										ATT	057	.057
Anderson et al.	0	USA	0	-	82	0	0	1	21	PU-BI		.7
(2011)					.0				7		580	01
										PU-		.4
										CSE	420	75
										BI-		.4
										CSE	380	62
Anderson & Groulx	0	USA	0	23.	98	0	0	0	10	PU-		.6
(2013)				0	.0				2	PEU	520	12
										PU-BI		.6
											540	47

PEU-		.7
BI	650	79
PU-		.2
USE	200	38
PEU-		.2
USE	190	26
BI-		.3
USE	320	87
PU-		.7
SN	590	94
PEU-		.6
SN	460	19
BI-SN		.9
	730	99*
USE-		.4
SN	320	35

									PU-		.6
									CSE	580	63
									PEU-		.7
									CSE	650	43
									BI-		.6
									CSE	590	87
									USE-		.2
									CSE	210	42
									SN-		.6
									CSE	530	93
Atif et al. (2015)	1	Australia	2 -	59	1	1	1	18	PU-		.6
				.0				4	PEU	656	56
									PU-		.8
									ATT	836	36
									PEU-		.5
									ATT	564	64

	PU-BI	٠	.6
		643	43
	PEU-		.5
BI		543	43
	ATT-		.5
BI		530	30
	PU-		.5
SN		526	26
	PEU-		.4
SN		480	80
	ATT-		.4
SN		421	21
	BI-SN		.4
		486	86
	PU-	•	.1
CSE		187	87

										PEU-		.5
										CSE	502	02
										ATT-		.0
										CSE	063	63
										BI-		.1
										CSE	124	24
										SN-		.3
										CSE	335	35
Attis (2014)	1	USA	0	-	-	1	0	0	11	PU-		.7
									2	PEU	760	92
										PU-BI		.3
											370	94
										PEU-		.4
										BI	380	04
										PU-		.5
										CSE	540	60

										PEU-		.5
										CSE	560	80
										BI-	•	.4
										CSE	390	13
Aypay et al. (2012)	0	Turkey	-	21.	-	0	1	1	75	PU-		.7
				0					4	PEU	720	20
										PU-	٠	.7
										ATT	710	10
										PEU-		.7
										ATT	700	00
										PU-BI	•	.7
											730	30
										PEU-	•	.6
										BI	650	50
										ATT-	٠	.6
										BI	680	80

											PU-		.4
										FC		430	30
											PEU-		.4
										FC		450	50
											ATT-		.4
										FC		440	40
											BI-FC	•	.4
												440	40
Baytiyeh (2014)	1	Lebanon	1	38.	56	0	1	1	16	i	PU-		.5
Baytiyeh (2014)	1	Lebanon	1	38. 3	56 .0	0	1	1	16 1	PEU		500	.5
Baytiyeh (2014)	1	Lebanon	1			0	1	1					
Baytiyeh (2014)	1	Lebanon	1			0	1	1			U	500	00
Baytiyeh (2014)	1	Lebanon	1			0	1	1			U	500	.4
Baytiyeh (2014)	1	Lebanon	1			0	1	1			U PU-BI PEU-	500	00 .4 40
Baytiyeh (2014)	1	Lebanon	1			0	1	1		PE	U PU-BI PEU-	500	00 .4 40 .4

									PEU-		.3
								S	SN	300	00
									BI-SN		.4
										420	20
									PU-		.0
								F	FC .	080	80
									PEU-		.4
								F	FC .	460	60
									BI-FC		.1
										180	80
									SN-		.2
								F	EC .	210	10
Bøe (2014)	1	Norway	2 -	49	0	1	0	17	PU-		.5
				.2				7 F	PEU	540	40
									PU-BI		.6
										600	00

										PEU-		.2
									I	3I	280	80
										PU-		.3
									I	FC	360	60
										PEU-		.1
									I	FC	190	90
										BI-FC		.6
											690	90
Bourgonjon et al.	1	Belgium	1	40.	57	1	0	1	50	PU-BI		.7
(2013)				0	.3				5		703	60
										PU-		.5
									S	SN	539	70
										BI-SN		.4
											449	83
Chen & Tseng (2012)	1	Taiwan	1	35.	59	1	0	1	40	PU-		.5
				3	.5				2 I	PEU	520	82

PU-		.5
ATT	535	93
PEU-		.5
ATT	510	78
PU-BI		.7
	707	68
PEU-		.6
BI	553	13
ATT-		.4
BI	437	80
PU-	٠	.4
CSE	404	38
PEU-		.6
CSE	560	19
ATT-		.3
CSE	355	89

										BI-		.4
										CSE	374	01
Chen (2016)	1	Taiwan	0	31.	95	0	1	1	35	PU-BI	٠	.5
				0	.5				3		530	30
										PU-	٠	.5
										CSE	540	40
										BI-	٠	.5
										CSE	510	10
Cheung & Sachs	0	Hong Kong	0	27.	-	1	0	1	57	PU-		.5
Cheung & Sachs (2006)	0	Hong Kong (China)	0	27. 8	-	1	0	1	57	PU- PEU	530	.5 92
	0		0		-	1	0	1	57			
	0		0		-	1	0	1	57	PEU	530	92
	0		0		-	1	0	1	57	PEU PU-	530	92 .9
	0		0		-	1	0	1	57	PEU PU- ATT	530 810	92 .9 31
	0		0		-	1	0	1	57	PEU PU- ATT PEU-	530 810	92 .9 31 .7

PEU-	•	.7
BI	630	29
ATT-		.8
BI	690	22
PU-		.3
USE	310	62
PEU-		.5
USE	500	74
ATT-		.4
ATT- USE	360	.4 25
USE	360	25
USE BI-	360	25 .4
USE BI- USE	360	25 .4 47
USE BI- USE PU-	360 370	25 .4 47 .5

									ATT-	٠	.6
									CSE	530	27
									BI-		.7
									CSE	610	39
									USE-		.5
									CSE	440	29
Chiu (2017)	1	Hong Kong	1 -	53	1	1	1	30	PU-	٠	.5
		(China)		.9				6	PEU	575	75
									PU-		.4
									ATT	486	86
									PEU-		.4
									ATT	453	53
									PU-BI		.3
										351	51
									PEU-	٠	.2
									BI	297	97

ATT-	•	.4
BI	447	47
PU-		.3
CSE	316	16
PEU-		.2
CSE	295	95
ATT-		.1
CSE	146	46
BI-		.2
CSE	265	65
PU-		.2
FC	227	27
PEU-		.0
FC	083	83
ATT-		.1
FC	182	82

									BI-FC		.1
										191	91
									CSE-	٠	.0
									FC	078	78
Chou (2012)	1	Taiwan	1 -	42	1	1	1	31	PU-		.4
				.0				8	PEU	482	82
									PU-		.5
									CSE	526	26
									PEU-		.4
									CSE	475	75
									PU-		.4
									FC	460	60
									PEU-		.4
									FC	429	29
									CSE-		.4
									FC	468	68

Cigdem & Topcu	1	Turkey	2	34.	-	1	0	1	11	PU-		.6
(2015)				2					5	PEU	610	51
										PU-BI		.9
											930	89
										PEU-		.6
										BI	611	67
										PU-		.7
										SN	678	77
										PEU-		.7
										SN	662	79
										BI-SN		.7
											668	83
										PU-		.4
										CSE	410	32
										PEU-		.6
										CSE	630	81

										В	I-		.4
										CSE		387	17
										S	N-		.5
										CSE		495	76
										P	U-		.5
										FC		492	69
										P	EU-		.9
										FC		833	88
										В	I-FC		.5
												489	79
										S	N-		.7
										FC		619	90
										C	SE-		.7
										FC		615	22
	Cote & Miliner	1	Japan	2 -	-	1	0	0	29	P	U-		.5
(20	15)									PEU		512	84

										PU-		.5
										ATT	461	32
										PEU-		.8
										ATT	754	79
										PU-BI		.4
											364	22
										PEU-	٠	.7
										BI	669	84
										ATT-		.7
										BI	595	05
De Smet et al. (2012)	1	Belgium	1	40.	57	1	0	1	50	PU-		.4
				0	.3				5	PEU	390	43
										PU-		.5
										USE	420	00
										PEU-		.5
										USE	460	29

											PU-	•	.4
										SN		410	61
											PEU-		.1
										SN		180	96
											USE-		.2
										SN		200	28
											PU-		.1
										FC		150	72
											PEU-		.5
										FC		460	11
											USE-		.2
										FC		210	44
											SN-		.2
										FC		200	20
Dreyer & Nel (2004)	1	South	2	47.	35	0	0	0	40		PU-		.5
		Africa		0	.0					PEU	J	450	49

PU-		.4
ATT	350	27
PEU-		.2
ATT	200	44
PU-		.3
USE	290	54
PEU-		.4
USE	390	76
ATT-		.3
USE	320	90
PU-		.2
PU- CSE	240	.2 93
	240	
CSE	240	93
CSE PEU-	·	93 .7

										USE-		.5
										CSE	440	37
Fathema et al. (2015)	1	USA	2	45.	46	1	1	1	56	PU-	٠	.7
				7	.8				0	PEU	709	09
										PU-	٠	.8
										ATT	885	85
										PEU-		.7
										ATT	768	68
										PU-BI		.7
											758	58
										PEU-		.5
										BI	589	89
										ATT-		.7
										BI	783	83
										PU-		.3
										USE	398	98

	.2
266	66
٠	.3
368	68
	.4
479	79
	.6
691	91
٠	.7
772	72
772	.6
772 678	
	.6
	.6 78
678	.6 78 .6
	266 368 479 691

										PU-	•	.4
										FC	440	40
										PEU-		.4
										FC	407	07
										ATT-		.4
										FC	467	67
										BI-FC		.5
											515	15
										USE-		.3
										FC	319	19
										CSE-		.4
										FC	404	04
Fong et al. (2014)	1	Hong Kong	2	-	-	1	0	1	13	PU-		.6
		(China) and							2	PEU	565	01
		Taiwan										
										PU-BI		.7
											705	34

										PEU-		.5
										BI	563	93
Garcia & Gomez	1	Spain	2	45.	43	1	1	1	44	PU-		.1
(2014)				1	.9				5	PEU	176	76
										PU-BI		.5
											557	57
										PEU-		.2
										BI	259	59
										PU-		.6
										SN	655	55
										PEU-	٠	-
										SN	031	.031
										BI-SN	•	.4
											427	27
										PU-		.2
										FC	274	74

											PEU-	•	.4
										FC		468	68
											BI-FC		.3
												362	62
											SN-		.1
										FC		182	82
Gyamfi (2016)	0	Ghana	-	22.	51	0	0	1	38	3	PU-	•	.1
				4	.0				0	PEU	U	098	12
											PU-	•	.1
										AT	Т	109	26
											PEU-		.1
										AT	Т	106	24
											PU-		.1
										US	Е	118	37
											PEU-		.0
										US	Е	000	00

										ATT-		.2
										USE	206	45
Harris et al. (2016)	1	Australia	2	45.	71	1	0	1	13	PU-		.8
				3	.0				1	ATT	720	31
										PU-BI		.8
											780	99
										ATT-		.7
										BI	630	42
										PU-		.3
										CSE	360	93
										ATT-		.4
										CSE	410	57
										BI-		.4
										CSE	420	67
Hew et al. (2016a)	1	Malaysia	0	-	-	1	1	1	10	PU-		.4
									75	ATT	436	36

PU-BI	٠	.6
	675	75
ATT-		.5
BI	532	32
PU-		.7
CSE	736	36
ATT-		.4
CSE	425	25
BI-		.6
CSE	670	70
PU-		.5
FC	578	78
ATT-		.6
FC	600	00
BI-FC		.6
	676	76

											CSE-		.5
											FC	552	52
	Hew et al. (2016b)	1	Malaysia	-	-	-	1	1	1	62	PU-		.4
										4	ATT	451	51
											PU-BI		.6
												660	60
											ATT-		.5
											BI	547	47
											PU-		.5
											FC	586	86
											ATT-		.5
											FC	547	47
											BI-FC		.5
												587	87
	Holden & Rada	1	USA	0	41.	83	0	0	1	99	PU-		.7
(2011)				2	.8					PEU	624	04

PU-		.7
ATT	650	17
PEU-		.7
ATT	652	09
PU-		.5
USE	513	73
PEU-		.3
USE	309	40
ATT-		.3
USE	353	80
PU-		.5
CSE	508	64
PEU-		.5
CSE	488	34
	100	
ATT-		.5

										USE-		.4
										CSE	395	28
Huang & Hsu (2007)	1	Taiwan	1	-	0.	1	0	0	12	PU-		.3
					0				3	PEU	337	84
- Sample 1										PU-BI		.7
											689	99
										PEU-		.4
										BI	353	14
										PU-	•	.0
										CSE	000	01
										PEU-		.3
										CSE	301	50
										BI-	•	.1
										CSE	102	20
										PU-		.1
										FC	094	10

									PEU-	•	.1
									FC	133	57
									BI-FC	•	.2
										187	24
									CSE-	٠	.0
									FC	009	11
Huang & Hsu (2007)	1	Taiwan	1 -	10	1	0	0	61	PU-		.4
				0.0					PEU	395	51
- Sample 2									PU-BI		.5
										500	81
									PEU-		.5
									BI	490	74
									PU-		.0
									CSE	024	28
									PEU-		.3
									CSE	337	91

										BI-		.2
										CSE	171	02
										PU-	•	.4
										FC	362	23
										PEU-		.3
										FC	319	76
										BI-FC		.5
											497	97
										CSE-		.1
										FC	093	10
Huntington &	1	USA	1	37.	52	0	0	1	57	PU-	٠	.6
Worrell (2013)				8	.6					PEU	661	89
										PU-	٠	.6
										CSE	559	44
										PEU-	٠	.5
										CSE	429	04

Huntington (2011)	1	USA	1	37.	47	1	0	0	57	PU-	•	.6
				8	.4					PEU	610	96
										PU-		.6
										CSE	559	43
										PEU-		.4
										CSE	429	98
Hur et al. (2015)	0	USA	0	21.	86	1	1	1	38	B PU-		.4
				0	.0				6	PEU	433	33
										PU-BI		.8
											831	31
										PEU-		.3
										BI	373	73
										PU-		.4
										CSE	488	88
										PEU-		.7
										CSE	774	74

								BI-		.5
								CSE	592	92
Ibili & Sahin (2016) ^a	1	Turkey	 52	1	1	1	27	PU-		.8
			.0				1	PEU	890	90
								PU-		.4
								ATT	423	23
								PEU-		.1
								ATT	187	87
								PU-BI		.3
									374	74
								PEU-		.8
								BI	820	20
								ATT-		.5
								BI	512	12
								PU-		.1
								USE	130	30

									PEU-		.3
									USE	312	12
									ATT-		.3
									USE	305	05
									BI-		.4
									USE	464	64
Juarez Collazo et al.	0	Belgium	- 2	3. 80	0	0	1	9.	3 PU-		.6
(2012)a			0	.0					PEU	600	85
									PU-	•	.2
									USE	190	21
									PEU-		-
									USE	030	.035
									PU-		.2
									CSE	190	19
									PEU-		-
									CSE	020	.023

										U	SE-	•	.1
										CSE		150	78
Jung (2015)	1	South	1	42.	57	1	1	1	18	P	U-	٠	.3
		Korea		4	.1				9	PEU		300	00
										P	U-BI	•	.2
												230	30
										P	EU-		.4
										BI		480	80
										P	U-		.2
										USE		280	80
										P	EU-		.1
										USE		190	90
										В	I-		.3
										USE		340	40
										P	U-		.3
										CSE		360	60

								PEU-		.4
								CSE	480	80
								BI-		.3
								CSE	320	20
								USE-		.2
								CSE	260	60
Kabakci-Yurdakul et	0	Turkey	 57	0	1	1	57	PU-		.6
al. (2014)			.4				9	PEU	620	20
								PU-		.7
								ATT	720	20
								PEU-		.7
								ATT	730	30
								PU-BI		.7
									760	60
								PEU-		.6
								BI	600	00

ATT-		.7
BI	710	10
PU-		.3
SN	390	90
PEU-		.3
SN	300	00
ATT-		.3
SN	330	30
BI-SN		.4
BI-SN	400	.4 00
BI-SN PU-		
		00
PU-	400	.4
PU- CSE	400	00 .4 90
PU- CSE PEU-	400 . 490	00 .4 90 .5

BI-		.5
CSE	540	40
SN-		.3
CSE	340	40
PU-		.3
FC	300	00
PEU-		.2
FC	270	70
ATT-		.2
FC	270	70
BI-FC		.2
	290	90
SN-		.2
FC	230	30
CSE-		.2
FC	270	70

Kannan & Narayanan	0	India	2	33.	15	1	1	1	40	PU-	٠	.2
(2015)				4	.0				0	ATT	287	87
										PU-BI		.6
											614	14
										ATT-		.2
										BI	242	42
Kelly (2014)	1	USA	2	43.	66	1	0	1	12	PU-		.9
				7	.0				8	PEU	790	01
										PU-BI		.8
											724	40
										PEU-	·	.8
										BI	700	20
										PU-	·	.6
										USE	574	68
										PEU-	٠	.6
										USE	556	53

										BI-	•	.6
										USE	554	62
										PU-		.4
										CSE	423	87
										PEU-		.5
										CSE	458	32
										BI-		.4
										CSE	352	16
										USE-		.3
										CSE	273	23
Kiraz & Ozdemir	0	Turkey	- 2	20.	66	0	0	1	32	PU-		.4
(2006)			0		.9				0	PEU	413	71
										PU-		.4
										ATT	430	96
										PEU-		.9
										ATT	960	99*

								PU-	•	.2
								USE	250	91
								PEU-		.1
								USE	103	21
								ATT-		.1
								USE	108	28
Kirmizi (2014)	0	Turkey	 77	0	1	1	21	PU-		.6
			.9				3	PEU	690	90
								PU-		.7
								ATT	760	60
								PEU-		.7
								ATT	710	10
								PU-BI		.0
									030	30
								PEU-		.1
								BI	180	80

										ATT-		.2
										BI	270	70
Koutromanos et al.	0	Greece	0	25.	83	1	0	1	15	PU-		.3
(2015)				8	.7				1	PEU	329	83
- Sample 1										PU-		.7
										ATT	565	02
										PEU-		.4
										ATT	349	47
										PU-BI		.6
											523	82
										PEU-		.4
										BI	327	39
										ATT-	٠	.6
										BI	462	62
Koutromanos et al.	1	Greece	0	25.	83	1	0	1	10	PU-		.1
(2015)				8	.7				6	PEU	136	55

- Sample 2]	PU-	•	.7
										ATT		625	57
]	PEU-	•	.1
										ATT		100	18
]	PU-BI	·	.5
												436	38
]	PEU-	•	.1
										BI		100	20
										1	ATT-	•	.6
										BI		514	56
Kreijns et al. (2013) ^a	1	The	1	46.	65	1	0	1	12		ATT-		.7
		Netherlands		4	.7				09	BI		750	98
										1	ATT-		.0
										SN		000	00
]	BI-SN		.1
												750	02

										ATT-		.8
										CSE	730	19
										BI-		.8
										CSE	810	99
										SN-		.0
										CSE	000	00
Kusano et al. (2013)	1	USA	0	42.	86	0	0	1	11	PU-		.7
				5	.5				1	PEU	647	08
- Sample 1										PU-		.5
										ATT	517	80
										PEU-		.6
										ATT	610	66
Kusano et al. (2013)	1	Japan	0	35.	52	0	0	1	67	PU-		.6
				7	.2					PEU	553	24
- Sample 2										PU-		.8
										ATT	747	40

										F	PEU-		.7
										ATT		674	28
Lai et al. (2013) ^a	1	Taiwan	0	-	-	1	0	1	16	F	PU-		.8
									0	PEU		749	55
										F	PU-		.5
										ATT		508	86
										F	PEU-		.3
										ATT		258	01
										I	PU-BI		.9
												872	99*
										I	PEU-		.8
										BI		743	71
										A	ATT-		.5
										BI		461	47
										F	PU-		.2
										CSE		257	96

										PEU-	٠	.4
										CSE	382	44
Lay et al. (2013)	1	Taiwan	1	38.	65	1	1	1	71	PU-		.5
				9	.8				9	PEU	593	93
										PU-	٠	.2
										USE	291	91
										PEU-		.1
										USE	112	12
Lee & Chen (2016)	1	Taiwan and	0	-	66	0	1	1	32	PU-		.4
Lee & Chen (2016)		Taiwan and Kinjiang (China)	0	-	.5	0	1	1	32 2	PEU	405	.4 05
Lee & Chen (2016)			0	-		0	1	1			405	
Lee & Chen (2016)			0	-		0	1	1		PEU		05
Lee & Chen (2016)			0	-		0	1	1		PEU PU-		05 .7
Lee & Chen (2016)			0	-		0	1	1		PEU PU- ATT	707	05 .7 07
Lee & Chen (2016)			0	-		0	1	1		PEU PU- ATT PEU-	707	05 .7 07 .4

										PEU-		.6
										CSE	610	10
										ATT-		.6
										CSE	634	34
Li et al. (2016)	0	USA	-	20.	74	0	0	1	79	PEU-	•	.4
				8	.7					ATT	380	67
										PEU-		.3
										BI	280	51
										ATT-	•	.3
										BI	320	75
										PEU-	-	.6
										CSE	560	70
										ATT-		.3
										CSE	330	69
										BI-	•	.3
										CSE	320	64

Lin et al. (2013)	1	USA	2	-	-	1	1	1	99	PU-		.2
									PE	EU	280	80
										PU-BI		.7
											740	40
										PEU-		.1
									BI		180	80
										PU-		.4
									SN	1	440	40
										PEU-		.2
									SN	1	200	00
										BI-SN		.4
											410	10
										PU-		-
									CS	SE	050	.050
										PEU-		.5
									CS	SE	500	00

												BI-		-
											CSE		100	.100
												SN-	•	.2
											CSE		240	40
												PU-		.5
											FC		540	40
												PEU-		.3
											FC		300	00
												BI-FC		.4
													480	80
												SN-		.6
											FC		650	50
												CSE-		.3
											FC		360	60
Liu (2011)	0	1	Taiwan	-	-	-	0	1	0	47		ATT-		.5
										0	BI		529	29

										ATT-	٠	.3
										CSE	308	08
										BI-		.4
										CSE	424	24
Luan & Teo (2009)	0	Malaysia	-	23.	74	0	1	1	24	PU-		.5
				4	.7				5	PEU	526	26
										PU-		.6
										ATT	681	81
										PEU-	٠	.5
										ATT	585	85
										PU-BI		.6
											654	54
										PEU-		.4
										BI	445	45
										ATT-		.6
										BI	684	84

Luan & Teo (2011)	0	Malaysia	-	23.	74	0	1	1	24	PU-		.4
				4	.7				5	PEU	490	90
										PU-		.6
										ATT	630	30
										PEU-		.5
										ATT	530	30
										PU-BI		.6
											630	30
										PEU-		.4
										BI	460	60
										ATT-		.6
										BI	620	20
Ma et al. (2005)	0	Sweden	-	32.	66	0	1	1	84	PU-		.2
				5	.5					PEU	280	80
										PU-BI		.5
											540	40

										PEU-		.1
										BI	151	51
										PU-		.0
										SN	000	00
										PEU-		.0
										SN	000	00
										BI-SN		.0
											000	00
Mac Callum et al.	1	New	2	43.	61	1	1	1	19	PU-		.0
(2014)		Zealand		8	.0				6	PEU	067	67
										PU-		.2
										PU- ATT	207	.2
										ATT	207	07
										ATT PEU-	207	07 .4

										PEU-		.0
										BI	076	76
										ATT-	٠	.0
										BI	006	06
										PU-		.0
										CSE	086	86
										PEU-		.1
										CSE	196	96
										ATT-		.3
										CSE	334	34
										BI-		.0
										CSE	012	12
Mamat et al. (2015)	0	Malaysia	-	22.	80	1	0	1	76	PU-		.8
				5	.3					PEU	740	23
										PU-BI		.8
											760	35

	PEU-		.8
BI		790	98
	PU-		.7
SN		720	83
	PEU-		.7
SN		630	08
	BI-SN		.7
		680	56
	PU-		.5
FC		510	84
	PEU-		.5
FC		430	09
	BI-FC		.5
		470	50
	SN-		.6
FC		560	48

McGill et al. (2011) ^a	1	Australia	2	46.	42	1	1	1	67	PU-		.2
				1	.2					USE	221	21
										PU-		.6
										SN	629	29
										USE-		.2
										SN	207	07
										PU-		.3
										FC	333	33
										USE-		.2
										FC	232	32
										SN-		.4
										FC	414	14
Nair & Das (2012)	1	India	1	35.	-	0	1	1	19	PU-		.6
				6					5	PEU	630	30
										PU-		.4
										ATT	429	29

									PEU-	٠	.7
									ATT	777	77
Nam et al. (2013)	1	USA	0 -	73	0	1	1	13	PU-		.4
				.0				6	PEU	420	20
									PU-BI		.7
										710	10
									PEU-		.5
									BI	550	50
									PU-	٠	.4
									CSE	420	20
									PEU-		.3
									CSE	360	60
									BI-		.5
									CSE	540	40
									PU-	٠	.3
									FC	350	50

								PEU-		.6
								FC	670	70
								BI-FC		.3
									330	30
								CSE-	٠	.3
								FC	380	80
Okazaki & dos	1	Brazil	2	 1	1	1	44	PU-	-	.6
Santos (2012)							6	PEU	610	10
								PU-		.6
								ATT	678	78
								PEU-		.5
								ATT	514	14
								PU-BI		.5
									599	99
								PEU-		.4
								BI	450	50

										ATT-	•	.8
										BI	860	60
										PU-	•	.1
										USE	119	19
										PEU-		.1
										USE	102	02
										ATT-	•	.1
										USE	193	93
										BI-	•	.2
										USE	230	30
Oshiro (2015) ^a	1	USA	0	-	-	0	0	0	11	PU-		-
									0	PEU	105	.124
										PU-B	Ι.	.8
											747	59
										PEU-		.6
										BI	582	81

										PU-		.6
										CSE	460	64
										PEU-		-
										CSE	149	.219
										BI-		.3
										CSE	267	82
										USE-		.6
										CSE	445	65
Park et al. (2007)	1	USA	2	-	-	1	0	1	19	PU-		.8
									1	PEU	660	05
										PU-	•	.3
										ATT	280	44
										PEU-		.2
										ATT	200	52
										PU-BI		.6
											580	91

										PEU-		.6
										BI	500	10
										ATT-		.0
										BI	070	86
										PU-		.2
										USE	230	75
										PEU-		.1
										USE	120	47
										ATT-		.3
										USE	250	08
										BI-		.1
										USE	140	67
Parkman (2015)	0	Abu Dhabi	-	-	-	0	0	0	88	PU-		.8
		(UAE)								PEU	661	89
										PU-		.8
										ATT	590	22

•	.7
584	89
	.9
750	99*
	.9
746	71
	.9
684	23
	.8
571	04
	.8
647	83
	.9
684	68
	.9
739	99*
	584 750 746 684 647 684

								PU-	٠	.7
								FC	523	21
								PEU-	•	.9
								FC	756	99*
								ATT-		.7
								FC	576	98
								BI-FC		.9
									739	86
								CSE-		.9
								FC	661	25
Perkmen et al. (2016)	0	Turkey	 60	0	0	1	21	PU-BI	•	.7
			.0				9		560	59
- Sample 1								PU-		.6
								CSE	510	07
								BI-		.8
								CSE	620	51

								PU-		.5
								FC	410	47
								BI-FC		.6
									430	62
								CSE-		.5
								FC	380	13
Perkmen et al. (2016)	0	Spain	 74	0	0	1	20	PU-BI		.5
			.0				9		370	00
- Sample 2								PU-		.3
								CSE	260	04
								BI-		.1
								CSE	110	51
								PU-		.6
								FC	470	07
								BI-FC		.3
									220	34

										(CSE-		.2
										FC		210	76
Perkmen et al. (2016)	0	USA	-	-	80	0	0	1	12	.]	PU-BI		.3
					.0				2			260	72
- Sample 3]	PU-		.4
										CSE		430	92
]	BI-		.3
										CSE		260	78
]	PU-		.5
										FC		430	88
]	BI-FC		.4
												280	87
										(CSE-		.3
										FC		280	90
Phua et al. (2012) ^a	1	Malaysia	1	39.	10	1	0	1	79]	PU-BI		.7
				0	0.0				9			625	25

										PEU-		.6
										BI	536	28
										ATT-	٠	.7
										BI	674	99
Pittalis & Christou	0	Cyprus	1	-	60	1	1	0	10	PU-		.5
(2010)					.0				5	PEU	538	38
										PU-		.6
										ATT	634	34
										PEU-		.8
										ATT	840	40
										PU-BI		.8
											891	91
										PEU-		.6
										BI	689	89
										ATT-		.8
										BI	815	15

Powers (2014)	1	USA	0	-	84	1	0	0	15	PU-		.7
					.5				5	PEU	701	64
										PU-		.7
										USE	588	39
										PEU-		.6
										USE	534	93
										PU-		.5
										CSE	486	76
										PEU-		.5
										CSE	435	32
										USE-		.6
										CSE	463	54
										PU-		.2
										FC	197	18
										PEU-		.3
										FC	295	37

										USE-		.0
										FC	032	42
										CSE-		.2
										FC	216	69
Pynoo et al. (2012)	1	Belgium	-	39.	70	1	0	1	91	PU-		.5
				7	.6				9	PEU	440	02
										PU-		.7
										ATT	610	04
										PEU-		.5
										ATT	480	59
										PU-BI		.7
											680	89
										PEU-		.3
										BI	330	87
										ATT-		.6
										BI	550	52

PU-		.4
USE	410	77
PEU-		.2
USE	210	47
ATT-		.4
USE	400	76
BI-		.6
USE	530	34
PU-		.2
SN	180	11
PEU-		.0
SN	060	71
ATT-		.1
SN	110	32
BI-SN		.2
	180	16

											USE-	•	.1
										SN		140	69
Sadeghi et al. (2014)	1	Iran	-	34.	37	0	0	1	27	,	PU-		.2
				7	.5				5	PEU		230	47
											PU-	•	.5
										ATT	,	460	12
											PEU-		.3
										ATT	,	350	93
											PU-BI		.4
												430	78
											PEU-		.2
										BI		190	14
											ATT-		.5
										BI		440	12
Salajan et al. (2011) ^a	1	USA	2	47.	54	1	0	0	18	}	PU-		.5
				8	.9				9	PEU		529	98

- Sample 1

PU-BI		.5
	485	49
PEU-		.4
BI	428	83
PU-		.5
USE	464	43
PEU-		.5
USE	433	06
PU-		.4
SN	354	32
PEU-		.4
SN	375	56
PU-		.3
CSE	313	53
PEU-		.5
CSE	521	87

Salajan et al. (2011) ^a	1	USA	2	47.	54	1	0	0	15	PU-		.5
				8	.9				7	PEU	538	57
- Sample 2										PU-B	Ι.	.4
											458	72
										PEU-		.4
										BI	393	07
										PU-		.4
										USE	456	66
										PEU-		.4
										USE	433	45
										PU-		.4
										SN	404	41
										PEU-		.3
										SN	322	54
										PU-		.3
										CSE	322	46

										PEU-		.6
										CSE	564	10
Salajan et al. (2015) ^a	1	USA	2	49.	56	1	0	1	17	PU-		.6
				1	.9				1	PEU	570	32
										PU-BI		.5
											455	14
										PEU-		.4
										BI	412	59
										PU-	٠	.5
										USE	522	94
										PEU-		.5
										USE	498	58
										BI-	•	.6
										USE	527	02
										PU-		.4
										SN	378	38

PEU-		.4
SN	392	48
BI-SN		.4
	418	87
USE-		.5
SN	444	21
PU-		.3
CSE	325	68
PEU-		.5
CSE	500	58
BI-		.3
CSE	337	83
USE-		.4
CSE	427	89
PU-		.7
FC	632	00

										PEU-		.6
										FC	600	54
										BI-FC		.5
											496	52
										USE-		.5
										FC	517	79
Sánchez-Gómez et al.	1	Spain	2	46.	44	1	1	0	50	PU-		.2
(2016)				7	.1				1	PEU	200	00
										PU-BI		.5
											585	85
										PEU-		.2
										BI	237	37
										PU-		.5
										SN	580	80
										PEU-		.1
										SN	116	16

BI-SN		.3
	325	25
PU-		.8
CSE	840	40
PEU-		.1
CSE	168	68
BI-		.4
CSE	470	70
SN-		.6
CSE	690	90
PU-		.0
FC	096	96
PEU-		.4
FC	480	80
BI-FC		.3
	314	14

										SN-	٠	.0
										FC	000	00
										CSE-		.0
										FC	000	00
Sánchez-Prieto et al.	0	Spain	-	21.	65	1	1	1	67	PU-		.3
(2017)				1	.2				8	PEU	361	61
										PU-BI		.7
											716	16
										PEU-		.3
										BI	340	40
										PU-		.4
										CSE	416	16
										PEU-		.5
										CSE	537	37
										BI-		.4
										CSE	477	77

Shiue (2007)	1	Taiwan	1	32.	61	0	0	1	24	PU-		.6
				2	.2				2	PEU	620	97
										PU-		.8
										ATT	710	40
										PEU-		.6
										ATT	550	22
										PU-BI		.8
											660	05
										PEU-		.6
										BI	560	53
										ATT-		.9
										BI	840	99*
										PU-		.8
										USE	720	68
										PEU-		.8
										USE	720	30

ATT-		.9
USE	750	09
BI-		.9
USE	770	63
PU-		.4
SN	300	17
PEU-		.3
SN	270	58
ATT-		.2
SN	200	79
BI-SN		.2
	140	02
USE-		.3
SN	250	56
PU-		.5
CSE	450	09

PEU-		.8
CSE	820	86
ATT-		.4
CSE	390	44
BI-		.5
CSE	470	51
USE-		.6
CSE	590	83
SN-		.3
511-	•	.3
CSE	290	87
CSE		87
CSE PU-	290	87 .1
CSE PU- FC	290	87 .1 43
CSE PU- FC PEU-	290 120	87 .1 43 .2

										BI-FC		.1
											090	11
										USE-		.1
										FC	150	83
										SN-	•	.5
										FC	360	06
										CSE-	•	.0
										FC	070	80
Shroff et al. (2013)	0	Hong Kong	-	-	-	1	1	1	77	PU-	•	.2
		(China)								PEU	220	20
										PU-		.1
										ATT	190	90
										PEU-	٠	.2
										ATT	280	80
Smith & Sivo (2012)	1	USA	0	40.	84	1	1	1	51	PU-		.6
				0	.0				7	PEU	680	80

										PU-BI		.6
											650	50
										PEU-		.6
										BI	630	30
Smith (2014)	0	USA	-	22.	75	1	0	0	23	PU-		.1
				3	.0				5	PEU	120	37
										PU-	•	.6
										ATT	600	63
										PEU-	•	.4
										ATT	400	63
Stols & Kriek (2011) ^a	1	South	1	45.	45	1	0	1	22	PU-		.9
		Africa		5	.5					ATT	889	99*
										PEU-		.9
										ATT	781	10
										PU-BI		.6
											551	39

										PEU-		.7
										BI	677	93
										ATT-		.6
										BI	551	53
										ATT-		.2
										SN	233	79
Sumak & Sorgo	1	Slovenia	0	44.	75	1	1	1	43	PU-		.4
(2016)				7	.6				8	PEU	449	49
- Sample 1										PU-		.7
										ATT	791	91
										PEU-		.5
										ATT	509	09
										PU-BI		.3
											362	62
										PEU-		.2
										BI	217	17

ATT-	•	.4
BI	412	12
PU-		.7
USE	781	81
PEU-		.5
USE	524	24
ATT-		.8
USE	852	52
BI-		.3
BI- USE	374	.3 74
USE		74
USE PU-	374	74 .4
USE PU- SN	374	74 .4 10
USE PU- SN PEU-	374 410	74 .4 10 .1

	BI-SN	•	.4
		437	37
	USE-		.3
SN		373	73
	PU-		.5
FC		534	34
	PEU-	٠	.7
FC		766	66
	ATT-	•	.5
FC		599	99
	BI-FC		.3
		355	55
	USE-		.6
FC		608	08
	SN-	٠	.3
FC		366	66

	Sumak & Sorgo	1	Slovenia	0	44.	83	1	1	1	46	PU-		.3
(20	16)				5	.5				0	PEU	392	92
	- Sample 2										PU-		.6
											ATT	682	82
											PEU-		.4
											ATT	446	46
											PU-BI	•	.3
												327	27
											PEU-		.1
											BI	188	88
											ATT-	•	.4
											BI	442	42
											PU-		.5
											USE	517	17
											PEU-		.4
											USE	437	37

ATT-		.5
USE	554	54
BI-		.5
USE	538	38
PU-		.2
SN	235	35
PEU-		.1
SN	142	42
ATT-		.2
SN	236	36
BI-SN		.1
	175	75
USE-		.2
SN	261	61
PU-		.3
FC	386	86

										PEU-		.7
										FC	774	74
										ATT-		.3
										FC	397	97
										BI-FC		.3
											307	07
										USE-		.6
										FC	634	34
										SN-		.2
										FC	265	65
Teo, Fan, & Du	0	Asian	0	28.	0.	0	1	1	16	PU-	·	.6
(2015)		country		5	0				9	PEU	680	80
- Sample 1										PU-	•	.6
										ATT	680	80
										PEU-	٠	.7
										ATT	730	30

										PU-BI		.3
											340	40
										PEU-		.3
										BI	300	00
										ATT-		.3
										BI	300	00
Teo, Fan, & Du	0	Asian	0	28.	10	0	1	1	17	PU-		.4
(2015)		country		5	0.0				0	PEU	400	00
- Sample 2										PU-		.5
										ATT	560	60
										PEU-		.4
										ATT	430	30
										PU-BI		.2
											230	30
										PEU-		.3
										BI	320	20

								ATT-		.3
								BI	360	60
Teo & Khlaisang et	0	Thailand	 76	0	0	1	96	PU-		.0
al. (2014)			.4				9	PEU	020	22
								PU-		.0
								ATT	039	45
								PEU-		.0
								ATT	045	52
								PU-		.0
								SN	047	55
								PEU-		.0
								SN	054	64
								ATT-		.1
								SN	108	29
								PU-		.0
								CSE	013	15

PEU-		.0
CSE	015	17
ATT-		.0
CSE	030	35
SN-		.0
CSE	036	43
PU-		.0
FC	005	06
PEU-		.0
FC	006	07
ATT-		.0
FC	012	14
SN-		.0
FC	014	17
CSE-		.0
FC	004	05

	Teo, Lee, & Chai	0	Singapore -	25.	63	0	0	1	23	PU-		.6
(20	08)			6	.6				9	PEU	530	28
										PU-		.7
										ATT	610	05
										PEU-		.5
										ATT	490	98
										PU-		.4
										SN	380	50
										PEU-		.3
										SN	270	38
										ATT-		.4
										SN	380	64
										PU-		.1
										FC	160	90
										PEU-		.3
										FC	300	75

											ATT-	٠	.3
											FC	270	29
											SN-		.3
											FC	300	75
	Teo, Lee, Chai, &	0	Singapore	-	24.	70	0	1	1	25	PU-		.3
Wo	ong (2009)				0	.0				0	PEU	360	60
	- Sample 1										PU-		.5
											ATT	570	70
											PEU-		.4
											ATT	480	80
											PU-BI		.1
												160	60
											PEU-		.1
											BI	170	70
											ATT-		.1
											BI	130	30

	Teo, Lee, Chai, &	0	Malaysia	-	23.	74	0	1	1	24	PU-		.4
Wo	ng (2009)				4	.7				5	PEU	440	40
	- Sample 2										PU-	•	.6
											ATT	630	30
											PEU-		.4
											ATT	470	70
											PU-BI		.6
												630	30
											PEU-		.4
											BI	410	10
											ATT-		.6
											BI	620	20
	Teo, Lee, Chai, &	0	Singapore	1	26.	67	1	1	1	48	PU-		.6
Che	oi (2009) ^a				2	.9				3	CSE	610	10
											PU-		.3
											FC	340	40

										CSE-		.4
										FC	460	60
Teo, Wong, & Chai	0	Malaysia	- :	23.	72	0	1	1	49	PU-		.4
(2008)		and Singapore	7		.3				5	PEU	440	40
										PU-		.6
										ATT	620	20
										PEU-		.5
										ATT	510	10
										PU-BI		.4
											430	30
										PEU-		.2
										BI	290	90
										ATT-		.3
										BI	360	60
Teo & Milutinović	0	Serbia	- :	22.	88	1	1	1	31	PU-		.2
(2015)			4		.5				3	PEU	279	79

PU-		.6
ATT	630	30
PEU-		.8
ATT	873	73
PU-BI		.3
	319	19
PEU-		.4
BI	441	41
ATT-		.5
BI	505	05
PU-		.2
SN	265	65
PEU-		.0
SN	093	93
ATT-		.0
SN	002	02

BI-SN		.0
	064	64
PU-		.1
CSE	107	07
PEU-		.2
CSE	297	97
ATT-		.2
CSE	222	22
BI-		.1
CSE	116	16
SN-		.0
SN- CSE	. 087	.0 87
	. 087	
CSE	087	87
CSE PU-		87 .1

										ATT-	•	.0
										FC	012	12
										BI-FC		.0
											031	31
										SN-		.0
										FC	053	53
										CSE-		.0
										FC	079	79
	0	Serbia	0	22.	88	0	0	1	22	PU-		.3
Teo et al. (2017)				5	.1				6	PEU	260	17
- Sample 1										PU-	٠	.6
										ATT	549	75
										PEU-	٠	.6
										ATT	497	41
										PU-BI		.2
											192	37

										PEU-		.3
										BI	265	44
										ATT-		.3
										BI	249	25
	0	Serbia	0	22.	88	0	0	1	22	PU-		.3
Teo et al. (2017)				5	.1				6	PEU	260	17
- Sample 2										PU-		.6
										ATT	551	77
										PEU-		.6
										ATT	507	54
										PU-BI		.2
											176	18
										PEU-		.1
										BI	101	31
										ATT-		.3
										BI	257	36

Teo & Noyes (2010)	0	Singapore	-	27.	51	0	1	1	15	PU-		.4
				0	.0				0	PEU	450	50
- Sample 1										PU-	٠	.6
										ATT	610	10
										PEU-		.4
										ATT	410	10
Teo & Noyes (2010)	0	UK	-	28.	63	0	1	1	14	PU-		.3
				2	.7				6	PEU	310	10
- Sample 2										PU-		.3
										ATT	380	80
										PEU-		.3
										ATT	350	50
Teo & Noyes (2011)	0	Singapore	-	26.	56	0	1	1	15	PU-		.5
				2	.9				3	PEU	540	40
										PU-		.4
										ATT	460	60

										PEU-		.4
										ATT	440	40
										PU-BI		.3
											350	50
										PEU-		.2
										BI	220	20
										ATT-		.2
										BI	210	10
Teo & Noyes (2014)	0	Singapore	-	26.	58	0	1	1	26	PU-		.5
Teo & Noyes (2014)	0	Singapore	-	26. 1	.0	0	1	1	26 4	PU- PEU	550	.5 50
Teo & Noyes (2014)	0	Singapore	-			0	1	1			550	
Teo & Noyes (2014)	0	Singapore	-			0	1	1		PEU	550	50
Teo & Noyes (2014)	0	Singapore	-			0	1	1		PEU	550	50
Teo & Noyes (2014)	0	Singapore	-			0	1	1		PEU PU-BI	550	50 .5 80
Teo & Noyes (2014)	0	Singapore	-			0	1	1		PEU PU-BI PEU-	550 580	50 .5 80 .4
Teo & Noyes (2014)	0	Singapore	-			0	1	1		PEU PU-BI PEU- BI	550 580	50 .5 80 .4 00

										PEU-	•	.4
										SN	430	30
										BI-SN		.3
											390	90
										PU-		.2
										FC	260	60
										PEU-	٠	.3
										FC	350	50
										BI-FC	٠	.2
											210	10
										SN-		.3
										FC	320	20
Teo, Ruangrit et al.	0	Thailand	-	20.	72	1	1	1	19	PU-	٠	.2
(2014) ^a				4	.9				81	CSE	207	07
										PU-	٠	.7
										FC	735	35

											CSE-	•	.1
											FC	185	85
	Teo & Tan (2012)	0	Singapore	-	24.	50	0	1	1	29	PEU-		.3
					8	.0				3	ATT	350	50
											PEU-		.3
											BI	370	70
											ATT-		.6
											BI	620	20
											PEU-		.2
											SN	200	00
											ATT-		.3
											SN	360	60
											BI-SN		.3
												370	70
	Teo, Ursavaş et al.	0	Turkey	0	19.	55	0	1	1	19	PU-		.3
(2	2011)				4	.8				7	PEU	300	00

										PU-		.6
										ATT	660	60
										PEU-	•	.5
										ATT	520	20
										PU-BI		.5
											570	70
										PEU-		.2
										BI	260	60
										ATT-		.5
										BI	500	00
Teo, Ursavaş et al.	0	Turkey	-	19.	58	0	1	1	48	PU-		.3
(2012)				4	.3				7	PEU	307	07
										PU-		.6
										ATT	632	32
										PEU-		.4
										ATT	462	62

PU-BI		.5
	586	86
PEU-		.2
BI	283	83
ATT-	٠	.4
BI	446	46
PU-	٠	.3
CSE	392	92
PEU-	٠	.2
CSE	284	84
ATT-		.3
CSE	301	01
BI-	٠	.4
CSE	427	27
PU-		.2
FC	255	55

									PEU-		.3
									FC	357	57
									ATT-		.2
									FC	224	24
									BI-FC		.3
										324	24
									CSE-		.3
									FC	358	58
Teo & van Schaik	0	Singapore -	23.	-	0	1	1	42	PU-		.5
(2012)			7					9	PEU	530	30
									PU-		.6
									ATT	630	30
									PEU-		.6
									ATT	650	50
									PU-BI	٠	.5
										570	70

PEU		.5
BI	510	10
ATT	·	.6
BI	690	90
PU-		.3
SN	380	80
PEU		.3
SN	350	50
ATT	· - .	.3
SN	370	70
BI-S	N .	.3
	370	70
PU-		.4
CSE	480	80
PEU		.8
CSE	850	50

ATT-		.6
CSE	600	00
BI-		.4
CSE	450	50
SN-		.2
CSE	290	90
PU-		.3
FC	320	20
PEU-		.5
FC	520	20
ATT-		.3
FC	360	60
BI-FC		.3
	310	10
SN-		.3
FC	340	40

									CSE-	•	.4
									FC	430	30
Teo & Wong (2013)	0	Singapore	- 24.	-	1	1	1	38	PU-		.8
			0					7	PEU	810	10
									PU-		.6
									FC	630	30
									PEU-	٠	.7
									FC	700	00
Teo & Zhou (2014)	0	Singapore	- 24.	64	0	1	1	31	PU-	•	.5
100 & 21104 (2011)	O	Singapore	21.						1.0	•	
100 & 2000 (2011)	V	Singapore	8	.6				4	PEU	517	17
100 & 200 (2011)	V	Singapore									
700 & 2nou (2011)	v	Singapore							PEU	517	17
	v	Singapore							PEU PU-	517	17 .6
	v	Singapore							PEU PU- ATT	517	.6 00
	v	Singapore							PEU PU- ATT PEU-	517 600	17 .6 00 .5

										PEU-		.4
										BI	405	05
										ATT-		.6
										BI	687	87
Teo, Zhou, & Noyes	1	Singapore	0	35.	76	0	1	1	59	PU-		.6
(2016)				0	.4				2	PEU	610	10
										PU-		.6
										ATT	630	30
										PEU-		.6
										ATT	670	70
										PU-BI		.6
											640	40
										PEU-		.5
										BI	590	90
										ATT-		.7
										BI	750	50

	PU-		.2
SN		200	00
	PEU-		.1
SN		110	10
	ATT-		.2
SN		220	20
	BI-SN		.2
		200	00
	PU-		.4
FC	PU-	430	.4
FC	PU- PEU-		
FC FC			30
		430	30
	PEU-	430	30 .4 20
FC	PEU-	430 . 420	30 .4 20 .5

										SN-		.1
										FC	140	40
Teo (2008) ^a	0	Singapore	0	24.	60	0	1	1	13	PU-		.3
				2	.4				9	PEU	310	10
										PU-		.2
										ATT	230	30
										PEU-		.6
										ATT	610	10
										PU-BI		.2
											280	80
										PEU-		.5
										BI	530	30
										ATT-		.5
										BI	530	30
										PU-		-
										USE	082	.082

PEU-	٠	.1
USE	195	95
ATT-		.2
USE	209	09
BI-		.2
USE	200	00
PU-		.2
CSE	248	48
PEU-		.5
CSE	507	07
ATT-		.3
CSE	314	14
BI-		.1
CSE	159	59
USE-		.2
CSE	230	30

Teo (2009b)	0	Singapore	0	23.	73	0	1	1	47	PU-		.4
				2	.9				5	PEU	440	40
										PU-	•	.6
										ATT	610	10
										PEU-		.4
										ATT	490	90
										PU-BI	٠	.4
											410	10
										PEU-		.3
										BI	300	00
										ATT-	٠	.4
										BI	400	00
										PU-	٠	.0
										CSE	090	90
										PEU-	•	-
										CSE	030	.030

											ATT-		.0
										CSI	Е	070	70
											BI-	•	.1
										CSI	Е	160	60
											PU-		.1
										FC		100	00
											PEU-		.2
										FC		250	50
											ATT-		.2
										FC		270	70
											BI-FC		.0
												050	50
											CSE-		-
										FC		070	.070
Teo (2009a)	0	Singapore	1	25.	63	0	1	1	28	3	PU-		.5
				6	.5				5	PEU	J	558	58

PU-		.7
ATT	748	48
PEU-		.5
ATT	547	47
PU-		.4
SN	469	69
PEU-		.3
SN	351	51
ATT-		.4
SN	487	87
PU-		.1
FC	131	31
PEU-		.2
FC	286	86
ATT-		.2
FC	270	70

										SN-		.2
										FC	261	61
Teo (2010b)	0	Singapore	1	27.	57	0	1	1	15	PU-	•	.4
				1	.3				7	PEU	470	70
										PU-		.4
										SN	480	80
										PEU-		.3
										SN	380	80
										PU-		.2
										FC	240	40
										PEU-		.2
										FC	290	90
										SN-		.3
										FC	380	80
Teo (2010e)	0	Malaysia	-	21.	68	0	1	1	19	PU-		.4
				7	.9				3	PEU	460	60

	.5
550	50
	.5
570	70
	.2
250	50
	.2
270	70
	.4
410	10
	.3
310	10
	.4
480	80
	.5
520	20
	550 570 250 270 410 480

										SN-		.2
										FC	270	70
Teo (2010a)	0	Singapore	-	24.	64	0	1	1	31	PU-		.6
				8	.9				3	PEU	650	50
										PU-		.6
										ATT	620	20
										PEU-		.5
										ATT	570	70
										PU-		.4
										SN	450	50
										PEU-		.4
										SN	400	00
										ATT-		.4
										SN	400	00
										PU-		.2
										FC	270	70

											PEU-		.3
										FC		320	20
											ATT-		.3
										FC		350	50
											SN-		.3
										FC		360	60
Teo (2010c)	0	Singapore	-	25.	63	0	0	1	23	3	PU-		.6
				6	.6				9	PE	U	560	48
											PU-		.7
										AT	T	650	39
											PEU-	٠	.6
										AT	T	550	43
											PU-	٠	.4
										SN	ſ	380	50
											PEU-		.3
										SN		270	29

											ATT-		.4
										SN		380	55
											PU-		.1
										FC		160	90
											PEU-		.3
										FC		270	29
											ATT-		.3
										FC		250	00
											SN-		.3
										FC		300	75
Teo (2010d)	0	Singapore	-	24.	-	1	1	1	38	3	PU-		.8
				0					7	PE	U	810	10
											PU-		.4
										FC		416	16
											PEU-		.6
										FC		649	49

Teo (2011)	1	Singapore	0	35.	76	0	1	1	59	PU-		.6
				3	.4				2	PEU	610	10
										PU-		.6
										ATT	600	00
										PEU-		.6
										ATT	640	40
										PU-BI		.6
											620	20
										PEU-		.5
										BI	590	90
										ATT-		.7
										BI	710	10
										PU-		.1
										SN	190	90
										PEU-		.1
										SN	110	10

											ATT-		.2
										SN		210	10
											BI-SN		.2
												200	00
											PU-		.3
										FC		390	90
											PEU-		.3
										FC		390	90
											ATT-		.4
										FC		470	70
											BI-FC		.4
												480	80
											SN-		.1
										FC		120	20
Teo (2012b)	0	Singapore	-	25.	63	0	1	1	23		PU-		.5
				6	.5				0	PEU	J	560	60

PU-		.6
ATT	620	20
PEU-		.5
ATT	550	50
PU-		.3
SN	390	90
PEU-		.2
SN	290	90
ATT-		.3
SN	380	80
PU-		.1
FC	170	70
PEU-		.2
FC	280	80
ATT-		.2
FC	230	30

										SN-		.3
										FC	320	20
Teo (2012a)	0	Singapore	-	22.	72	0	1	1	15	PU-		.5
				4	.0				7	PEU	540	40
										PU-		.6
										ATT	640	40
										PEU-		.5
										ATT	560	60
										PU-BI		.5
											540	40
										PEU-		.3
										BI	380	80
										ATT-		.6
										BI	610	10
										PU-		.4
										SN	440	40

	PEU-		.3
SN		380	80
	ATT-		.4
SN		420	20
	BI-SN		.3
		390	90
	PU-		.3
FC		310	10
	PEU-		.3
FC		380	80
	ATT-		.3
FC		350	50
	BI-FC		.2
		250	50
	SN-		.3
FC		320	20

Teo (2013)	1	Singapore	0	35.	-	0	1	1	38	PU-		.6
				0					5	PEU	640	40
										PU-		.6
										ATT	650	50
										PEU-		.6
										ATT	650	50
										PU-BI		.6
											610	10
										PEU-		.6
										BI	650	50
										ATT-		.7
										BI	750	50
										PU-		.1
										SN	110	10
										PEU-		.1
										SN	150	50

									ATT-	•	.2
								Sì	1	220	20
									BI-SN		.2
										220	20
									PU-		.4
								FC		410	10
									PEU-		.4
								FC		460	60
									ATT-		.5
								FC		590	90
									BI-FC		.5
										530	30
									SN-		.1
								FC	2	150	50
Tokel & Isler (2015)	0	Turkey	- 22.	26	1	0	1	46	PU-		.4
			0	.1				PI	EU	330	02

										PU-		7
										ATT	630	83
										PEU-		6
										ATT	500	14
										PU-BI		9
											738	3 23
										PEU-		3
										BI	311	84
										ATT-		6
										BI	527	63
Ulrich (2009) ^a	1	USA	2	-	-	1	1	0	28	B PU-		6
									5	PEU	640	40
										ATT-		4
										BI	470	70
										ATT-		1
										USE	170	70

									BI-		.2
									USE	220	20
Waheed (2010)	1	Pakistan	2 -	-	1	0	0	93	PU-	٠	.7
									PEU	590	72
									PU-BI		.7
										620	47
									PEU-		.8
									BI	680	59
									PU-		.7
									CSE	610	88
									PEU-	٠	.6
									CSE	450	09
									BI-	٠	.6
									CSE	560	99
									PU-	•	.1
									FC	160	95

										PEU-		.5
										FC	440	62
										BI-FC		.4
											380	47
										CSE-		.2
										FC	200	52
Wang & Wang	1	Taiwan	2	45.	22	1	1	1	26	PU-		.4
(2009)				0	.0				8	PEU	482	82
										PU-BI		.2
											284	84
										PEU-		.4
										BI	429	29
										PU-		.3
										SN	305	05
										PEU-		.3
										SN	393	93

BI-SN		.4
	419	19
PU-		.3
CSE	364	64
PEU-		.2
CSE	271	71
BI-		.2
CSE	276	76
SN-		.4
CSE	425	25
PU-		.3
FC	378	78
PEU-		.3
FC	340	40
BI-FC		.2
	207	07

										SN-		.2
										FC	277	77
										CSE-		.2
										FC	292	92
Watts (2009)	1	USA	-	38.	83	0	0	0	24	PU-		.2
				5	.3				7	PEU	205	40
										PU-	٠	.4
										USE	359	30
										PEU-	٠	.4
										USE	392	78
										PU-		.3
										CSE	351	94
										PEU-		.4
										CSE	363	15
										USE-		.6
										CSE	576	75

	0	Malaysia	-	22.	64	0	0	1	30	PU-		.7
Wong et al. (2012)				9	.2				2	PEU	650	08
										PU-		.5
										ATT	510	80
										PEU-		.3
										ATT	350	77
										PU-BI		.5
											500	81
										PEU-		.4
										BI	410	52
										ATT-		.4
										BI	420	83
										PU-		.5
										CSE	520	84
										PEU-		.5
										CSE	470	00

										ATT-		.6
										CSE	570	33
										BI-		.4
										CSE	410	66
Wong, Teo, & Russo	0	Australia	0	19.	98	1	1	1	15	PU-	•	.1
(2013)				5	.1				9	PEU	110	10
										PU-BI		.4
											470	70
										PEU-		.2
										BI	290	90
										PU-		.1
										SN	150	50
										PEU-		.0
										SN	070	70
										BI-SN		.1
											150	50

									PU-		.0
									FC	070	70
									PEU-		.2
									FC	220	20
									BI-FC		.1
										130	30
									SN-		.1
									FC	100	00
	0	Malaysia	0 -	98	1	1	1	14	PU-		.0
		and Macau		.0				9	PEU	065	65
Wong et al. (2014)		(China)									
									PU-		.1
									SN	162	62
									PEU-		.0
									SN	046	46
									PU-		.3
									CSE	362	62

												PEU-		.1
											CSE		177	77
												SN-	•	.1
											CSE		174	74
												PU-	•	.0
											FC		078	78
												PEU-	•	.2
											FC		215	15
												SN-	•	.1
											FC		105	05
												CSE-		.1
											FC		118	18
Wong (2015)	0	Hong Kong	0	25.	69	C)	1	1	23		PU-		.5
		(China)		6	.7					4	PEU		500	00
												PU-		.6
											ATT		640	40

	PEU-		.5
AT	Γ	550	50
	PU-BI		.5
		550	50
	PEU-		.4
BI		480	80
	ATT-		.5
BI		590	90
	PU-		.4
SN		410	10
	PEU-		.3
SN		300	00
	ATT-		.3
SN		340	40
	BI-SN		.3
		310	10

PU-		.3
CSE	390	90
PEU-		.4
CSE	450	50
ATT-		.4
CSE	400	00
BI-		.3
CSE	300	00
SN-		.3
SN- CSE	300	.3
CSE		00
CSE PU-	300	.3
CSE PU- FC	300	00 .3 90
CSE PU- FC PEU-	300 390	00 .3 90 .5

										BI-FC		.3
											390	90
										SN-		.3
										FC	390	90
										CSE-		.5
										FC	520	20
Wong, Osman et al.	0	Malaysia	-	23.	64	0	1	1	30	PU-		.6
(2013)				4	.2				2	PEU	649	49
										PU-		.5
										ATT	525	25
										PEU-		.4
										ATT	408	08
										PU-BI		.5
											521	21
										PEU-		.4
										BI	406	06

									ATT-		.4
									BI	418	18
Wong et al. (2015)	0	Australia	0	- 98	1	0	1	15	PU-		.0
				.1				6	PEU	060	77
									PU-BI		.5
										430	81
									PEU-		.3
									BI	280	97
									PU-		.2
									SN	160	18
									PEU-		.6
									SN	460	59
									BI-SN		.2
										150	25
									PU-		.3
									CSE	330	69

PEU-		.5
CSE	460	40
BI-		.9
CSE	800	84
SN-		.1
CSE	160	99
PU-		.0
FC	080	96
PEU-		.2
FC	220	78
BI-FC		.1
	130	72
SN-		.1
FC	110	47
CSE-		.1
FC	170	86

Wong (2016)	1	Hong Kong	0	42.	73	0	1	1	18	PU-		.4
		(China)		1	.0				5	PEU	410	10
										PU-		.5
										ATT	540	40
										PEU-		.5
										ATT	510	10
										PU-BI		.4
											400	00
										PEU-		.4
										BI	430	30
										ATT-		.5
										BI	540	40
										PU-		.4
										FC	430	30
										PEU-		.5
										FC	560	60

									ATT-		.4
									FC	440	40
									BI-FC		.5
										500	00
Wu, Chang, & Guo	1	Taiwan	1	- 35	0	1	1	22	PU-		.3
(2008)				.0				6	PEU	383	83
									PU-BI	•	.7
										702	02
									PEU-	•	.4
									BI	415	15
									PU-		.4
									CSE	456	56
									PEU-		.5
									CSE	578	78
									BI-	-	.6
									CSE	636	36

Wu & Liu (2015)	1	Taiwan	0	-	80	1	0	1	34	PU-		.5
					.6				0	PEU	467	34
										PU-		.7
										ATT	634	33
										PEU-	•	.6
										ATT	610	74
										PU-BI		.6
											562	26
										PEU-		.5
										BI	494	27
										ATT-		.7
										BI	681	34
Wu et al. (2016)	1	Shanghai	2	-	52	0	0	1	14	PU-		.1
		(China)			.8				4	PEU	110	32
										PU-		.9
										ATT	750	44

									PEU-	•	.1
									ATT	110	38
									PU-B	Ι.	.7
										620	97
									PEU-		.2
									BI	200	55
									ATT-		.9
									BI	670	00
Yeni & Gecu-	0	Turkey	0 -	- 59	0	0	1	20	PU-		.4
Yeni & Gecu- Parmaksiz (2016)	0	Turkey	0 -	.0	0	0	1	20 8	PU- PEU	414	.4 61
	0	Turkey	0 -		0	0	1			414	
	0	Turkey	0 -		0	0	1		PEU	414	61
	0	Turkey	0 -		0	0	1		PEU	414 I . 591	61 .6
	0	Turkey	0 -		0	0	1		PEU PU-B	414 I . 591	61 .6 36
	0	Turkey	0 -		0	0	1		PEU PU-BI	414 I . 591	61 .6 36 .1

										PEU-		.2
										SN	230	75
										BI-SN		.6
											595	89
Yeung et al. (2012) ^a	0	Singapore	1	30.	66	0	1	1	32	PU-	•	.2
				0	.3				3	USE	230	30
										PU-		.7
										CSE	760	60
										USE-		.3
										CSE	340	40
Yuen & Ma (2002)	0	Hong Kong	-	23.	75	0	1	1	18	PU-		.5
		(China)		6	.1				6	PEU	580	80
										PU-BI		.4
											430	30
										PEU-		.2
										BI	249	49

											PU-		.5
										US	E	522	22
											PEU-	٠	.3
										US	E	303	03
											BI-		.4
										US	Е	493	93
Yuen & Ma (2008)	1	Hong Kong	. 3	1.	59	1	0	1	15	;	PU-		.5
		(China)	9		.2				2	PE	U	414	06
											PU-BI		.1
												086	21
											PEU-	•	.5
										BI		390	79
											PU-	•	.8
										SN		619	02
											PEU-	٠	.4
										SN		360	94

											BI-SN		.2
												140	20
											PU-		.0
										CS	Е	066	76
											PEU-		.3
										CS	Е	300	66
											BI-	•	.1
										CS	Е	117	64
											SN-		.0
										CS	Е	000	00
Yusop (2015)	0	Malaysia	0	23.	79	1	0	1	10)	PU-	•	.6
				0	.0				0	AT	T	517	72
											PU-BI		.8
												703	67
											ATT-		.6
										BI		492	44

										PU-		.7
										USE	621	82
										ATT-		.6
										USE	519	94
										BI-		.7
										USE	624	92
										PU-		.8
										SN	750	79
										ATT-		.8
										SN	719	94
										BI-SN		.8
											710	38
										USE-		.7
										SN	604	28
Zhang & Xu (2011)	1	USA	2	-	38	0	0	1	68	PU-		.6
					.2					PEU	630	60

										PU-BI		.8
											730	03
										PEU-		.6
										BI	630	97
	1	Macau	1	31.	46	1	1	1	19	ATT-		.2
Zhou et al. (2016)		(China)		9	.3				0	BI	285	85
										ATT-		.2
										SN	213	13
										BI-SN		.2
											214	14
										ATT-		.5
										CSE	584	84
										BI-		.2
										CSE	273	73
										SN-		.0
										CSE	000	00

Note. * The correction for unreliability resulted in a correlation of 1. To achieve positive definiteness of the correlation matris, this

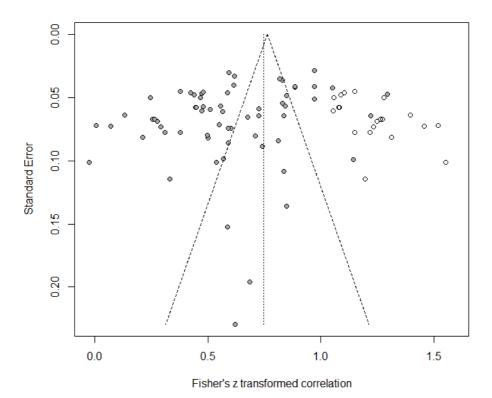
correlation has been constrained to 0.999. a: These correlation matrices were excluded from the meta-analysis due to non-positive definiteness.

S3. Assessment of publication bias

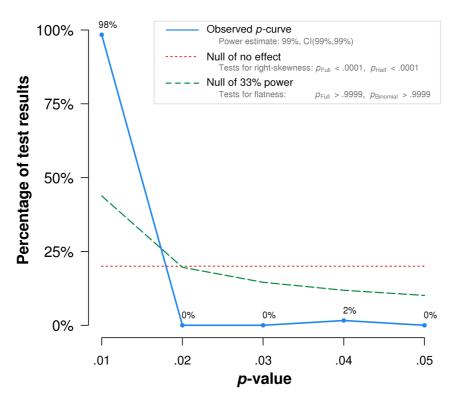
This meta-analysis is based on correlation matrices extracted from primary studies of teachers' technology acceptance. These matrices comprise a set of correlations among TAM variables which might be prone to publication bias. As traditional methods to assess publication bias have not yet been conceptualized for correlation matrices, we present their application to single correlations, treating them as independent. This analysis of publication bias is based on random-effects models with inverse variance weighting for single correlations. In the main text, however, we examine publication bias of correlation matrices using subgroup analyses. The following results comprise funnel plots (with trim and fill) and the *P*-curves for each correlation. *P*-curves were created using the *P*-curve App (Simonsohn, Nelson, & Simmons, 2017).

ATT-BI correlation

Funnel plot (with trim and fill)



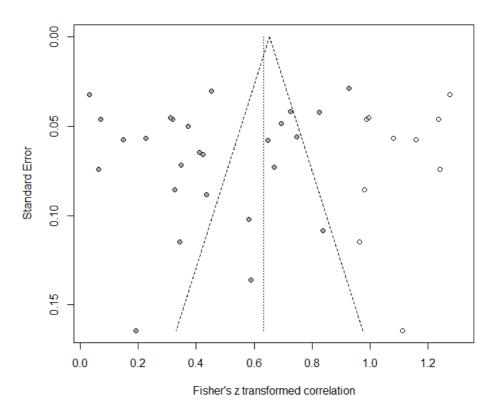
P-Curve



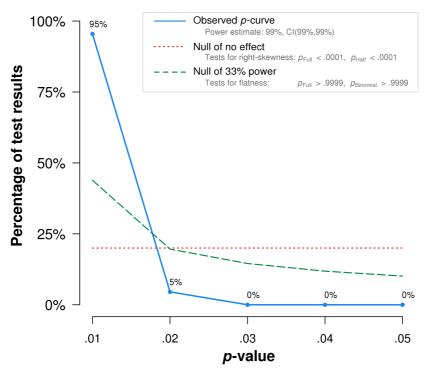
Note: The observed p-curve includes 62 statistically significant (p < .05) results, of which 61 are p < .025. There were 3 additional results entered but excluded from p-curve because they were p > .05.

ATT-CSE correlation

Funnel plot (with trim and fill)



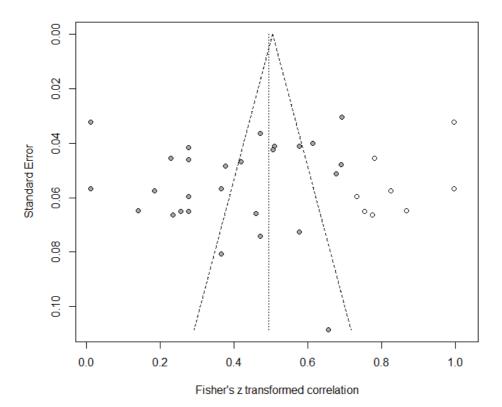
P-Curve

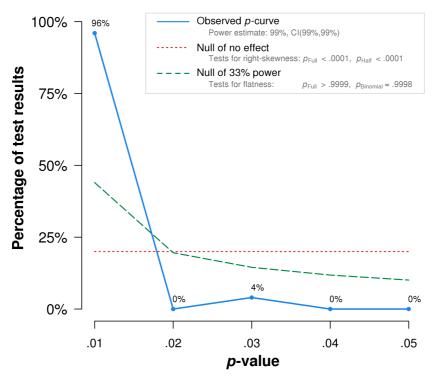


Note: The observed p-curve includes 22 statistically significant (p < .05) results, of which 22 are p < .025. There were 4 additional results entered but excluded from p-curve because they were p > .05.

ATT-FC correlation

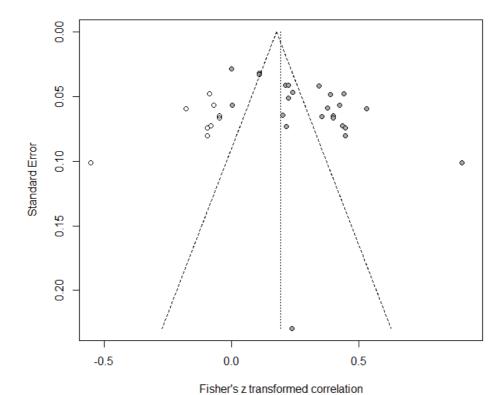
Funnel plot (with trim and fill)

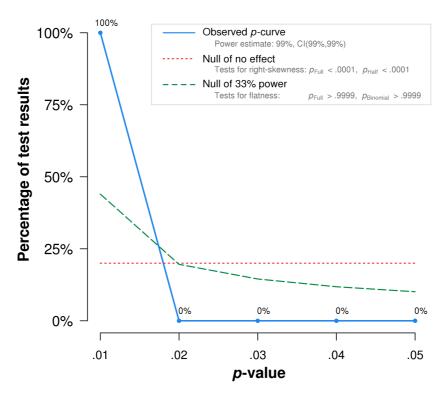




Note: The observed p-curve includes 25 statistically significant (p < .05) results, of which 24 are p < .025. There were 2 additional results entered but excluded from p-curve because they were p > .05.

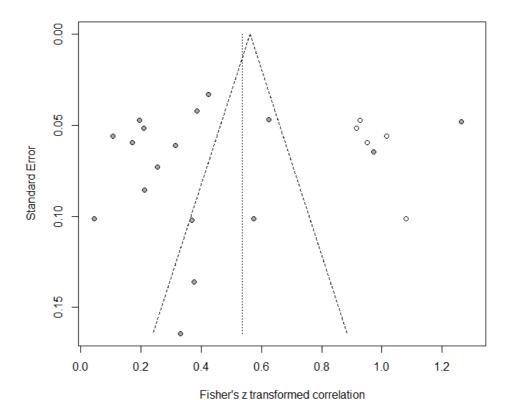
ATT-SN correlation

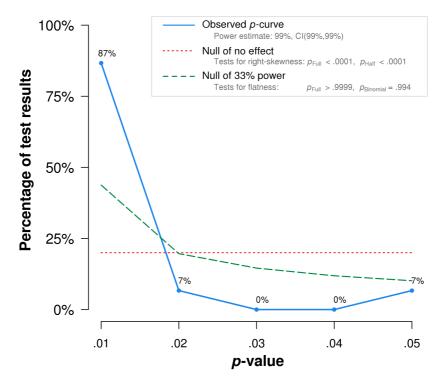




Note: The observed p-curve includes 22 statistically significant (p < .05) results, of which 22 are p < .025. There were 3 additional results entered but excluded from p-curve because they were p > .05.

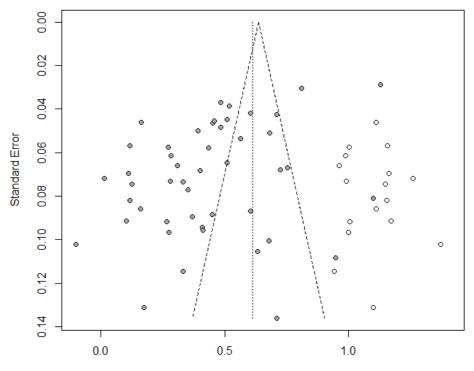
ATT-USE correlation



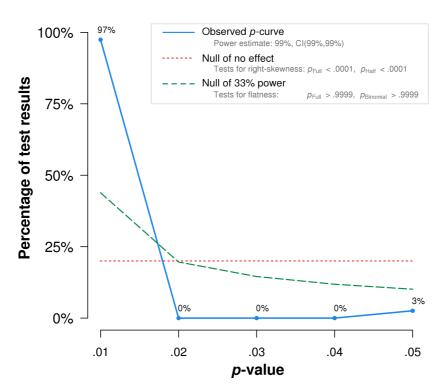


Note: The observed p-curve includes 15 statistically significant (p < .05) results, of which 14 are p < .025. There were 2 additional results entered but excluded from p-curve because they were p > .05.

BI-CSE correlation

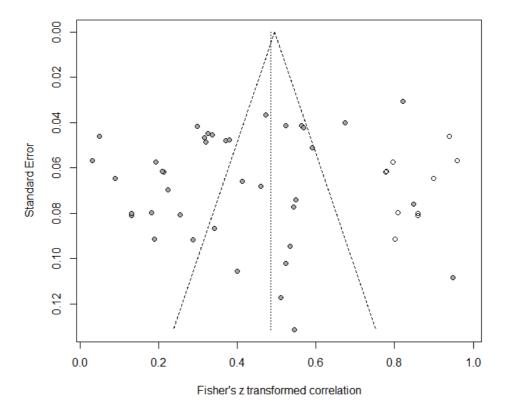


Fisher's z transformed correlation

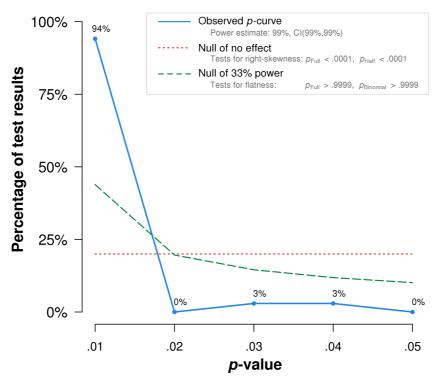


Note: The observed p-curve includes 39 statistically significant (p < .05) results, of which 38 are p < .025. There were 8 additional results entered but excluded from p-curve because they were p > .05.

BI-FC correlation

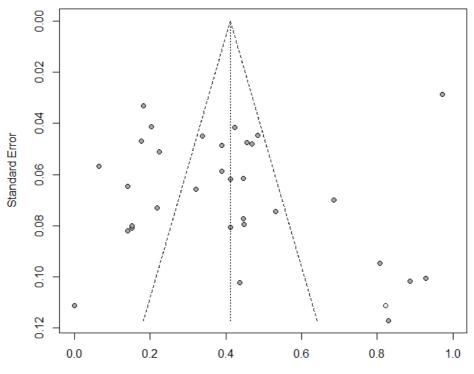


P-Curve

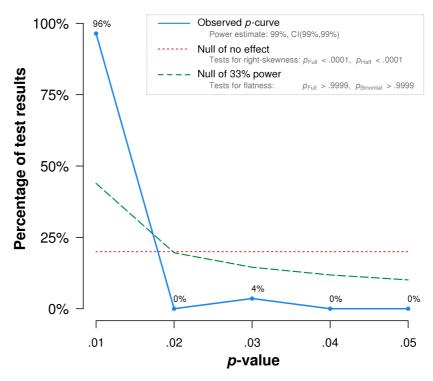


Note: The observed p-curve includes 34 statistically significant (p < .05) results, of which 33 are p < .025. There were 5 additional results entered but excluded from p-curve because they were p > .05.

BI-SN correlation

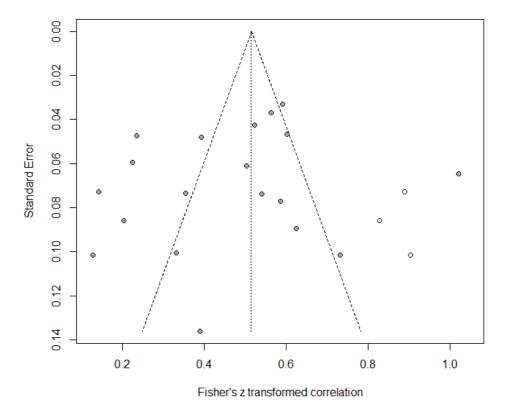


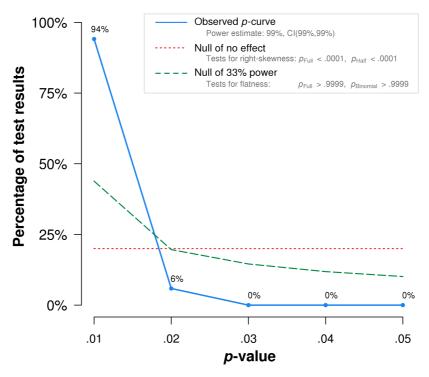
Fisher's z transformed correlation



Note: The observed p-curve includes 28 statistically significant (p < .05) results, of which 27 are p < .025. There were 5 additional results entered but excluded from p-curve because they were p > .05.

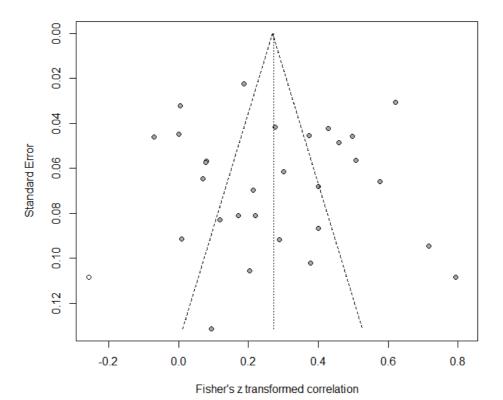
BI-USE correlation

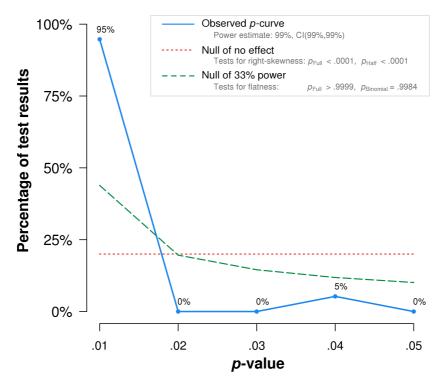




Note: The observed p-curve includes 17 statistically significant (p < .05) results, of which 17 are p < .025. There were 2 additional results entered but excluded from p-curve because they were p > .05.

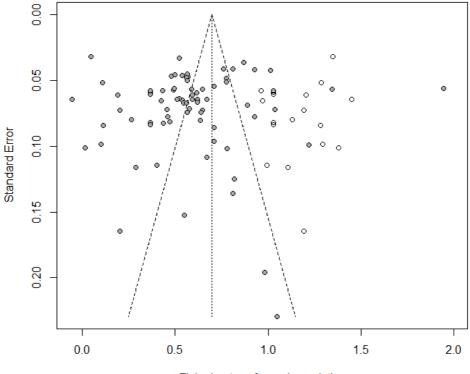
CSE-FC correlation



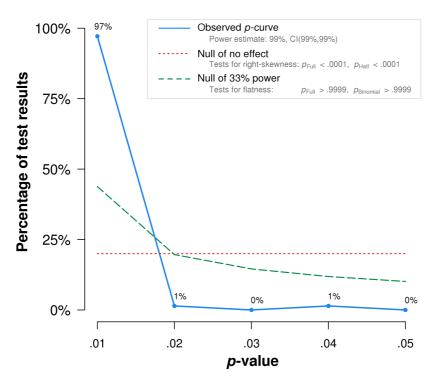


Note: The observed p-curve includes 19 statistically significant (p < .05) results, of which 18 are p < .025. There were 10 additional results entered but excluded from p-curve because they were p > .05.

PEU-ATT correlation

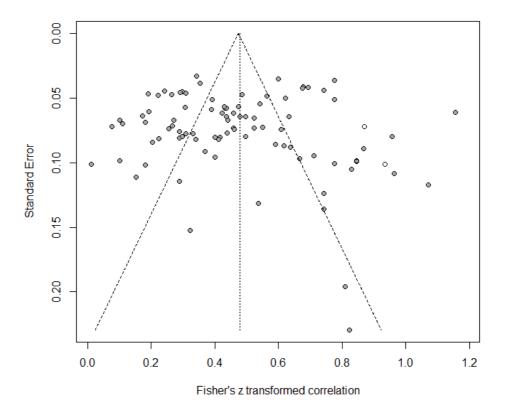


Fisher's z transformed correlation

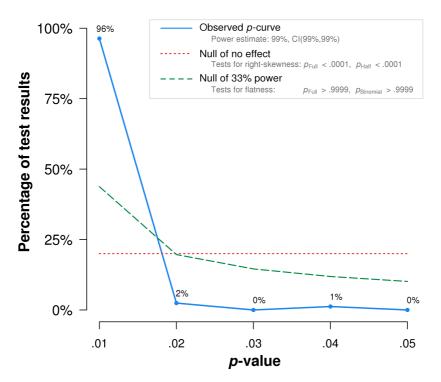


Note: The observed p-curve includes 70 statistically significant (p < .05) results, of which 69 are p < .025. There were 6 additional results entered but excluded from p-curve because they were p > .05.

PEU-BI correlation

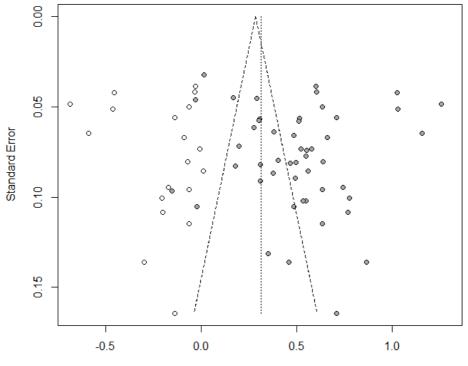


P-Curve



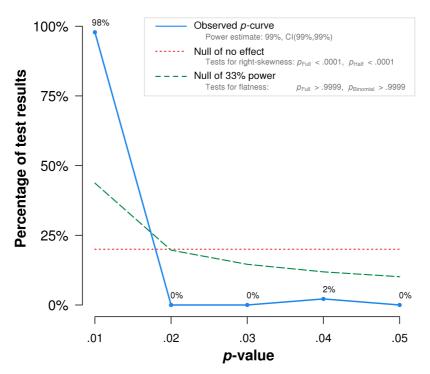
Note: The observed p-curve includes 82 statistically significant (p < .05) results, of which 81 are p < .025. There were 7 additional results entered but excluded from p-curve because they were p > .05.

PEU-CSE correlation



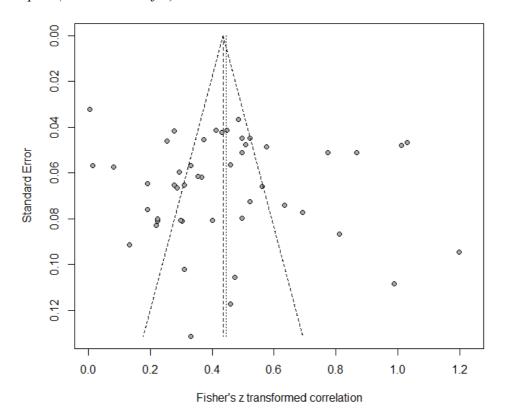
Fisher's z transformed correlation

P-Curve

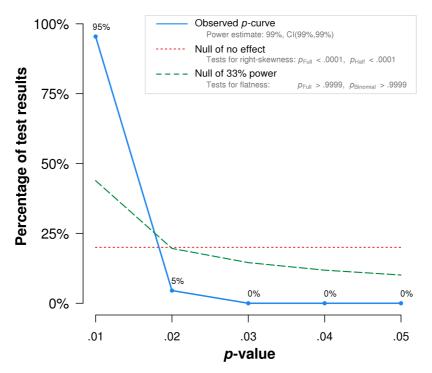


Note: The observed p-curve includes 46 statistically significant (p < .05) results, of which 45 are p < .025. There were 4 additional results entered but excluded from p-curve because they were p > .05.

PEU-FC correlation

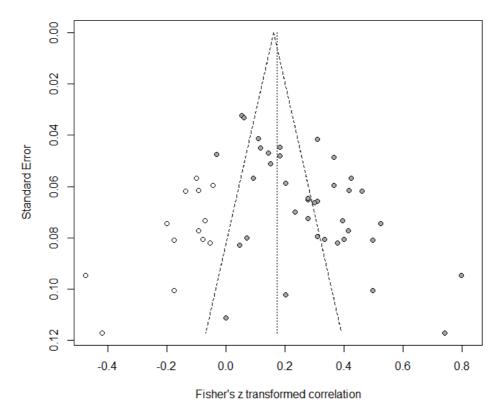


P-Curve

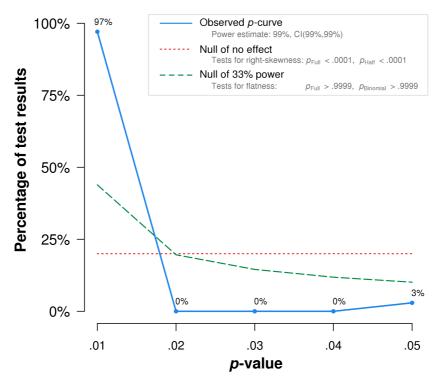


Note: The observed p-curve includes 44 statistically significant (p < .05) results, of which 44 are p < .025. There were 4 additional results entered but excluded from p-curve because they were p > .05.

PEU-SN correlation



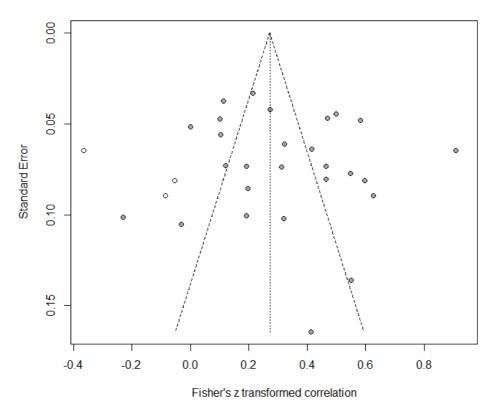
P-Curve

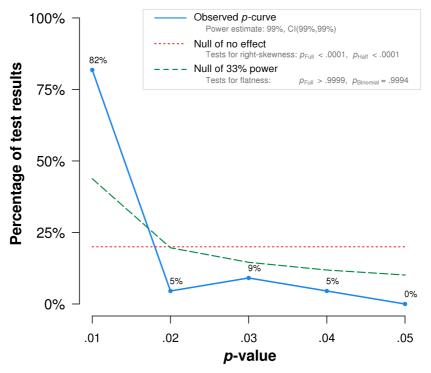


Note: The observed p-curve includes 34 statistically significant (p < .05) results, of which 33 are p < .025. There were 7 additional results entered but excluded from p-curve because they were p > .05.

PEU-USE correlation

Funnel plot (with trim and fill)

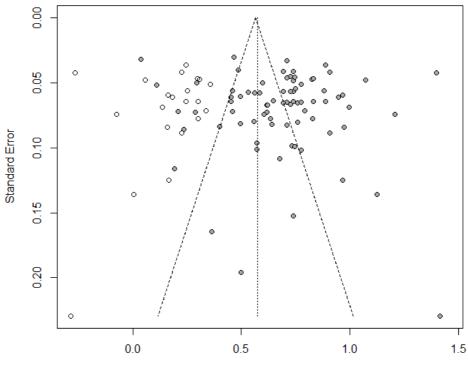




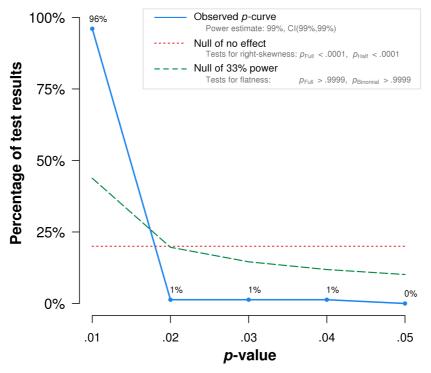
Note: The observed p-curve includes 22 statistically significant (p < .05) results, of which 21 are p < .025. There were 5 additional results entered but excluded from p-curve because they were p > .05.

PU-ATT correlation

Funnel plot (with trim and fill)



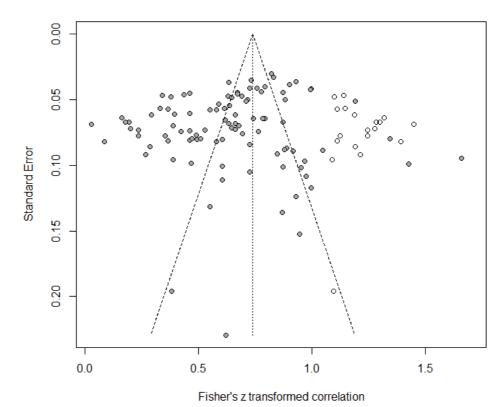
Fisher's z transformed correlation

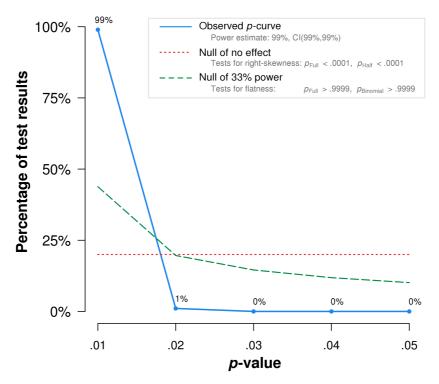


Note: The observed p-curve includes 76 statistically significant (p < .05) results, of which 74 are p < .025. There were 2 additional results entered but excluded from p-curve because they were p > .05.

PU-BI correlation

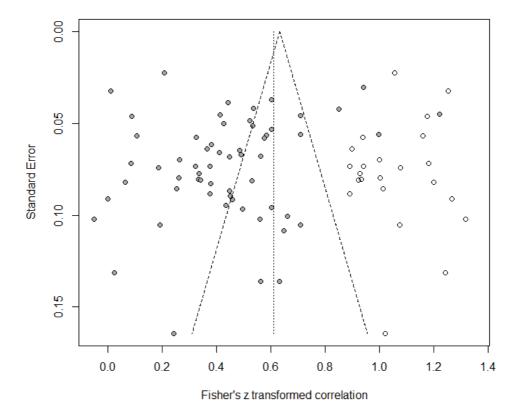
Funnel plot (with trim and fill)

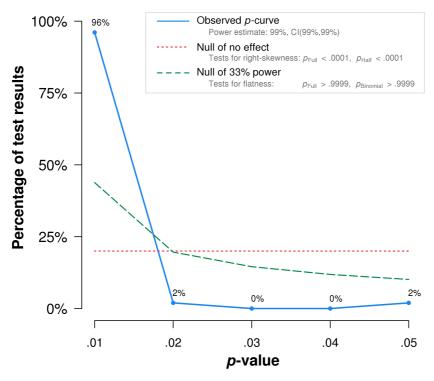




Note: The observed p-curve includes 95 statistically significant (p < .05) results, of which 95 are p < .025. There were 3 additional results entered but excluded from p-curve because they were p > .05.

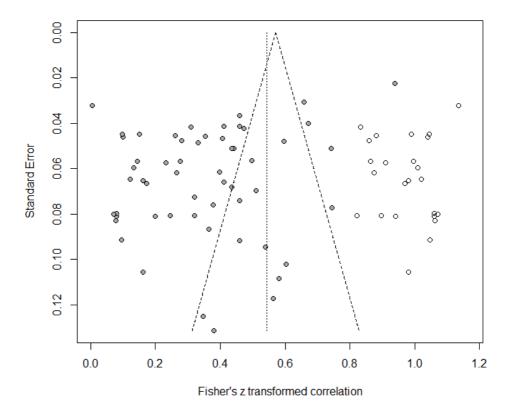
PU-CSE correlation

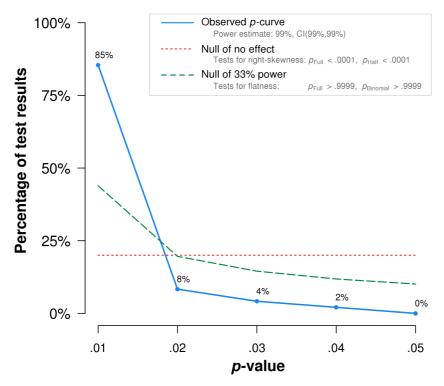




Note: The observed p-curve includes 51 statistically significant (p < .05) results, of which 50 are p < .025. There were 9 additional results entered but excluded from p-curve because they were p > .05.

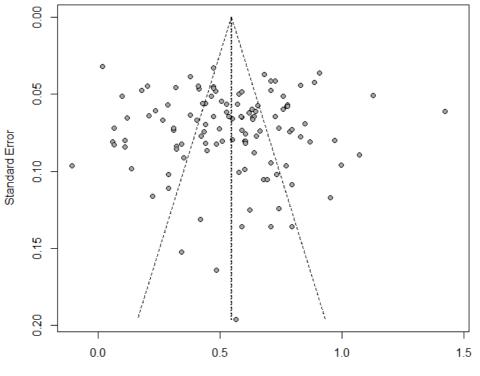
PU-FC correlation



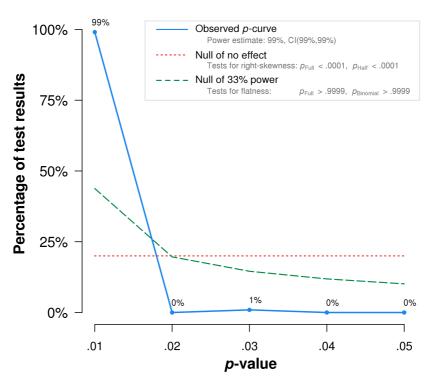


Note: The observed p-curve includes 48 statistically significant (p < .05) results, of which 45 are p < .025. There were 8 additional results entered but excluded from p-curve because they were p > .05.

PU-PEU correlation

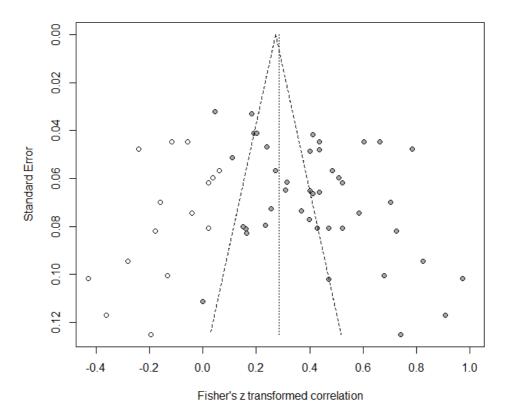


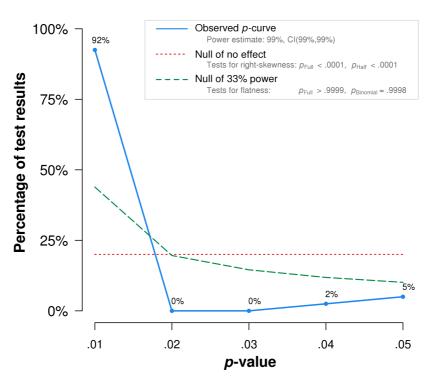
Fisher's z transformed correlation



Note: The observed p-curve includes 107 statistically significant (p < .05) results, of which 106 are p < .025. There were 11 additional results entered but excluded from p-curve because they were p > .05.

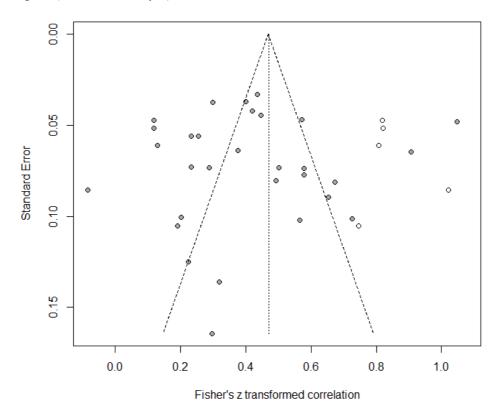
PU-SN correlation



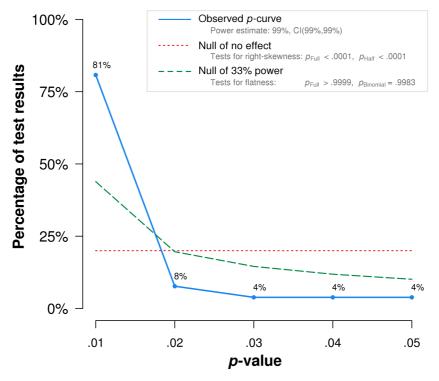


Note: The observed p-curve includes 40 statistically significant (p < .05) results, of which 37 are p < .025. There were 3 additional results entered but excluded from p-curve because they were p > .05.

PU-USE correlation

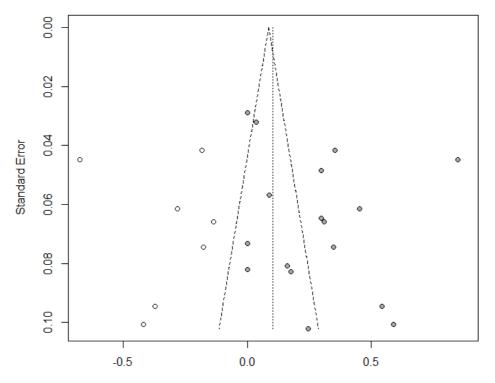


P-Curve

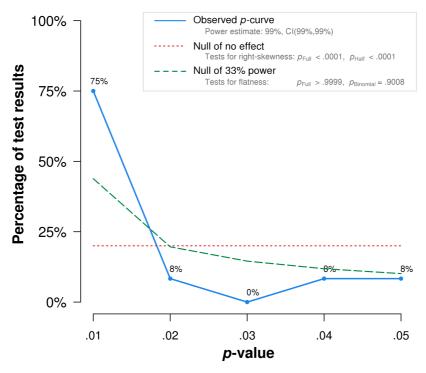


Note: The observed p-curve includes 26 statistically significant (p < .05) results, of which 24 are p < .025. There were 4 additional results entered but excluded from p-curve because they were p > .05.

SN-CSE correlation

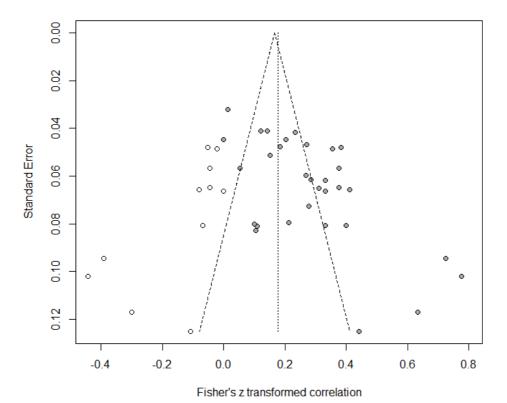


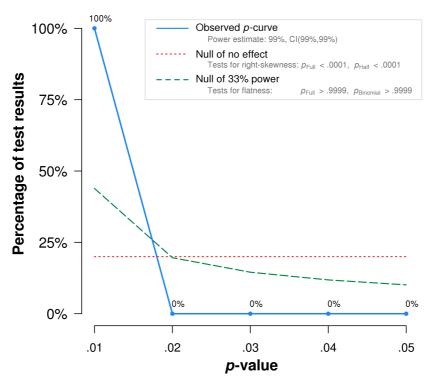
Fisher's z transformed correlation



Note: The observed p-curve includes 12 statistically significant (p < .05) results, of which 10 are p < .025. There were 5 additional results entered but excluded from p-curve because they were p > .05.

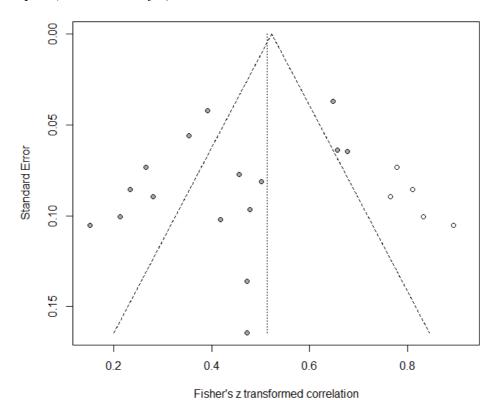
SN-FC correlation



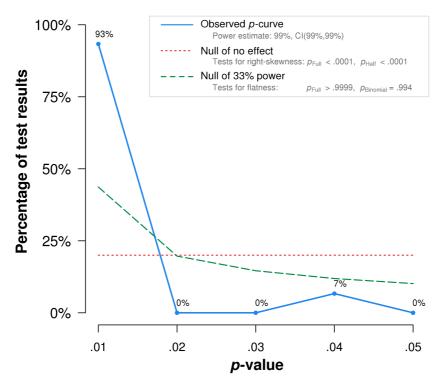


Note: The observed p-curve includes 26 statistically significant (p < .05) results, of which 26 are p < .025. There were 6 additional results entered but excluded from p-curve because they were p > .05.

USE-CSE correlation



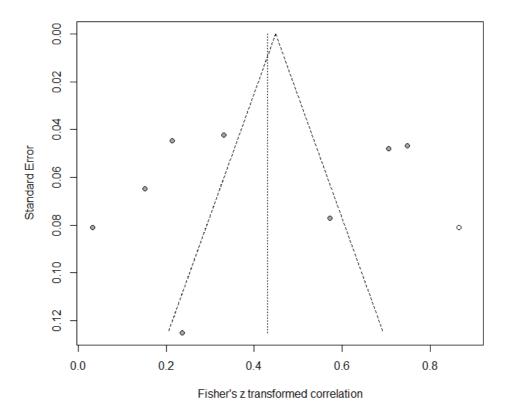
P-Curve



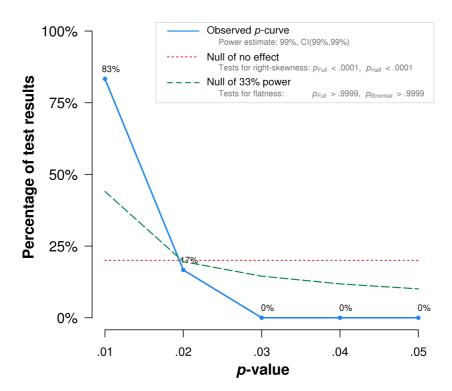
Note: The observed p-curve includes 15 statistically significant (p < .05) results, of which 14 are p < .025. There was one additional result entered but excluded from p-curve because it was p > .05.

USE-FC correlation

Funnel plot (with trim and fill)



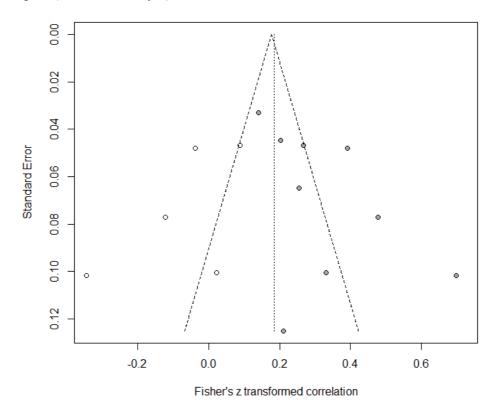
P-Curve



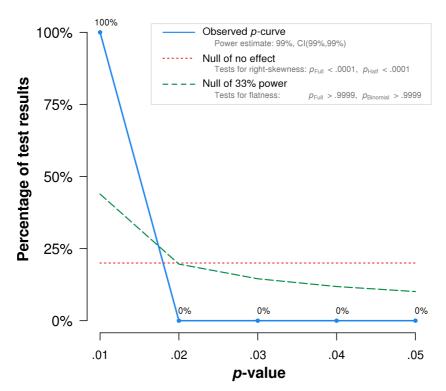
Note: The observed ρ -curve includes 6 statistically significant (ρ < .05) results, of which 6 are ρ < .025. There were 2 additional results entered but excluded from ρ -curve because they were ρ > .05.

USE-SN correlation

Funnel plot (with trim and fill)



P-Curve



Note: The observed p-curve includes 8 statistically significant (p < .05) results, of which 8 are p < .025. There was one additional result entered but excluded from p-curve because it was p > .05.

Rosenberg's fail-safe Ns

The fail-safe *N*s indicate the number of unpublished study samples needed to achieve a statistically insignificant effect size (correlation). They all indicate that a considerable number of studies would have been needed, pointing to a limited degree of publication bias.

*Table S3-1*Rosenberg's fail-safe *N*s for each of the twenty-eight TAM correlations

	1.	2.	3.	4.	5.	6.	7.
1	-						
. PEU							
2	20756	-					
. PU	7						
3	10189	14373	-				
	4	6					
ATT							
4	93040	21806	10587	-			
. BI		8	2				
5	4131	9263	3170	5418	-		
. USE							
6	5872	16665	3419	1211	432	-	
. SN				7			
7	27256	44758	11038	3481	253	110	-
. FC				7	2	7	
8	27527	38157	10955	1858	769	385	528
. CSE				4		5	9

S4. Heterogeneity tests for subgroup models

In the following, an account is given to the heterogeneity tests of correlation matrices (TSSEM-Stage 1) for each subgroup of teacher samples. Random-effects models were specified for these subsamples (Table S4-1).

Table S4-1

Results of the heterogeneity tests corresponding to Models 1 and 2 within teacher subsamples

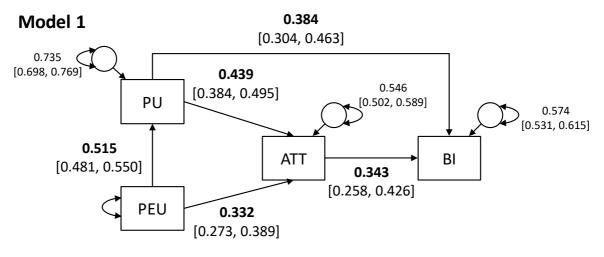
Subgroup	Q	df	р	I^2
Model 1		-		
Asian samples	7,432.7	314	< .001	87.9–94.4 %
Non-Asian	4,327.7	150	< .001	90.1–95.7 %
samples				
Pre-service	7,903.8	252	< .001	88.2-96.0 %
teachers				
In-service teachers	3,611.8	212	< .001	89.4–95.7 %
Technology in	6,628.7	274	< .001	87.8–95.0 %
general				
Specific	5,265.3	190	< .001	90.4–96.6 %
technologies				
Model 2				
Asian samples	7,894.1	334	< .001	83.5-94.3 %
Non-Asian	5,441.9	191	< .001	78.7–95.7 %
samples				
Pre-service	8,020.0	267	< .001	68.7–96.0 %
teachers	,			
In-service teachers	4,775.5	258	< .001	87.7–95.6 %
Technology in	7,072.0	296	< .001	83.5-95.0 %
general				
Specific	6,361.8	229	< .001	80.7–96.6 %
technologies	•			

S5. Sensitivity analyses

All subsequent findings are based on attenuated correlations (i.e., correlations corrected for measurement error if the underlying variables were manifest). The first table shows the results of the heterogeneity tests of correlation matrices at the first TSSEM stage. Due to the occurrence of five non-positive definite matrices after the attenuation, the sample reduced to $k = 119 \ (N = 34,543^1)$ matrices.

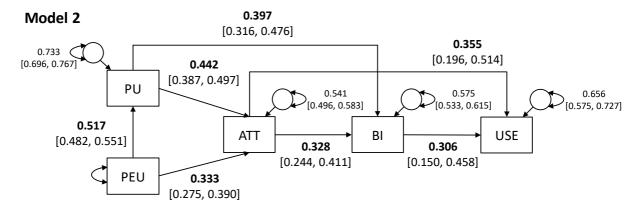
Table S5-1
Heterogeneity tests of correlation matrices

Model	Q	df	р	I^2
Model 1	13,027.5	447	< .001	92.3-96.3 %
Model 2	14,443.4	502	< .001	87.2-96.3 %
Model 3	30,319.3	911	< .001	84.0-96.2 %
Model 4	32,477.2	982	< .001	84.0–96.2 %



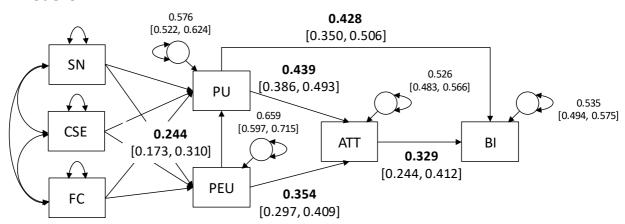
 $\chi^{2}(1)=8.8$, p=.003, CFI=0.998, RMSEA=0.015, SRMR=0.025, AIC=6.8, BIC=-1.7

¹ Due to a different selection of study samples here than in the sample of unattenuated correlation matrices (non-positive definiteness of attenuated correlation matrices), this sample size differs from that reported in the paper.

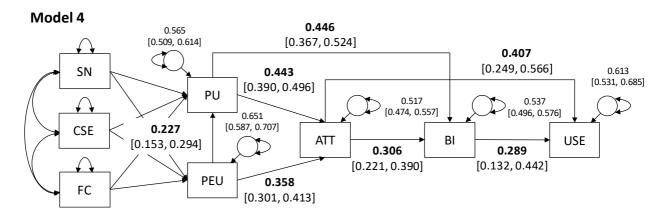


 $\chi^{2}(3)$ =14.2, p=.003, CFI=0.997, RMSEA=0.010, SRMR=0.039, AIC=8.2, BIC=-17.1

Model 3



 $\chi^2(7)$ =64.3, p<.001, CFI=0.990, RMSEA=0.015, SRMR=0.047, AIC=50.3, BIC=-8.8



 $\chi^2(12)$ =99.9, p<.001, CFI=0.985, RMSEA=0.015, SRMR=0.075, AIC=75.9, BIC=-25.5

Figure S5-1. Structural equation models after unreliability corrections.

*Table S5-2*Effects of external variables in Models 3 and 4

External variables	Perceived usefulness	Perceived ease of
		use
<i>b</i> [95% LBC	IJ	
Model 3		
Subjective norm	0.291 [0.221, 0.360]	0.095 [0.020, 0.165]
Computer self-	0.247 [0.162, 0.328]	0.387 [0.315, 0.458]
efficacy		
Facilitating	0.136 [0.071, 0.197]	0.293 [0.226, 0.356]
conditions		
I	R^2 42.4 %	34.1 %
Model 4		
Subjective norm	0.294 [0.223, 0.354]	0.094 [0.018, 0.165]
Computer self-	0.271 [0.186, 0.352]	0.399 [0.327, 0.470]
efficacy		
Facilitating	0.138 [0.073, 0.199]	0.289 [0.222, 0.354]
conditions		
	R ² 43.5 %	34.9 %

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