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; Siddiq, Hatlevik, Olsen, Throndsen, & Scherer, 2016). Second, teachers and teacher educators are encouraged to include technology in their teaching—as a tool to facilitate learning or as a means to formative assessment (Shute & Rahimi, 2017; Straub, 2009). It has become the designated aim of education to help students to become digitally literate citizens who can cope with the complexities and dynamics in today's societies (Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014). This development, however, necessitates the meaningful inclusion of technology in teaching and learning contexts (OECD, 2015; Siddiq, Scherer, & Tondeur, 2016). An extensive body of literature has dealt with the factors associated with this inclusion by focusing on teachers' adoption of technology (Straub, 2009). One model though has dominated the research landscape—the Technology Acceptance Model (TAM). The TAM comprises several variables explaining behavioral intentions and the use of technology directly or indirectly (i.e., perceived usefulness, perceived ease of use, attitudes toward technology), and has been extended by external variables, such as self-efficacy, subjective norms, 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 meta-analysis. We present the definitions applied to this meta-analysis in Table 1. Overall, perceived ease of use and perceived usefulness, the most important factors in the TAM, refer to the degrees to which a person believes that using technology would be free from effort (PEU) and that using technology would enhance their job or task performance (PU). In this context, “free from effort” means “free from difficulty or great effort”, as Davis (1989) in his seminal paper specified. PEU therefore refers to the effort a person estimates it would take to use technology and is closely related to competence beliefs (Scherer, Siddiq, & Teo, 2015). These two perceptions, PEU and PU, directly relate to another TAM-core variable, attitudes toward technology (ATT). Most commonly, the TAM comprises at least one outcome variable: behavioral intention (BI) and/or technology use (USE). Inspired by the Theory of

Reasoned Action, the former refers to intended behavior, whereas the latter refers to observable behavior, that is, the actual use of technology. In most versions of the TAM, BI predicts USE—however, the direction of this link is not deterministic because positive user experience may also determine future behavioral intentions (Straub, 2009). Finally, external variables in the TAM refer to perceptions of how important others consider the use of technology (SN), perceptions of one's own capabilities of mastering computer- or technology-related tasks (CSE), and perceptions of external control, that is, the organizational support for technology use (FC) in terms of organizational resources and support structures (Taylor & Todd, 1995).

Given the variety of variables within the TAM, different versions of the model have been studied empirically (Taylor & Todd, 1995). The most prominent versions are depicted in 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 pre- and in-service teachers and different nationalities (Teo, Lee, Chai, & Wong, 2009). Such studies could oftentimes not identify full invariance across groups of teachers, and the resultant findings highlight that the TAM may not fully apply to all contexts and groups of teachers to the same extent. Fifth, variables characterizing persons, contexts, and the measurement of variables may moderate the relations within the TAM (Straub, 2009).

The prominence of the TAM and the availability of primary research studies resulted in several meta-analyses that synthesized the relations and paths within the TAM in various contexts. Table 2 provides a brief account of these meta-analyses. These meta-analyses mainly focused on the TAM core variables (i.e., PEU, PU, and ATT) and outcome variables, such as behavioral intentions and technology use (Marangunić & Granić, 2015). The contexts in which the relations among them were studied vary substantially: Whereas some meta-analyses included any TAM study that had been conducted until the date of review (e.g., King & He, 2006; Schepers & Wetzels, 2007), others included only TAM studies targeted at specific educational contexts, such as e-learning platforms or instruction (e.g., Ritter, 2017; Šumak et al., 2011).

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

Once correlations are pooled in previous meta-analyses, the resultant correlations, path coefficients, or correlation matrices are then submitted to moderator analyses—moderating variables target, for instance, types of users, technologies, and cultures. By and large, the effects identified in these meta-analyses suggest: (a) strong relations between PEU and PU; (b) larger effects of PU on BI than of PEU on BI; and (c) mediocre to strong ATT–BI and BI–USE relations. These effects, however, varied considerably across meta-analyses, sometimes ranging from insignificant and close-to-zero effects to strong, positive, and significant effects. This variation, in fact, points to some inconsistencies across meta-analyses, as the following example illustrates: The effects of both perceived ease of use and usefulness on teachers' attitudes toward technology differ considerably. Whereas Ritter (2017) reports a strong positive effect of PEU on ATT ($\beta_{PEU\text{-}ATT} = .52$) and a weak positive effect of PU on ATT ($\beta_{PU\text{-}ATT} = .16$), Schepers and Wetzels (2007) found the opposite ($\beta_{PEU\text{-}ATT} = .26$, $\beta_{PU\text{-}ATT} = .46$)—so did L. Zhang, Zhu, and Liu (2012) in their meta-analysis ($\beta_{PEU\text{-}ATT} = .07$, $\beta_{PU\text{-}ATT} = .24$). 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—f*ull texts or secondary resources that describe the study in sufficient detail must have been available.
2. *Sample*—the study focused on a sample of in- or pre-service teachers in K-12, college, or university education.
3. *Constructs*—the study assessed at least three of the TAM constructs. These include: (a) Perceived usefulness; (b) Perceived ease of use; (c) Outcome variables such as intentions to use digital technology for teaching (often labelled as behavioral intentions) or actual use or attitudes toward use; (d) External variables such as subjective norms, technology self-efficacy, or facilitating conditions.
4. *Reporting of statistics*—the study reported the statistics necessary to retrieve the correlations among the relevant TAM constructs (see 3.). Minimal reporting included at least one of the following types of information: (a) correlation matrix; (b) variance-covariance matrix; (c) standardized path coefficients in a path or structural equation model including the correlations among exogenous variables.
5. *Context*—the TAM was studied for a digital device, technology, software, or system.

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

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 (*p*s $< .05$) 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 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 ≥ .95, RMSEA ≤ .08, and SRMR ≤ .10; Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005). We compared competing models with respect to their information criteria (Akaike's Information Criterion [AIC], Bayesian Information Criterion [BIC])—the model with smaller values is preferred—and the results of the Likelihood-ratio test (LRT). Nevertheless, we note that these guidelines do not represent "golden rules" (Marsh, Hau, & Wen, 2004). For instance, they do not fully apply to structural equation models with complex factor structures (Khojasteh & Lo, 2015).

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

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

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 *N*s indicated that a considerable amount of studies would have been necessary to nullify the TAM correlations. Finally, all *p*-curves suggested the dominance of small *p*-values, indicated by right-skewed distributions. These findings suggest only a limited degree of publication bias in the extracted correlations.

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 I^2 supported the heterogeneity of single correlations within matrices. For all subgroups, Models 1 and 2 showed a good fit to the data.

Sample origin. Despite the large number of studies originating from Asian teacher samples, the differences in model parameters between Asian and non-Asian samples were marginal (see 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 in-service teachers. Overall, only small differences in model parameters between these two groups of teachers existed. Some of these differences, however, resulted in larger variance explanations of behavioral intentions (pre-service teachers: R^2 = 36.7 %; in-service teachers: R^2 = 44.3 %) and technology use for in-service teachers (pre-service teachers: R^2 = 21.7 %; in-service teachers: R^2 = 35.4 %).

Specificity of technologies. Finally, we compared Models 1 and 2 between studies focusing on technology or computers in general and studies focusing on specific technologies (see Figure 6). These comparisons revealed differences in the direct effects PU→BI and ATT→USE with larger effects for specific technologies. In fact, the ATT→USE relation was insignificant for studies referring to 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 ($\beta_{SN\text{-}PEU}$ = .20, $\beta_{SN\text{-}PU}$ = .30). This finding was confirmed in our meta-analysis for teacher samples, yet with smaller effects on PEU (Model 3: $\beta_{SN\text{-}PEU}$ = .09, $\beta_{SN\text{-}PU}$ = .28). Moreover, the effects varied across studies, indicating possible context- or sample-specificity. Hence, subjective norms played a larger role of teachers' perceptions of the usefulness of technology in educational contexts. From our perspective, this finding needs further attention and substantive backing, because subjective norm—that is, teachers' perceptions that most people think they should use technology—refers to a different belief system than perceived usefulness—that is, teachers' perceptions of the usefulness of technology for teaching and learning (Antonietti & Giorgetti, 2006; Schepers & Wetzels, 2007). Whereas the former takes other people, for instance, teacher colleagues, supervisors, or fellow students, as the frame of reference, the latter uses the technology itself as a static entity to frame a reference. Along the same lines, the connection between SN and PEU should be weak, as PEU indicates teachers' perceptions of the ease of using technology—another belief with a reference to technology rather than people. Nevertheless, PEU—as it is defined here—may well be explained by teachers' *self-efficacy*, because it interferes with beliefs about the extent to which a person can perform tasks with technology (Scherer & Siddiq, 2015). Indeed, our meta-analysis confirms this expectation (Model 3: $\beta_{CSE\text{-}PEU}$ = .37, $\beta_{CSE\text{-}PU}$ = .23), and is in line with the results reported by Abdullah and Ward (2016) ($\beta_{CSE\text{-}PEU}$ = .35, $\beta_{CSE\text{-}PU}$ = .17) and Scherer et al. (2015) ($\beta_{CSE\text{-}PEU}$'s = .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: $\beta_{FC\text{-}PEU} = .30$) and PU (Model 3: $\beta_{FC\text{-}PU} = .12$), with stronger effects on PEU. Once again, perceptions of possible barriers that are related to school or classroom resources are linked to perceptions of how easy the use of technology may be. This finding brings into play the responsibilities schools have to create conditions that allow teachers to use technology for teaching and learning (Fraillon et al., 2014).

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

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 in-service 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.

References

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

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior, 56*, 238-256. doi:10.1016/j.chb.2015.11.036

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

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

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

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

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

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

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

Beller, M. (2013). Technologies in Large-Scale Assessments: New Directions, Challenges, and Opportunities. In M. v. Davier, E. Gonzalez, I. Kirsch, & K. Yamamoto (Eds.), *The Role of International Large-Scale Assessments: Perspectives from Technology, Economy, and Educational Research* (pp. 25-45). Dordrecht: Springer Science+Business Media. doi:10.1007/978-94-007-4629-9_3

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

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

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

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

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

*Cheung, E. Y. M., & Sachs, J. (2006). Test of the Technology Acceptance Model for a Web-Based Information System in a Hong Kong Chinese Sample. *Psychological Reports, 99*(3), 691-703. doi:10.2466/PR0.99.3.691-703

Cheung, M. W.-L. (2009). Constructing Approximate Confidence Intervals for Parameters With Structural Equation Models. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(2), 267-294. doi:10.1080/10705510902751291

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

Cheung, M. W.-L. (2015). *Meta-Analysis: A Structural Equation Modeling Approach*. Chichester, West Sussex: John Wiley & Sons, Ltd.

Cheung, M. W.-L., & Chan, W. (2005). Meta-Analytic Structural Equation Modeling: A Two-Stage Approach. *Psychological Methods, 10*(1), 40-64. doi:10.1037/1082-989X.10.1.40

Cheung, M. W.-L., & Cheung, S. F. (2016). Random-Effects Models for Meta-Analytic Structural Equation Modeling: Review, Issues, and Illustrations. *Research Synthesis Methods, 7*(2), 140-155. doi:10.1002/jrsm.1166

Cheung, M. W.-L., & Hong, R. Y. (2017). Applications of meta-analytic structural equation modeling in health psychology: Examples, issues, and recommendations. *Health Psychology Review, 11*(3), 265-279. doi:10.1080/17437199.2017.1343678

Churchill, G. A., & Peter, J. P. (1984). Research Design Effects on the Reliability of Rating Scales: A Meta-Analysis. *Journal of Marketing Research, 21*(4), 360-375. doi:10.2307/3151463

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

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

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. doi:10.2307/249008

Duval, S., & Tweedie, R. (2000). Trim and Fill: A Simple Funnel-Plot–Based Method of Testing and Adjusting for Publication Bias in Meta-Analysis. *Biometrics, 56*(2), 455-463. doi:10.1111/j.0006-341X.2000.00455.x

Enders, C. K. (2010). *Applied Missing Data Analysis*. New York, NY: Guilford Press.

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

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

Flórez, F. B., Casallas, R., Hernández, M., Reyes, A., Restrepo, S., & Danies, G. (2017). Changing a Generation's Way of Thinking: Teaching Computational Thinking Through Programming. *Review of Educational Research, 87*(4), 834-860. doi:10.3102/0034654317710096

Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Gebhardt, E. (2014). *Preparing for Life in a Digital Age - The IEA International Computer and Information Literacy Study International Report*. Heidelberg, New York, Dordrecht, London: Springer International Publishing. doi:10.1007/978-3-319-14222-7

Gnambs, T., & Staufenbiel, T. (2016). Parameter accuracy in meta-analyses of factor structures. *Research Synthesis Methods, 7*(2), 168-186. doi:10.1002/jrsm.1190

Higgins, J. P. T., & Green, S. (2011). *Cochrane Handbook for Systematic Reviews of Interventions* (Vol. 4). Chichester, West Sussex: John Wiley & Sons.

Hong, R. Y., & Cheung, M. W.-L. (2015). The Structure of Cognitive Vulnerabilities to Depression and Anxiety: Evidence for a Common Core Etiologic Process Based on a Meta-Analytic Review. *Clinical Psychological Science, 3*(6), 892-912. doi:10.1177/2167702614553789

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

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

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

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

Jak, S. (2015). *Meta-Analytic Structural Equation Modelling*. Utrecht, The Netherlands: Springer. doi:10.1007/978-3-319-27174-3

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

Khojasteh, J., & Lo, W.-J. (2015). Investigating the Sensitivity of Goodness-of-Fit Indices to Detect Measurement Invariance in a Bifactor Model. *Structural Equation Modeling: A Multidisciplinary Journal, 22*(4), 531-541. doi:10.1080/10705511.2014.937791

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

*Kirmizi, Ö. (2014). Measuring Technology Acceptance Level of Turkish Pre-Service English Teachers by Using Technology Acceptance Model. *Educational Research and Reviews, 9*(23), 1323-1333.

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

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling*. New York, NY: The Guilford Press.

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

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

Lawless, K. A., & Pellegrino, J. W. (2007). Professional Development in Integrating Technology Into Teaching and Learning: Knowns, Unknowns, and Ways to Pursue Better Questions and Answers. *Review of Educational Research, 77*(4), 575-614. doi:10.3102/0034654307309921

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems, 12*, 752-780.

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

Little, T. D. (2013). *Longitudinal Structural Equation Modeling*. New York, NY: Guilford Press.

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

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

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

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indexes and Dangers in Overgeneralizing Hu and Bentler's (1999) Findings. *Structural Equation Modeling: A Multidisciplinary Journal, 11*(3), 320-341. doi:10.1207/s15328007sem1103_2

Mei, B., Brown, G. T. L., & Teo, T. (2017). Toward an Understanding of Preservice English as a Foreign Language Teachers' Acceptance of Computer-Assisted Language Learning 2.0 in the People's Republic of China. *Journal of Educational Computing Research*. doi:10.1177/0735633117700144

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

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

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group, e. a. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLOS Medicine, 6*(7), 1-6. doi:10.1371/journal.pmed.1000097

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

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

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

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

OECD. (2015). *Students, Computers and Learning: Making the Connection*. Paris: OECD Publishing. doi:10.1787/9789264239555-en

Peterson, R. A., & Brown, S. P. (2005). On the Use of Beta Coefficients in Meta-Analysis. *Journal of Applied Psychology, 90*(1), 175-181. doi:10.1037/0021-9010.90.1.175

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

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

Raykov, T., & Marcoulides, G. A. (2013). Meta-Analysis of Scale Reliability Using Latent Variable Modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(2), 338-353. doi:10.1080/10705511.2013.769396

Ritter, N. L. (2017). Technology Acceptance Model of Online Learning Management Systems in Higher Education: A Meta-Analytic Structural Equation Model. *International Journal of Learning Management Systems, 5*(1), 1-15. doi:10.18576/ijlms/050101

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

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

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

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

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

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

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

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

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

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

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

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). P-Curve: A Key to the File-Drawer. *Journal of Experimental Psychology: General, 143*(2), 534-547. doi:10.1037/a0033242

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2017). P-curve *Online App Version 4.0.*

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

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

Straub, E. T. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research, 79*(2), 625-649. doi:10.3102/0034654308325896

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

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

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

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research, 6*(2), 144-176. doi:10.1287/isre.6.2.144

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

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

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

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

*Teo, T., & van Schaik, P. (2012). Understanding the Intention to Use Technology by Preservice Teachers: An Empirical Test of Competing Theoretical Models. *International Journal of Human–Computer Interaction, 28*(3), 178-188. doi:10.1080/10447318.2011.581892

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

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

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decision Sciences, 39*(2), 273-315. doi:10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425-478. doi:10.2307/30036540

von Davier, A. A., Hao, J., Liu, L., & Kyllonen, P. (2017). Interdisciplinary research agenda in support of assessment of collaborative problem solving: lessons learned from developing a Collaborative Science Assessment Prototype. *Computers in Human Behavior, 76*, 631-640. doi:10.1016/j.chb.2017.04.059

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

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

Wright, S. (1934). The method of path coefficients. *The annals of mathematical statistics, 5*(3), 161-215. doi:10.1214/aoms/1177732676

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

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

Zhang, P., Aikman, S. N., & Sun, H. (2008). Two Types of Attitudes in ICT Acceptance and Use. *International Journal of Human–Computer Interaction, 24*(7), 628-648. doi:10.1080/10447310802335482

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

Table 2

Overview of selected meta-analyses synthesizing TAM studies

Meta-analysis	TAM core variables	*k*	Moderators	MASEM approach	Fixed Effects (β)							
					PEU→PU	PEU→ATT	PEU→BI	PU→ATT	PU→BI	ATT→BI	ATT→USE	BI→USE
Gerow et al. (2013)	PEU, PU, BI, USE	185	T	Univariate-*r*	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-*r*	0.48*	0.26*	0.12*	0.46*	0.38*	0.18*	-	0.55*
Šumak et al. (2011)	PEU, PU, ATT, BI, USE	51	U, T	Univariate-*r*	0.40*	0.29*	0.24*	0.51*	0.40*	0.33*	0.33*	0.44*
Wu & Du (2012)	PEU, PU, BI, USE	103	V	Univariate-*r*	0.50*	-	-	-	-	-	-	-
Zhang et al. (2012)	PEU, PU, ATT, BI, USE	58	C	Univariate-*r*	0.27*	0.07	0.17*	0.24*	0.07	0.27*	-	0.24*

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

Table 3

Discrete characteristics of study samples included in the meta-analysis

Discrete variable	*k*	% of study samples
Teacher sample characteristics		
Context of teaching		
Primary school	26	20.97 %
Special education	2	1.61 %
Early childhood education	7	5.65 %
Secondary school	19	15.32 %
College	4	3.23 %
University	18	14.52 %
Not specified	48	38.71 %
Teacher level		
Pre-service teachers	64	51.61 %
In-service teachers	60	48.39 %
Location of the study sample		
Abu Dhabi (UAE)	1	0.81 %
Australia	4	3.23 %
Belgium	3	2.42 %
Brazil	1	0.81 %
Cyprus	1	0.81 %
Ghana	1	0.81 %
Greece	2	1.61 %
Hong Kong (China)	7	5.65 %
India	2	1.61 %
Iran	1	0.81 %
Japan	2	1.61 %
Lebanon	1	0.81 %
Macau (China)	1	0.81 %
Malaysia	11	8.87 %
New Zealand	1	0.81 %
Norway	1	0.81 %
Pakistan	1	0.81 %
Saudi Arabia	1	0.81 %
Serbia	3	2.42 %
Shanghai (China)	1	0.81 %
Singapore	20	16.13 %
Slovenia	2	1.61 %
South Africa	1	0.81 %
South Korea, Republic of Korea	1	0.81 %
Spain	4	3.23 %
Sweden	1	0.81 %
Taiwan	11	8.87 %
Thailand	1	0.81 %
Turkey	10	8.06 %
United Kingdom	1	0.81 %
United States of America	20	16.13 %
Mixed (Asian)	6	4.84 %

Study methods		
Representation of TAM variables		
Manifest variables	52	41.94 %
Latent variables	72	58.06 %
Manifest and latent variables	0	0.00 %
Model fit evaluation		
Model fit was evaluated	73	58.87 %
Model fit was not evaluated	51	41.13 %
If model fit was evaluated, the fit was...[a]		
Poor	2	1.61 %
Mediocre	5	4.03 %
Acceptable	24	19.35 %
Close	42	33.87 %
Type technology in the TAM		
Technology in general	70	56.45 %
Specific technologies	54	43.55 %
Study characteristics		
Publication status		
Published	107	86.29 %
Grey literature	17	13.71 %
Publication year		
2002	1	0.81 %
2003	0	0.00 %
2004	1	0.81 %
2005	1	0.81 %
2006	2	1.61 %
2007	4	3.23 %
2008	4	3.23 %
2009	7	5.65 %
2010	10	8.06 %
2011	9	7.26 %
2012	14	11.29 %
2013	13	10.48 %
2014	16	12.90 %
2015	20	16.13 %
2016	21	16.94 %
2017	1	0.81 %

Note. k = Number of study samples (and correlation matrices). a: The following guidelines have been used to categorize model fit (e.g., Little, 2013): Poor (RMSEA > .10, CFI < .85), mediocre (.08 < RMSEA ≤ .10, .85 ≤ CFI < .90), acceptable (.05 < RMSEA ≤ .08, .90 ≤ CFI < .95), and close (RMSEA ≤ .05, CFI ≥ .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 teachers	64.7 %	19.6 %	16.1 %	0.0 %	100.0 %
Reliability coefficients [b]					
PU	.888	.058	18.6 %	.720	.990
PEU	.869	.066	25.0 %	.729	.990
ATT	.850	.076	46.8 %	.620	.985
BI	.840	.114	36.3 %	.517	.979
USE	.830	.070	88.7 %	.668	.918
SN	.825	.101	69.4 %	.610	.960
CSE	.857	.085	63.7 %	.561	.982
FC	.828	.104	62.9 %	.540	.990

Note. All statistics are based on k = 124 study samples (correlation matrices).

[a] Only the between-sample standard deviation is reported without considering within-sample variation.

[b] Reliability coefficients were mostly reported as Cronbach's α or McDonald's ω.

Table 5

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

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

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

Table 6

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

	PU	PEU	ATT	BI	SN	CSE	FC
PEU							
r	.48*						
95% CI	[.45, .51]						
ρ	.50*						
τ^2	0.025*						
$SE(\tau^2)$	0.004						
I^2	93.1 %						
ATT							
r	.59*	.52*					
95% CI	[.55, .62]	[.49, .56]					
ρ	.62*	.54*					
τ^2	0.020*	0.024*					
$SE(\tau^2)$	0.004	0.004					
I^2	92.8 %	94.7 %					
BI							
r	.55*	.42*	.52*				
95% CI	[.52, .58]	[.39, .45]	[.48, .57]				
ρ	.58*	.44*	.55*				
τ^2	0.025*	0.019*	0.027*				
$SE(\tau^2)$	0.004	0.004	0.006				
I^2	94.6 %	88.3 %	93.7 %				
SN							
r	.39*	.27*	.32*	.36*			
95% CI	[.34, .44]	[.22, .31]	[.27, .38]	[.30, .41]			
ρ	.40*	.26*	.33*	.35*			
τ^2	0.024*	0.016*	0.016*	0.022*			
$SE(\tau^2)$	0.006	0.004	0.005	0.006			

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

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

Table 7

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

External variables *b* [95% LBCI]	Perceived usefulness	Perceived ease of use
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:

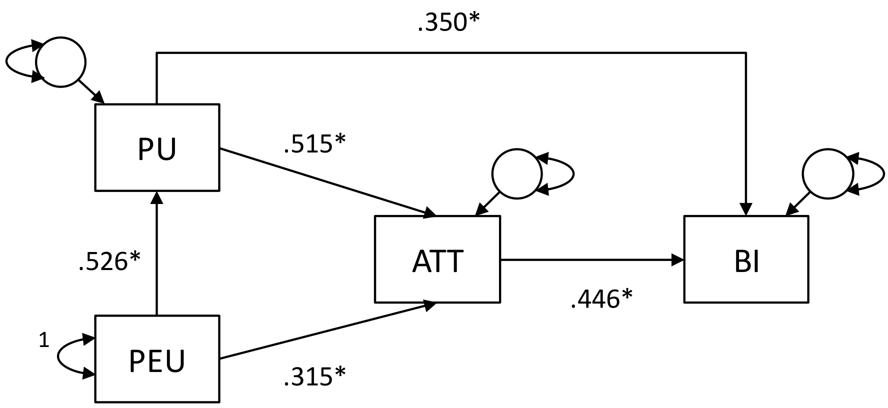


Figure S1. Original structural equation model describing technology acceptance.

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 → BI (i.e., direct effect), PU → ATT → BI (i.e., indirect effect), and PU ← PEU → ATT → 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, 0.515×0.446, 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.

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

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 M*plus* (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.

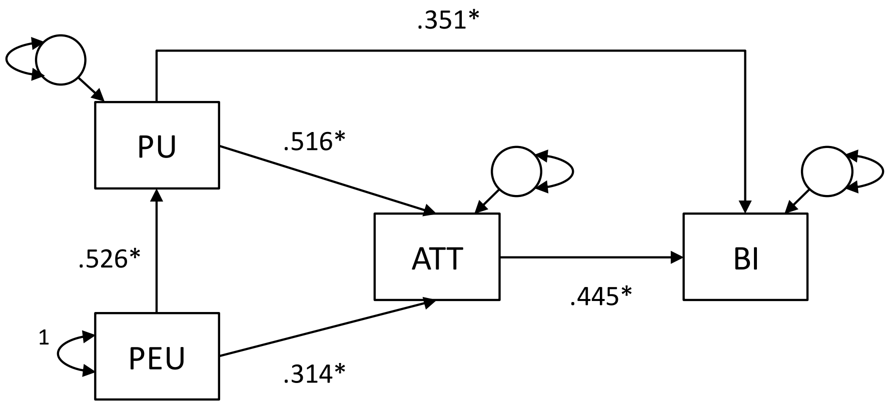


Figure S2. Recreated structural equation model describing technology acceptance.

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-service teachers*, *1 = in-service teachers*)
Level	Educational level (*0 = 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	Teachers	Country/Region	Level	Mean age [years]	Female [%]	Technology	Measure	Status	*N*	Variables	*r*	ρ
Ahmad et al. (2010)	1	Malaysia	2	39.7	60.0	0	1	1	731	PU-BI	.560	.560
										PU-USE	.380	.380
										BI-USE	.510	.510
										PU-CSE	.540	.540
										BI-CSE	.450	.450
										USE-CSE	.570	.570
Ahmad et al. (2015)[a]	0	Nigeria	-	-	59.0	1	0	1	100	PEU-ATT	.013	.015

										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] - Sample 2	1	USA	2	47.7	49.0	0	1	0	245	PU-PEU	.564	.564
										PU-ATT	.424	.424
										PEU-ATT	.057	-.057
Anderson et al. (2011)	0	USA	0	-	82.0	0	0	1	217	PU-BI	.580	.701
										PU-CSE	.420	.475
										BI-CSE	.380	.462
Anderson & Groulx (2013)	0	USA	0	23.0	98.0	0	0	0	102	PU-PEU	.520	.612
										PU-BI	.540	.647

PEU-BI	.650	.779
PU-USE	.200	.238
PEU-USE	.190	.226
BI-USE	.320	.387
PU-SN	.590	.794
PEU-SN	.460	.619
BI-SN	.730	.999*
USE-SN	.320	.435

										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	.	.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- CSE	. 502	.5 02
										ATT- CSE	. 063	.0 63
										BI- CSE	. 124	.1 24
										SN- CSE	. 335	.3 35
Attis (2014)	1	USA	0	-	-	1	0	0	11 2	PU- PEU	. 760	.7 92
										PU-BI	. 370	.3 94
										PEU- BI	. 380	.4 04
										PU- CSE	. 540	.5 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-	.	.7
										ATT	710	10
										PEU-	.	.7
										ATT	700	00
										PU-BI	.	.7
											730	30
										PEU-	.	.6
										BI	650	50
										ATT-	.	.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	PU-	.	.5
				3	.0				1	PEU	500	00
										PU-BI	.	.4
											440	40
										PEU-	.	.4
										BI	460	60
										PU-	.	.2
										SN	230	30

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

										PEU-	.	.2
										BI	280	80
										PU-	.	.3
										FC	360	60
										PEU-	.	.1
										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
										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	PEU	520	82

PU-ATT	.535	.593
PEU-ATT	.510	.578
PU-BI	.707	.768
PEU-BI	.553	.613
ATT-BI	.437	.480
PU-CSE	.404	.438
PEU-CSE	.560	.619
ATT-CSE	.355	.389

										BI-	.	.4
										CSE	374	01
Chen (2016)	1	Taiwan	0	31.	95	0	1	1	35	PU-BI	.	.5
				0	.5				3		530	30
										PU-	.	.5
										CSE	540	40
										BI-	.	.5
										CSE	510	10
Cheung & Sachs	0	Hong Kong	0	27.	-	1	0	1	57	PU-	.	.5
(2006)		(China)		8						PEU	530	92
										PU-	.	.9
										ATT	810	31
										PEU-	.	.7
										ATT	670	57
										PU-BI	.	.8
											700	24

PEU-BI	.630	.729
ATT-BI	.690	.822
PU-USE	.310	.362
PEU-USE	.500	.574
ATT-USE	.360	.425
BI-USE	.370	.447
PU-CSE	.510	.597
PEU-CSE	.700	.805

										ATT-	.	.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-	.	.5
		(China)			.9				6	PEU	575	75
										PU-	.	.4
										ATT	486	86
										PEU-	.	.4
										ATT	453	53
										PU-BI	.	.3
											351	51
										PEU-	.	.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-	.	.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 (2015)	1	Turkey	2	34.2	-	1	0	1	115	PU-PEU	.610	.651
										PU-BI	.930	.989
										PEU-BI	.611	.667
										PU-SN	.678	.777
										PEU-SN	.662	.779
										BI-SN	.668	.783
										PU-CSE	.410	.432
										PEU-CSE	.630	.681

										BI-CSE	.387	.417
										SN-CSE	.495	.576
										PU-FC	.492	.569
										PEU-FC	.833	.988
										BI-FC	.489	.579
										SN-FC	.619	.790
										CSE-FC	.615	.722
Cote & Miliner (2015)	1	Japan	2	-	-	1	0	0	29	PU-PEU	.512	.584

										PU-ATT	.461	.532
										PEU-ATT	.754	.879
										PU-BI	.364	.422
										PEU-BI	.669	.784
										ATT-BI	.595	.705
De Smet et al. (2012)	1	Belgium	1	40.0	57.3	1	0	1	505	PU-PEU	.390	.443
										PU-USE	.420	.500
										PEU-USE	.460	.529

										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	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
CSE	240	93
PEU-	.	.7
CSE	610	44
ATT-	.	.2
CSE	190	32

										USE-	.	.5
										CSE	440	37
Fathema et al. (2015)	1	USA	2	45.	46	1	1	1	56	PU-	.	.7
				7	.8				0	PEU	709	09
										PU-	.	.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

PEU-	.	.2
USE	266	66
ATT-	.	.3
USE	368	68
BI-	.	.4
USE	479	79
PU-	.	.6
CSE	691	91
PEU-	.	.7
CSE	772	72
ATT-	.	.6
CSE	678	78
BI-	.	.6
CSE	611	11
USE-	.	.3
CSE	373	73

										PU-FC	.440	.440
										PEU-FC	.407	.407
										ATT-FC	.467	.467
										BI-FC	.515	.515
										USE-FC	.319	.319
										CSE-FC	.404	.404
Fong et al. (2014)	1	Hong Kong (China) and Taiwan	2	-	-	1	0	1	132	PU-PEU	.565	.601
										PU-BI	.705	.734

											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-	.	-
										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	PU-	.	.1
				4	.0				0	PEU	098	12
										PU-	.	.1
										ATT	109	26
										PEU-	.	.1
										ATT	106	24
										PU-	.	.1
										USE	118	37
										PEU-	.	.0
										USE	000	00

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

PU-BI	.675	.675
ATT-BI	.532	.532
PU-CSE	.736	.736
ATT-CSE	.425	.425
BI-CSE	.670	.670
PU-FC	.578	.578
ATT-FC	.600	.600
BI-FC	.676	.676

										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-ATT	.650	.717
PEU-ATT	.652	.709
PU-USE	.513	.573
PEU-USE	.309	.340
ATT-USE	.353	.380
PU-CSE	.508	.564
PEU-CSE	.488	.534
ATT-CSE	.524	.561

										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-	.	.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-	.	.6
Worrell (2013)				8	.6					PEU	661	89
										PU-	.	.6
										CSE	559	44
										PEU-	.	.5
										CSE	429	04

Huntington (2011)	1	USA	1	37.8	47.4	1	0	0	57	PU-PEU	.610	.696
										PU-CSE	.559	.643
										PEU-CSE	.429	.498
Hur et al. (2015)	0	USA	0	21.0	86.0	1	1	1	386	PU-PEU	.433	.433
										PU-BI	.831	.831
										PEU-BI	.373	.373
										PU-CSE	.488	.488
										PEU-CSE	.774	.774

										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	-	23.	80	0	0	1	93	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

										USE-	.	.1
										CSE	150	78
Jung (2015)	1	South	1	42.	57	1	1	1	18	PU-	.	.3
		Korea		4	.1				9	PEU	300	00
										PU-BI	.	.2
											230	30
										PEU-	.	.4
										BI	480	80
										PU-	.	.2
										USE	280	80
										PEU-	.	.1
										USE	190	90
										BI-	.	.3
										USE	340	40
										PU-	.	.3
										CSE	360	60

										PEU-CSE	.480	.480
										BI-CSE	.320	.320
										USE-CSE	.260	.260
Kabakci-Yurdakul et al. (2014)	0	Turkey	-	-	57.4	0	1	1	579	PU-PEU	.620	.620
										PU-ATT	.720	.720
										PEU-ATT	.730	.730
										PU-BI	.760	.760
										PEU-BI	.600	.600

ATT-	.	.7
BI	710	10
PU-	.	.3
SN	390	90
PEU-	.	.3
SN	300	00
ATT-	.	.3
SN	330	30
BI-SN	.	.4
	400	00
PU-	.	.4
CSE	490	90
PEU-	.	.5
CSE	540	40
ATT-	.	.6
CSE	620	20

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 (2015)	0	India	2	33.4	15.0	1	1	1	400	PU-ATT	.287	.287
										PU-BI	.614	.614
										ATT-BI	.242	.242
Kelly (2014)	1	USA	2	43.7	66.0	1	0	1	128	PU-PEU	.790	.901
										PU-BI	.724	.840
										PEU-BI	.700	.820
										PU-USE	.574	.668
										PEU-USE	.556	.653

										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	-	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-	.	.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-ATT	.625	.757
										PEU-ATT	.100	.118
										PU-BI	.436	.538
										PEU-BI	.100	.120
										ATT-BI	.514	.656
Kreijns et al. (2013)[a]	1	The Netherlands	1	46.4	65.7	1	0	1	1209	ATT-BI	.750	.798
										ATT-SN	.000	.000
										BI-SN	.750	.102

										ATT-CSE	.730	.819
										BI-CSE	.810	.899
										SN-CSE	.000	.000
Kusano et al. (2013) - Sample 1	1	USA	0	42.5	86.5	0	0	1	111	PU-PEU	.647	.708
										PU-ATT	.517	.580
										PEU-ATT	.610	.666
Kusano et al. (2013) - Sample 2	1	Japan	0	35.7	52.2	0	0	1	67	PU-PEU	.553	.624
										PU-ATT	.747	.840

										PEU-ATT	.674	.728
Lai et al. (2013)[a]	1	Taiwan	0	-	-	1	0	1	160	PU-PEU	.749	.855
										PU-ATT	.508	.586
										PEU-ATT	.258	.301
										PU-BI	.872	.999*
										PEU-BI	.743	.871
										ATT-BI	.461	.547
										PU-CSE	.257	.296

										PEU- CSE	. 382	.4 44
Lay et al. (2013)	1	Taiwan	1	38. 9	65 .8	1	1	1	71 9	PU- PEU	. 593	.5 93
										PU- USE	. 291	.2 91
										PEU- USE	. 112	.1 12
Lee & Chen (2016)	1	Taiwan and Xinjiang (China)	0	-	66 .5	0	1	1	32 2	PU- PEU	. 405	.4 05
										PU- ATT	. 707	.7 07
										PEU- ATT	. 456	.4 56
										PU- CSE	. 611	.6 11

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

Lin et al. (2013)	1	USA	2	-	-	1	1	1	99	PU-PEU	.280	.280
										PU-BI	.740	.740
										PEU-BI	.180	.180
										PU-SN	.440	.440
										PEU-SN	.200	.200
										BI-SN	.410	.410
										PU-CSE	.050	-.050
										PEU-CSE	.500	.500

										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	Taiwan	-	-	-	0	1	0	47	ATT-	.	.5
									0	BI	529	29

										ATT-	.	.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-	.	.5
										ATT	585	85
										PU-BI	.	.6
											654	54
										PEU-	.	.4
										BI	445	45
										ATT-	.	.6
										BI	684	84

Luan & Teo (2011)	0	Malaysia	-	23.4	74.7	0	1	1	245	PU-PEU	.490	.490
										PU-ATT	.630	.630
										PEU-ATT	.530	.530
										PU-BI	.630	.630
										PEU-BI	.460	.460
										ATT-BI	.620	.620
Ma et al. (2005)	0	Sweden	-	32.5	66.5	0	1	1	84	PU-PEU	.280	.280
										PU-BI	.540	.540

										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
										ATT	207	07
										PEU-	.	.4
										ATT	426	26
										PU-BI	.	.1
											199	99

										PEU-	.	.0
										BI	076	76
										ATT-	.	.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	46.1	42.2	1	1	1	67	PU-USE	.221	.221
										PU-SN	.629	.629
										USE-SN	.207	.207
										PU-FC	.333	.333
										USE-FC	.232	.232
										SN-FC	.414	.414
Nair & Das (2012)	1	India	1	35.6	-	0	1	1	195	PU-PEU	.630	.630
										PU-ATT	.429	.429

										PEU-	.	.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-	.	.4
										CSE	420	20
										PEU-	.	.3
										CSE	360	60
										BI-	.	.5
										CSE	540	40
										PU-	.	.3
										FC	350	50

										PEU-FC	.670	.670
										BI-FC	.330	.330
										CSE-FC	.380	.380
Okazaki & dos Santos (2012)	1	Brazil	2	-	-	1	1	1	446	PU-PEU	.610	.610
										PU-ATT	.678	.678
										PEU-ATT	.514	.514
										PU-BI	.599	.599
										PEU-BI	.450	.450

										ATT-BI	.860	.860
										PU-USE	.119	.119
										PEU-USE	.102	.102
										ATT-USE	.193	.193
										BI-USE	.230	.230
Oshiro (2015)[a]	1	USA	0	-	-	0	0	0	110	PU-PEU	.105	-.124
										PU-BI	.747	.859
										PEU-BI	.582	.681

										PU-CSE	.460	.664
										PEU-CSE	.149	-.219
										BI-CSE	.267	.382
										USE-CSE	.445	.665
Park et al. (2007)	1	USA	2	-	-	1	0	1	191	PU-PEU	.660	.805
										PU-ATT	.280	.344
										PEU-ATT	.200	.252
										PU-BI	.580	.691

										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

PEU-	.	.7
ATT	584	89
PU-BI	.	.9
	750	99*
PEU-	.	.9
BI	746	71
ATT-	.	.9
BI	684	23
PU-	.	.8
CSE	571	04
PEU-	.	.8
CSE	647	83
ATT-	.	.9
CSE	684	68
BI-	.	.9
CSE	739	99*

										PU-	.	.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-FC	.410	.547
										BI-FC	.430	.662
										CSE-FC	.380	.513
Perkmen et al. (2016) - Sample 2	0	Spain	-	-	74.0	0	0	1	209	PU-BI	.370	.500
										PU-CSE	.260	.304
										BI-CSE	.110	.151
										PU-FC	.470	.607
										BI-FC	.220	.334

										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-	.	.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	-	84.5	1	0	0	155	PU-PEU	.701	.764
										PU-USE	.588	.739
										PEU-USE	.534	.693
										PU-CSE	.486	.576
										PEU-CSE	.435	.532
										USE-CSE	.463	.654
										PU-FC	.197	.218
										PEU-FC	.295	.337

									USE-FC	.032	.042
									CSE-FC	.216	.269
Pynoo et al. (2012)	1	Belgium	-	39.7	70.6	1	0	1	919	PU-PEU	.440	.502
									PU-ATT	.610	.704
									PEU-ATT	.480	.559
									PU-BI	.680	.789
									PEU-BI	.330	.387
									ATT-BI	.550	.652

PU-USE	.410	.477
PEU-USE	.210	.247
ATT-USE	.400	.476
BI-USE	.530	.634
PU-SN	.180	.211
PEU-SN	.060	.071
ATT-SN	.110	.132
BI-SN	.180	.216

										USE-SN	.140	.169
Sadeghi et al. (2014)	1	Iran	-	34.7	37.5	0	0	1	275	PU-PEU	.230	.247
										PU-ATT	.460	.512
										PEU-ATT	.350	.393
										PU-BI	.430	.478
										PEU-BI	.190	.214
										ATT-BI	.440	.512
Salajan et al. (2011)[a]	1	USA	2	47.8	54.9	1	0	0	189	PU-PEU	.529	.598

- 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] - Sample 2	1	USA	2	47.8	54.9	1	0	0	157	PU-PEU	.538	.557
										PU-BI	.458	.472
										PEU-BI	.393	.407
										PU-USE	.456	.466
										PEU-USE	.433	.445
										PU-SN	.404	.441
										PEU-SN	.322	.354
										PU-CSE	.322	.346

										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-	.	.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-FC	.000	.000
										CSE-FC	.000	.000
Sánchez-Prieto et al. (2017)	0	Spain	-	21.1	65.2	1	1	1	678	PU-PEU	.361	.361
										PU-BI	.716	.716
										PEU-BI	.340	.340
										PU-CSE	.416	.416
										PEU-CSE	.537	.537
										BI-CSE	.477	.477

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-USE	.750	.909
BI-USE	.770	.963
PU-SN	.300	.417
PEU-SN	.270	.358
ATT-SN	.200	.279
BI-SN	.140	.202
USE-SN	.250	.356
PU-CSE	.450	.509

PEU-CSE	.820	.886
ATT-CSE	.390	.444
BI-CSE	.470	.551
USE-CSE	.590	.683
SN-CSE	.290	.387
PU-FC	.120	.143
PEU-FC	.190	.216
ATT-FC	.140	.168

										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-	.	.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	.650	.650
										PEU-BI	.630	.630
Smith (2014)	0	USA	-	22.3	75.0	1	0	0	235	PU-PEU	.120	.137
										PU-ATT	.600	.663
										PEU-ATT	.400	.463
Stols & Kriek (2011)[a]	1	South Africa	1	45.5	45.5	1	0	1	22	PU-ATT	.889	.999*
										PEU-ATT	.781	.910
										PU-BI	.551	.639

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

ATT-BI	.412	.412
PU-USE	.781	.781
PEU-USE	.524	.524
ATT-USE	.852	.852
BI-USE	.374	.374
PU-SN	.410	.410
PEU-SN	.180	.180
ATT-SN	.414	.414

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

Sumak & Sorgo (2016) - Sample 2	1	Slovenia	0	44.5	83.5	1	1	1	460	PU-PEU	.392	.392
										PU-ATT	.682	.682
										PEU-ATT	.446	.446
										PU-BI	.327	.327
										PEU-BI	.188	.188
										ATT-BI	.442	.442
										PU-USE	.517	.517
										PEU-USE	.437	.437

ATT-USE	.554	.554
BI-USE	.538	.538
PU-SN	.235	.235
PEU-SN	.142	.142
ATT-SN	.236	.236
BI-SN	.175	.175
USE-SN	.261	.261
PU-FC	.386	.386

										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-	.	.7
										ATT	730	30

									PU-BI	.340	.340
									PEU-BI	.300	.300
									ATT-BI	.300	.300
Teo, Fan, & Du (2015) - Sample 2	0	Asian country	0	28.5	100.0	0	1	1	170	PU-PEU	.400	.400
									PU-ATT	.560	.560
									PEU-ATT	.430	.430
									PU-BI	.230	.230
									PEU-BI	.320	.320

									ATT- BI	. 360	.3 60
Teo & Khlaisang et al. (2014)	0	Thailand	-	-	76 .4	0	0	1	96 9	PU- PEU	. 020	.0 22
									PU- ATT	. 039	.0 45
									PEU- ATT	. 045	.0 52
									PU- SN	. 047	.0 55
									PEU- SN	. 054	.0 64
									ATT- SN	. 108	.1 29
									PU- CSE	. 013	.0 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
(2008)				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-	.	.3
										FC	270	29
										SN-	.	.3
										FC	300	75
Teo, Lee, Chai, &	0	Singapore	-	24.	70	0	1	1	25	PU-	.	.3
Wong (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, & Wong (2009) - Sample 2	0	Malaysia	-	23.4	74.7	0	1	1	245	PU-PEU	.440	.440
										PU-ATT	.630	.630
										PEU-ATT	.470	.470
										PU-BI	.630	.630
										PEU-BI	.410	.410
										ATT-BI	.620	.620
Teo, Lee, Chai, & Choi (2009)[a]	0	Singapore	1	26.2	67.9	1	1	1	483	PU-CSE	.610	.610
										PU-FC	.340	.340

										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-ATT	.630	.630
PEU-ATT	.873	.873
PU-BI	.319	.319
PEU-BI	.441	.441
ATT-BI	.505	.505
PU-SN	.265	.265
PEU-SN	.093	.093
ATT-SN	.002	.002

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
CSE	087	87
PU-	.	.1
FC	143	43
PEU-	.	.0
FC	015	15

										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-	.	.6
										ATT	549	75
										PEU-	.	.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) - Sample 1	0	Singapore	-	27.0	51.0	0	1	1	150	PU-PEU	.450	.450
										PU-ATT	.610	.610
										PEU-ATT	.410	.410
Teo & Noyes (2010) - Sample 2	0	UK	-	28.2	63.7	0	1	1	146	PU-PEU	.310	.310
										PU-ATT	.380	.380
										PEU-ATT	.350	.350
Teo & Noyes (2011)	0	Singapore	-	26.2	56.9	0	1	1	153	PU-PEU	.540	.540
										PU-ATT	.460	.460

										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
				1	.0				4	PEU	550	50
										PU-BI	.	.5
											580	80
										PEU-	.	.4
										BI	400	00
										PU-	.	.4
										SN	480	80

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

										CSE-FC	.185	.185
Teo & Tan (2012)	0	Singapore	-	24.8	50.0	0	1	1	293	PEU-ATT	.350	.350
										PEU-BI	.370	.370
										ATT-BI	.620	.620
										PEU-SN	.200	.200
										ATT-SN	.360	.360
										BI-SN	.370	.370
Teo, Ursavaş et al. (2011)	0	Turkey	0	19.4	55.8	0	1	1	197	PU-PEU	.300	.300

										PU-ATT	.660	.660
										PEU-ATT	.520	.520
										PU-BI	.570	.570
										PEU-BI	.260	.260
										ATT-BI	.500	.500
Teo, Ursavaş et al. (2012)	0	Turkey	-	19.4	58.3	0	1	1	487	PU-PEU	.307	.307
										PU-ATT	.632	.632
										PEU-ATT	.462	.462

PU-BI	.	.5
	586	86
PEU-	.	.2
BI	283	83
ATT-	.	.4
BI	446	46
PU-	.	.3
CSE	392	92
PEU-	.	.2
CSE	284	84
ATT-	.	.3
CSE	301	01
BI-	.	.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	.	.5
											570	70

PEU-BI	.510	.510
ATT-BI	.690	.690
PU-SN	.380	.380
PEU-SN	.350	.350
ATT-SN	.370	.370
BI-SN	.370	.370
PU-CSE	.480	.480
PEU-CSE	.850	.850

ATT-CSE	.600	.600
BI-CSE	.450	.450
SN-CSE	.290	.290
PU-FC	.320	.320
PEU-FC	.520	.520
ATT-FC	.360	.360
BI-FC	.310	.310
SN-FC	.340	.340

										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-	.	.7
										FC	700	00
Teo & Zhou (2014)	0	Singapore	-	24.	64	0	1	1	31	PU-	.	.5
				8	.6				4	PEU	517	17
										PU-	.	.6
										ATT	600	00
										PEU-	.	.5
										ATT	527	27
										PU-BI	.	.5
											548	48

										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		430	30
	PEU-	.	.4
FC		420	20
	ATT-	.	.5
FC		520	20
	BI-FC	.	.5
		510	10

										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-USE	.195	.195
ATT-USE	.209	.209
BI-USE	.200	.200
PU-CSE	.248	.248
PEU-CSE	.507	.507
ATT-CSE	.314	.314
BI-CSE	.159	.159
USE-CSE	.230	.230

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	.	.4
											410	10
										PEU-	.	.3
										BI	300	00
										ATT-	.	.4
										BI	400	00
										PU-	.	.0
										CSE	090	90
										PEU-	.	-
										CSE	030	.030

										ATT-	.	.0
										CSE	070	70
										BI-	.	.1
										CSE	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	PU-	.	.5
				6	.5				5	PEU	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

PU- ATT	. 550	.5 50
PEU- ATT	. 570	.5 70
PU- SN	. 250	.2 50
PEU- SN	. 270	.2 70
ATT- SN	. 410	.4 10
PU- FC	. 310	.3 10
PEU- FC	. 480	.4 80
ATT- FC	. 520	.5 20

										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- FC	. 320	.3 20
									ATT- FC	. 350	.3 50
									SN- FC	. 360	.3 60
Teo (2010c)	0	Singapore	-	25. 6	63 .6	0	0	1	23 9	PU- PEU	. 560	.6 48
									PU- ATT	. 650	.7 39
									PEU- ATT	. 550	.6 43
									PU- SN	. 380	.4 50
									PEU- SN	. 270	.3 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	PU-	.	.8
				0					7	PEU	810	10
										PU-	.	.4
									FC		416	16
										PEU-	.	.6
									FC		649	49

Teo (2011)	1	Singapore	0	35. 3	76 .4	0	1	1	59 2	PU- PEU	. 610	.6 10
										PU- ATT	. 600	.6 00
										PEU- ATT	. 640	.6 40
										PU-BI	. 620	.6 20
										PEU- BI	. 590	.5 90
										ATT- BI	. 710	.7 10
										PU- SN	. 190	.1 90
										PEU- SN	. 110	.1 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	560	60

PU-ATT	.620	.620
PEU-ATT	.550	.550
PU-SN	.390	.390
PEU-SN	.290	.290
ATT-SN	.380	.380
PU-FC	.170	.170
PEU-FC	.280	.280
ATT-FC	.230	.230

										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	-	0	1	1	385	PU-PEU	.640	.640
										PU-ATT	.650	.650
										PEU-ATT	.650	.650
										PU-BI	.610	.610
										PEU-BI	.650	.650
										ATT-BI	.750	.750
										PU-SN	.110	.110
										PEU-SN	.150	.150

										ATT-	.	.2
										SN	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	150	50
Tokel & Isler (2015)	0	Turkey	-	22.	26	1	0	1	46	PU-	.	.4
				0	.1					PEU	330	02

										PU-ATT	.630	.783
										PEU-ATT	.500	.614
										PU-BI	.738	.923
										PEU-BI	.311	.384
										ATT-BI	.527	.663
Ulrich (2009)[a]	1	USA	2	-	-	1	1	0	285	PU-PEU	.640	.640
										ATT-BI	.470	.470
										ATT-USE	.170	.170

										BI- USE	. 220	.2 20
Waheed (2010)	1	Pakistan	2	-	-	1	0	0	93	PU- PEU	. 590	.7 72
										PU-BI	. 620	.7 47
										PEU- BI	. 680	.8 59
										PU- CSE	. 610	.7 88
										PEU- CSE	. 450	.6 09
										BI- CSE	. 560	.6 99
										PU- FC	. 160	.1 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	.419	.419
PU-CSE	.364	.364
PEU-CSE	.271	.271
BI-CSE	.276	.276
SN-CSE	.425	.425
PU-FC	.378	.378
PEU-FC	.340	.340
BI-FC	.207	.207

										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-	.	.4
										USE	359	30
										PEU-	.	.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- CSE	. 570	.6 33
										BI- CSE	. 410	.4 66
Wong, Teo, & Russo (2013)	0	Australia	0	19. 5	98 .1	1	1	1	15 9	PU- PEU	. 110	.1 10
										PU-BI	. 470	.4 70
										PEU- BI	. 290	.2 90
										PU- SN	. 150	.1 50
										PEU- SN	. 070	.0 70
										BI-SN	. 150	.1 50

									PU-FC	.070	.070
									PEU-FC	.220	.220
									BI-FC	.130	.130
									SN-FC	.100	.100
Wong et al. (2014)	0	Malaysia and Macau (China)	0	-	98.0	1	1	1	149	PU-PEU	.065	.065
									PU-SN	.162	.162
									PEU-SN	.046	.046
									PU-CSE	.362	.362

										PEU-CSE	.177	.177
										SN-CSE	.174	.174
										PU-FC	.078	.078
										PEU-FC	.215	.215
										SN-FC	.105	.105
										CSE-FC	.118	.118
Wong (2015)	0	Hong Kong (China)	0	25.6	69.7	0	1	1	234	PU-PEU	.500	.500
										PU-ATT	.640	.640

PEU-ATT	.550	.550
PU-BI	.550	.550
PEU-BI	.480	.480
ATT-BI	.590	.590
PU-SN	.410	.410
PEU-SN	.300	.300
ATT-SN	.340	.340
BI-SN	.310	.310

PU- CSE	. 390	.3 90
PEU- CSE	. 450	.4 50
ATT- CSE	. 400	.4 00
BI- CSE	. 300	.3 00
SN- CSE	. 300	.3 00
PU- FC	. 390	.3 90
PEU- FC	. 510	.5 10
ATT- FC	. 430	.4 30

										BI-FC	.390	.390
										SN-FC	.390	.390
										CSE-FC	.520	.520
Wong, Osman et al. (2013)	0	Malaysia	-	23.4	64.2	0	1	1	302	PU-PEU	.649	.649
										PU-ATT	.525	.525
										PEU-ATT	.408	.408
										PU-BI	.521	.521
										PEU-BI	.406	.406

										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-CSE	.460	.540
BI-CSE	.800	.984
SN-CSE	.160	.199
PU-FC	.080	.096
PEU-FC	.220	.278
BI-FC	.130	.172
SN-FC	.110	.147
CSE-FC	.170	.186

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-FC	.440	.440
										BI-FC	.500	.500
Wu, Chang, & Guo (2008)	1	Taiwan	1	-.0	35	0	1	1	226	PU-PEU	.383	.383
										PU-BI	.702	.702
										PEU-BI	.415	.415
										PU-CSE	.456	.456
										PEU-CSE	.578	.578
										BI-CSE	.636	.636

Wu & Liu (2015)	1	Taiwan	0	-	80.6	1	0	1	340	PU-PEU	.467	.534
										PU-ATT	.634	.733
										PEU-ATT	.610	.674
										PU-BI	.562	.626
										PEU-BI	.494	.527
										ATT-BI	.681	.734
Wu et al. (2016)	1	Shanghai (China)	2	-	52.8	0	0	1	144	PU-PEU	.110	.132
										PU-ATT	.750	.944

										PEU-ATT	.110	.138
										PU-BI	.620	.797
										PEU-BI	.200	.255
										ATT-BI	.670	.900
Yeni & Gecu-Parmaksiz (2016)	0	Turkey	0	-	59 .0	0	0	1	208	PU-PEU	.414	.461
										PU-BI	.591	.636
										PEU-BI	.110	.122
										PU-SN	.607	.706

										PEU-SN	.230	.275
										BI-SN	.595	.689
Yeung et al. (2012)[a]	0	Singapore	1	30.0	66.3	0	1	1	323	PU-USE	.230	.230
										PU-CSE	.760	.760
										USE-CSE	.340	.340
Yuen & Ma (2002)	0	Hong Kong (China)	-	23.6	75.1	0	1	1	186	PU-PEU	.580	.580
										PU-BI	.430	.430
										PEU-BI	.249	.249

										PU-	.	.5
										USE	522	22
										PEU-	.	.3
										USE	303	03
										BI-	.	.4
										USE	493	93
Yuen & Ma (2008)	1	Hong Kong	-	31.	59	1	0	1	15	PU-	.	.5
		(China)		9	.2				2	PEU	414	06
										PU-BI	.	.1
											086	21
										PEU-	.	.5
										BI	390	79
										PU-	.	.8
										SN	619	02
										PEU-	.	.4
										SN	360	94

										BI-SN	.	.2
											140	20
										PU-	.	.0
										CSE	066	76
										PEU-	.	.3
										CSE	300	66
										BI-	.	.1
										CSE	117	64
										SN-	.	.0
										CSE	000	00
Yusop (2015)	0	Malaysia	0	23.	79	1	0	1	10	PU-	.	.6
				0	.0				0	ATT	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

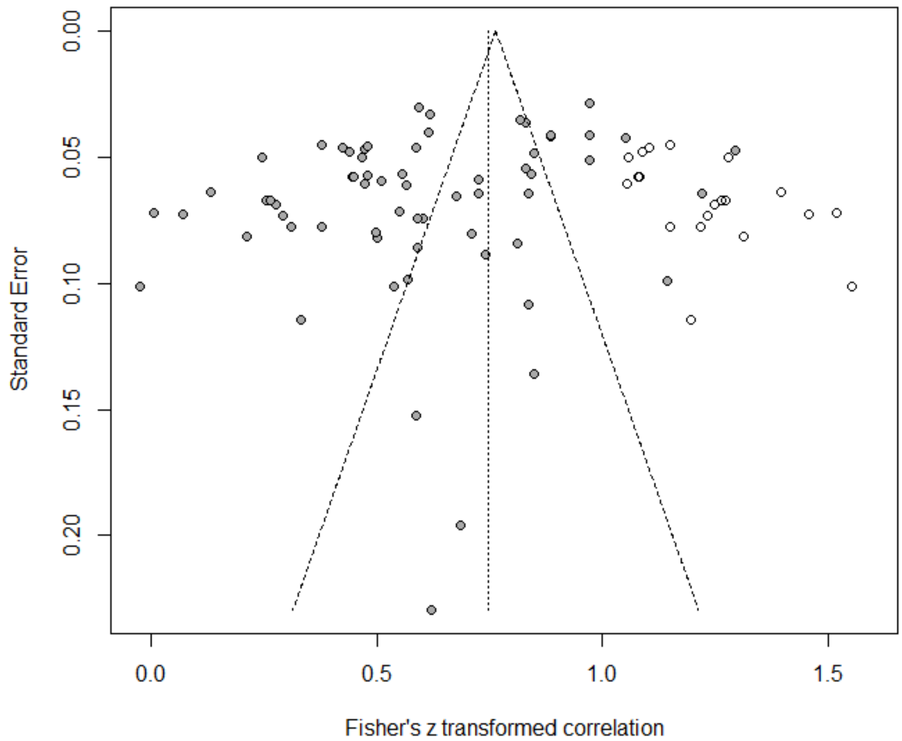
Note. * The correction for unreliability resulted in a correlation of 1. To achieve positive definiteness of the correlation matris, this correlation has been constrained to 0.999. a: These correlation matrices were excluded from the meta-analysis due to non-positive definiteness.

S3. Assessment of publication bias

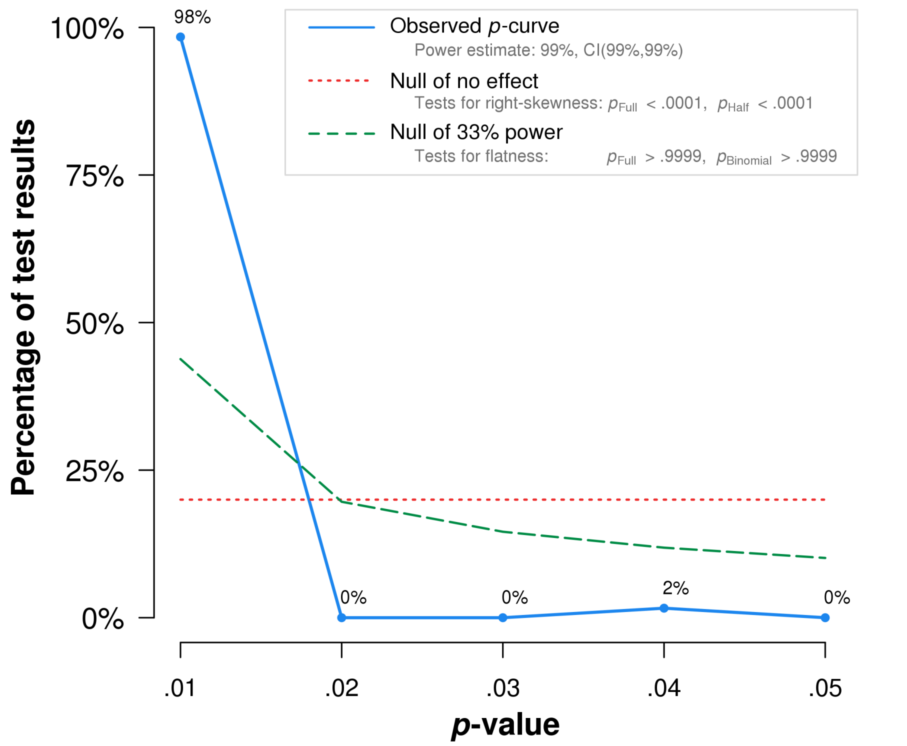
This meta-analysis is based on correlation matrices extracted from primary studies of teachers' technology acceptance. These matrices comprise a set of correlations among TAM variables which might be prone to publication bias. As traditional methods to assess publication bias have not yet been conceptualized 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)



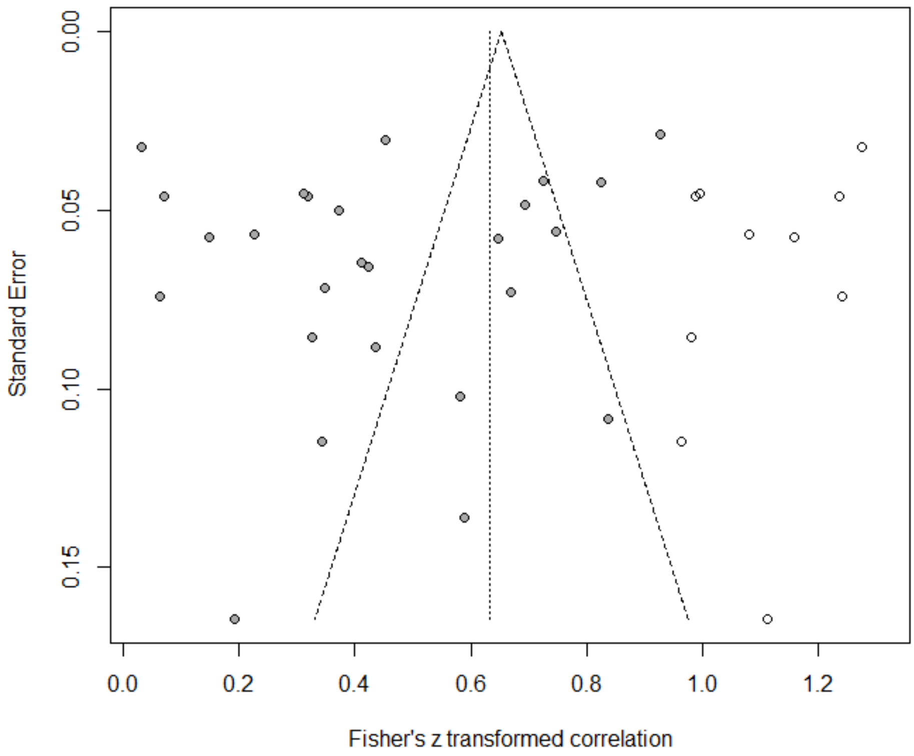
P-Curve



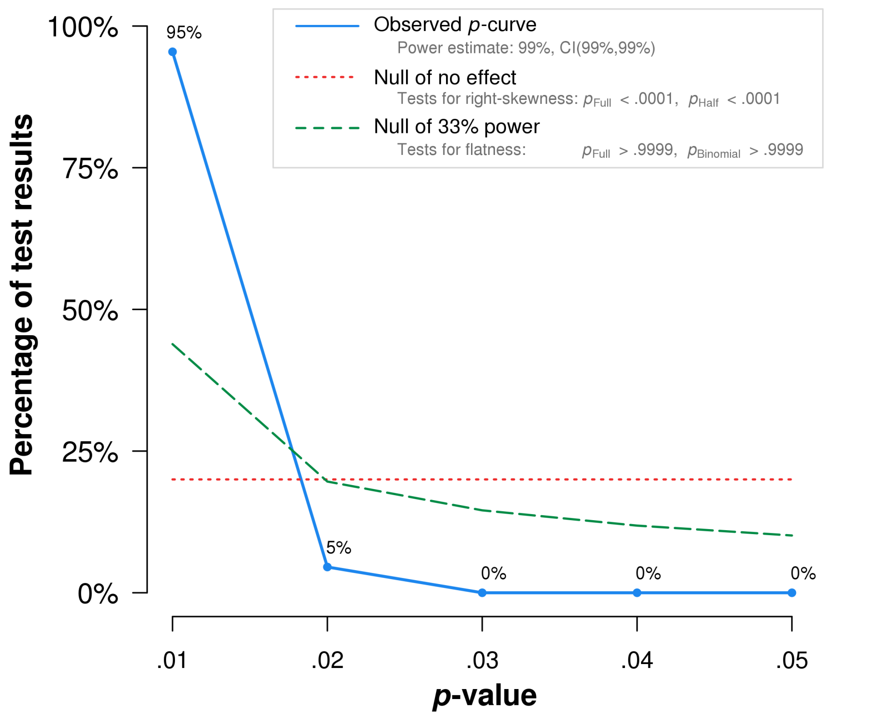
Note: The observed *p*-curve includes 62 statistically significant ($p < .05$) results, of which 61 are $p < .025$. There were 3 additional results entered but excluded from *p*-curve because they were $p > .05$.

ATT–CSE correlation

Funnel plot (with trim and fill)



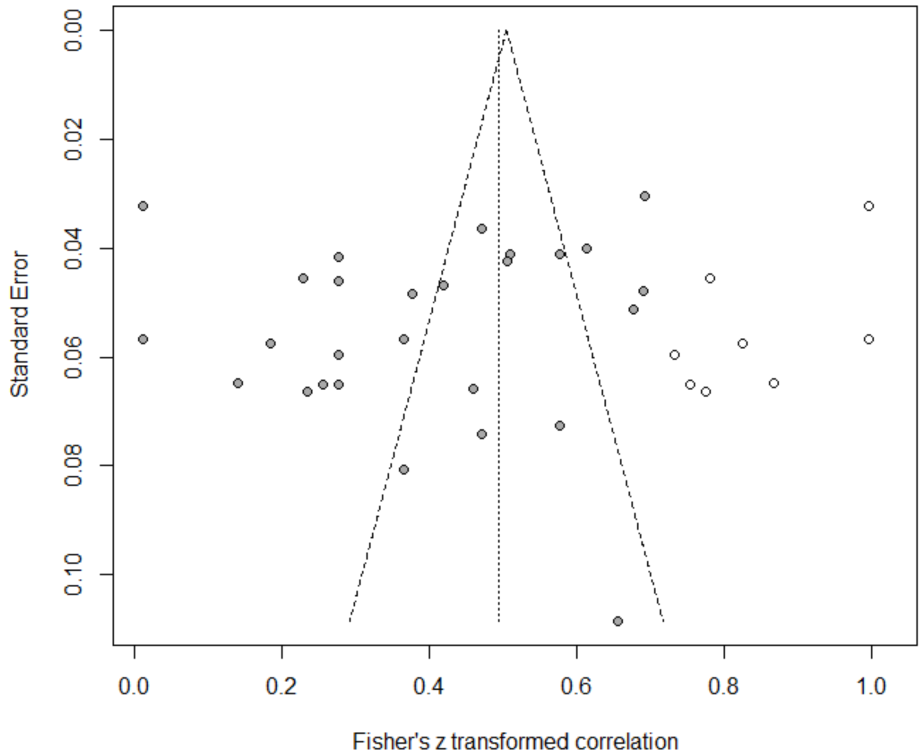
P-Curve



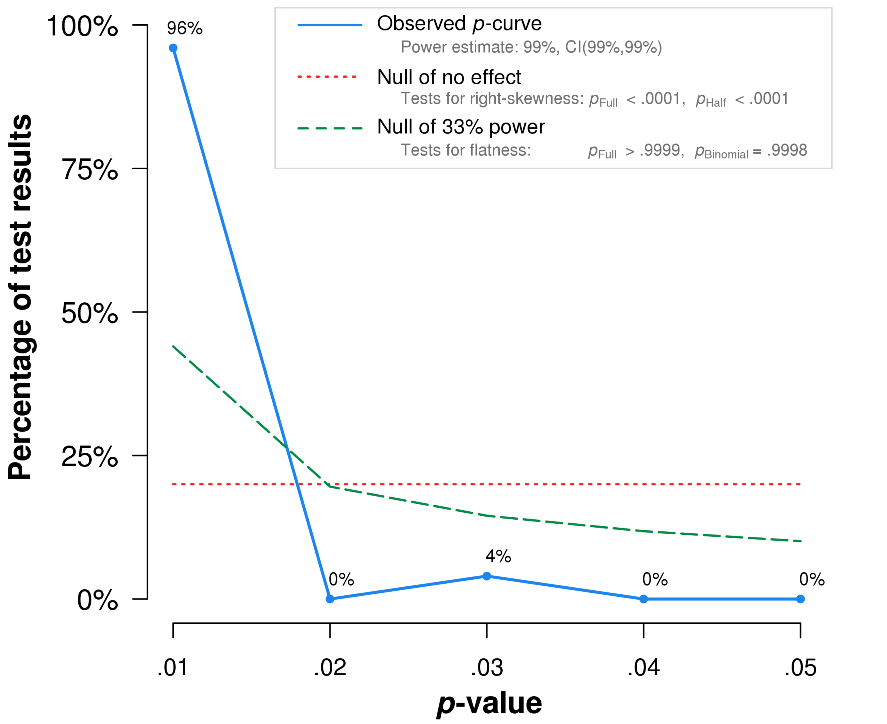
Note: The observed *p*-curve includes 22 statistically significant ($p < .05$) results, of which 22 are $p < .025$. There were 4 additional results entered but excluded from *p*-curve because they were $p > .05$.

ATT–FC correlation

Funnel plot (with trim and fill)



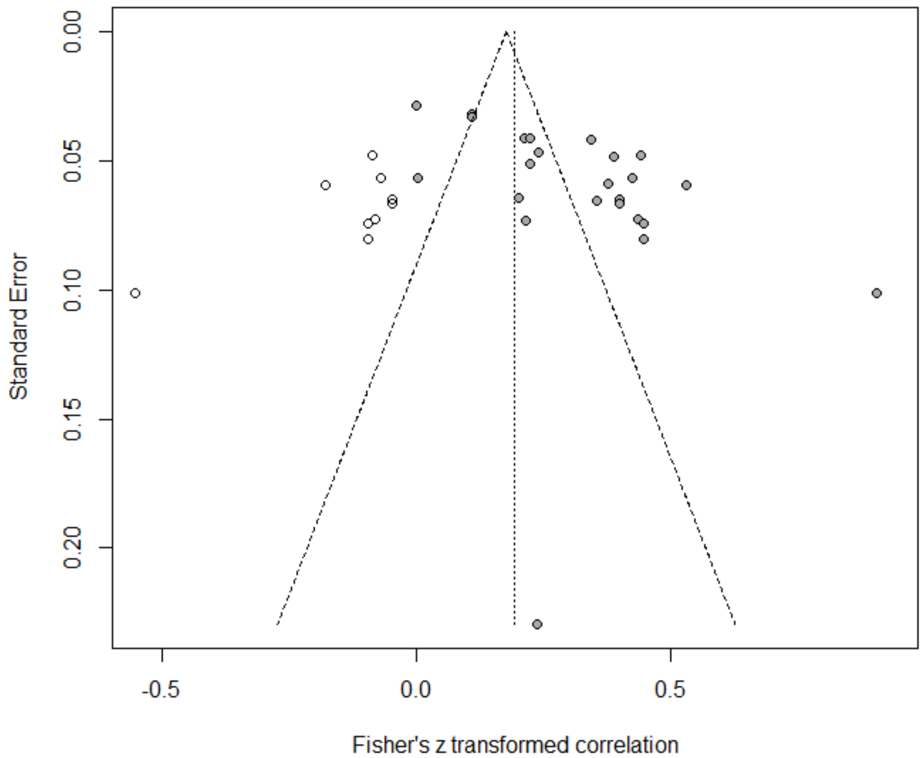
P-Curve



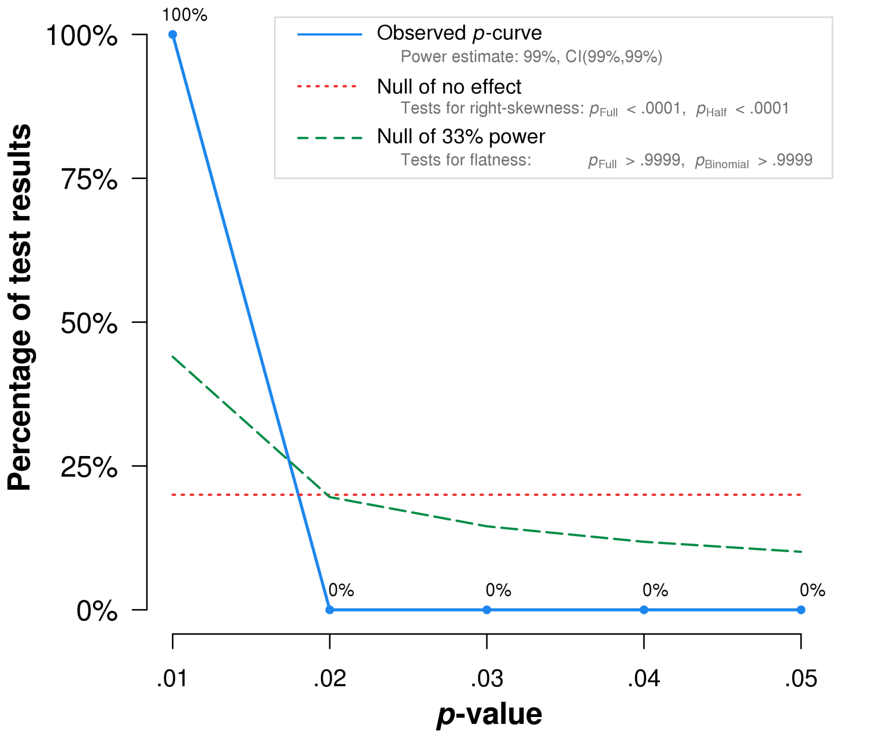
Note: The observed *p*-curve includes 25 statistically significant ($p < .05$) results, of which 24 are $p < .025$. There were 2 additional results entered but excluded from *p*-curve because they were $p > .05$.

ATT–SN correlation

Funnel plot (with trim and fill)



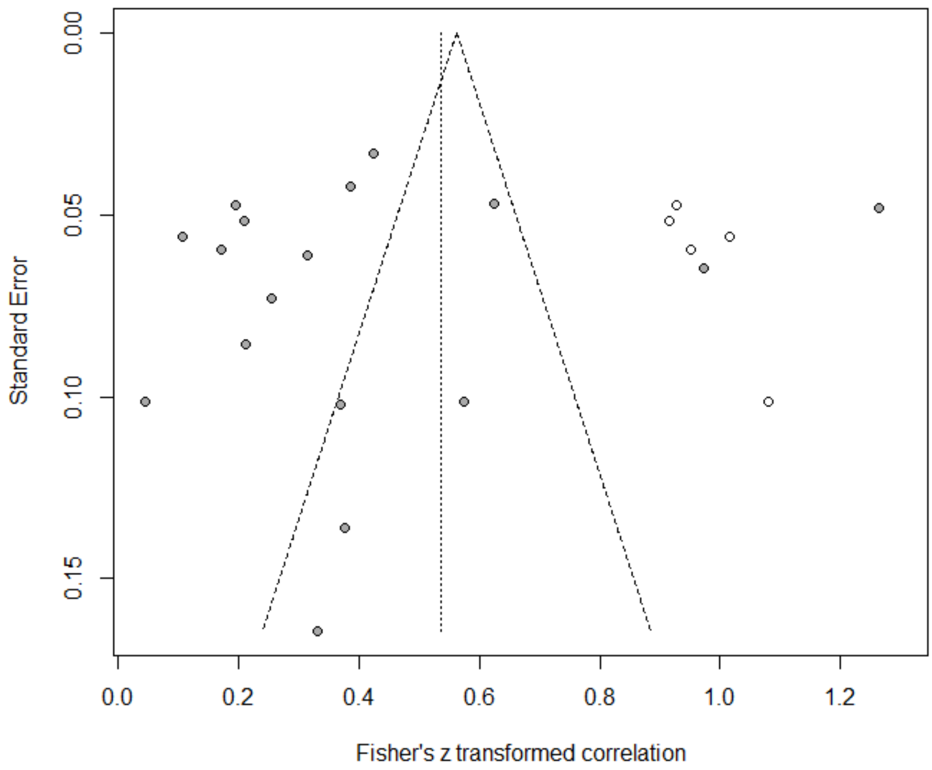
P-Curve



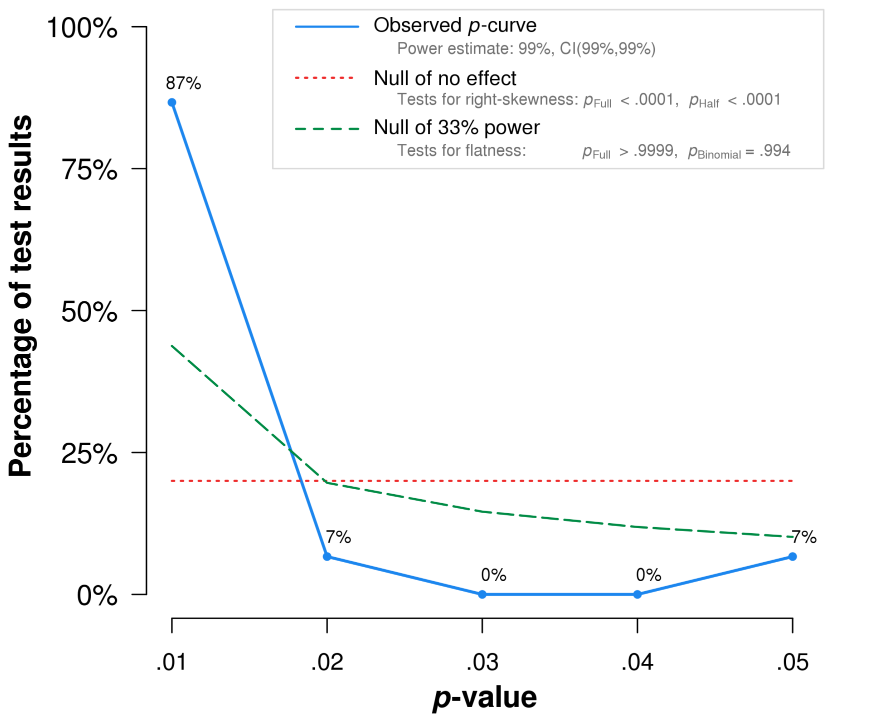
Note: The observed *p*-curve includes 22 statistically significant ($p < .05$) results, of which 22 are $p < .025$. There were 3 additional results entered but excluded from *p*-curve because they were $p > .05$.

ATT–USE correlation

Funnel plot (with trim and fill)



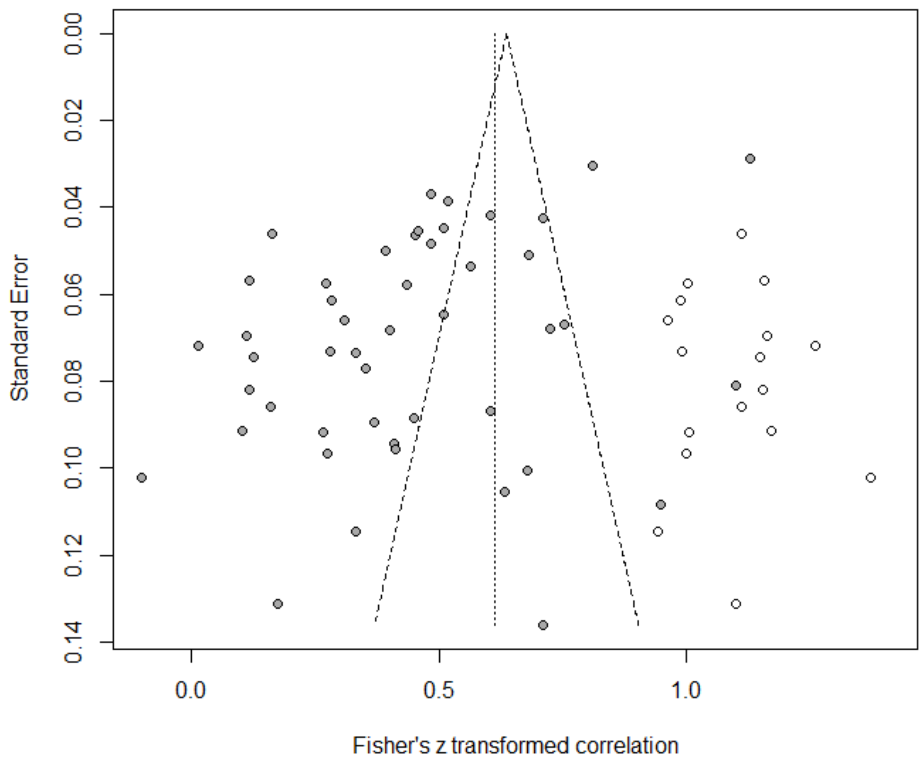
P-Curve



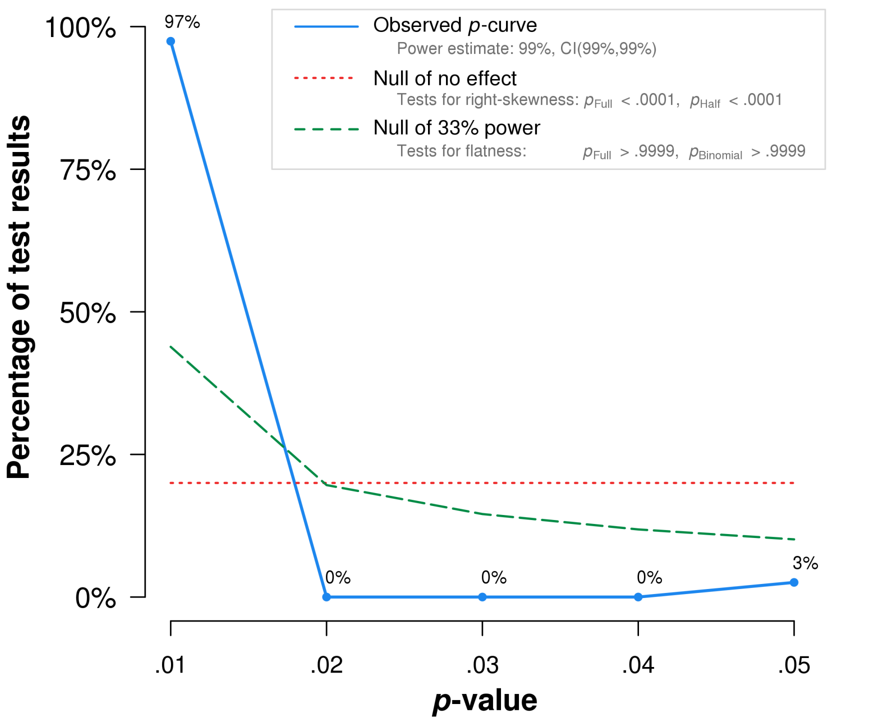
Note: The observed p-curve includes 15 statistically significant (p < .05) results, of which 14 are p < .025.
There were 2 additional results entered but excluded from p-curve because they were p > .05.

BI–CSE correlation

Funnel plot (with trim and fill)



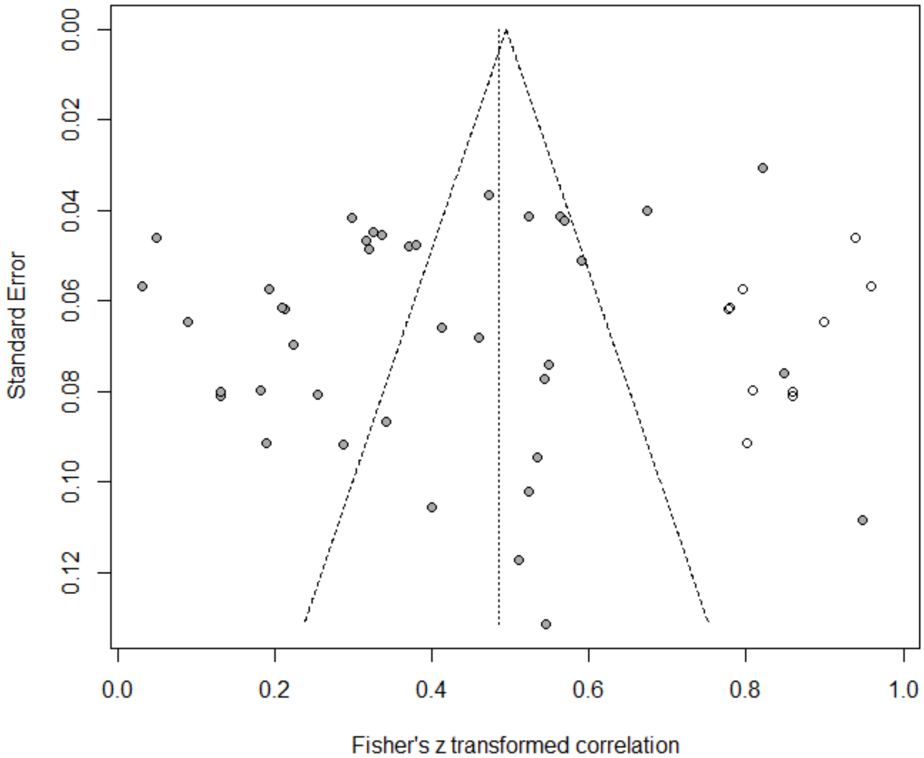
P-Curve



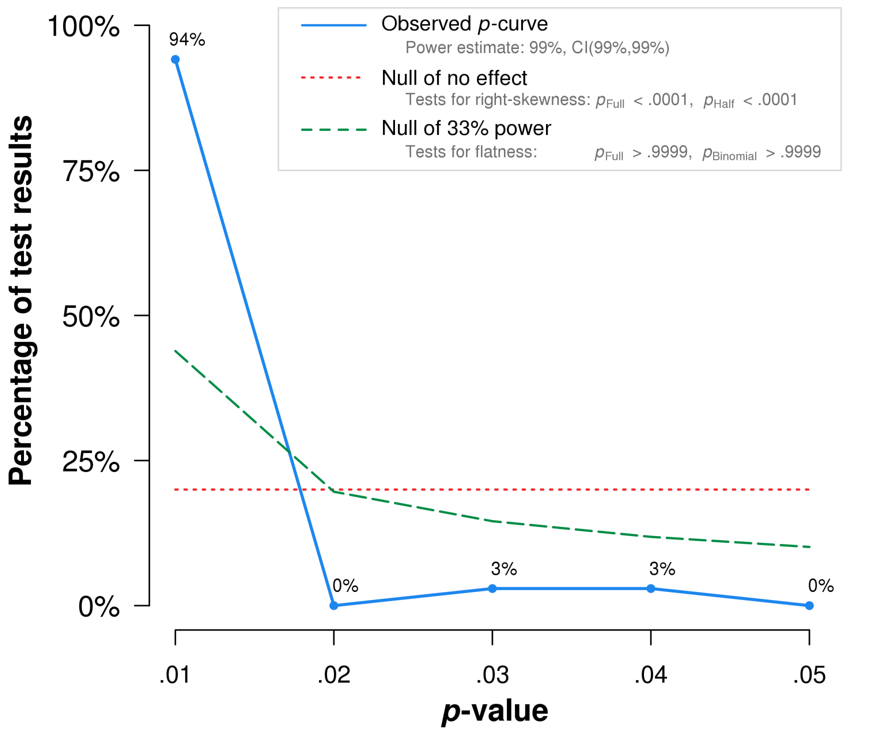
Note: The observed *p*-curve includes 39 statistically significant ($p < .05$) results, of which 38 are $p < .025$. There were 8 additional results entered but excluded from *p*-curve because they were $p > .05$.

BI–FC correlation

Funnel plot (with trim and fill)



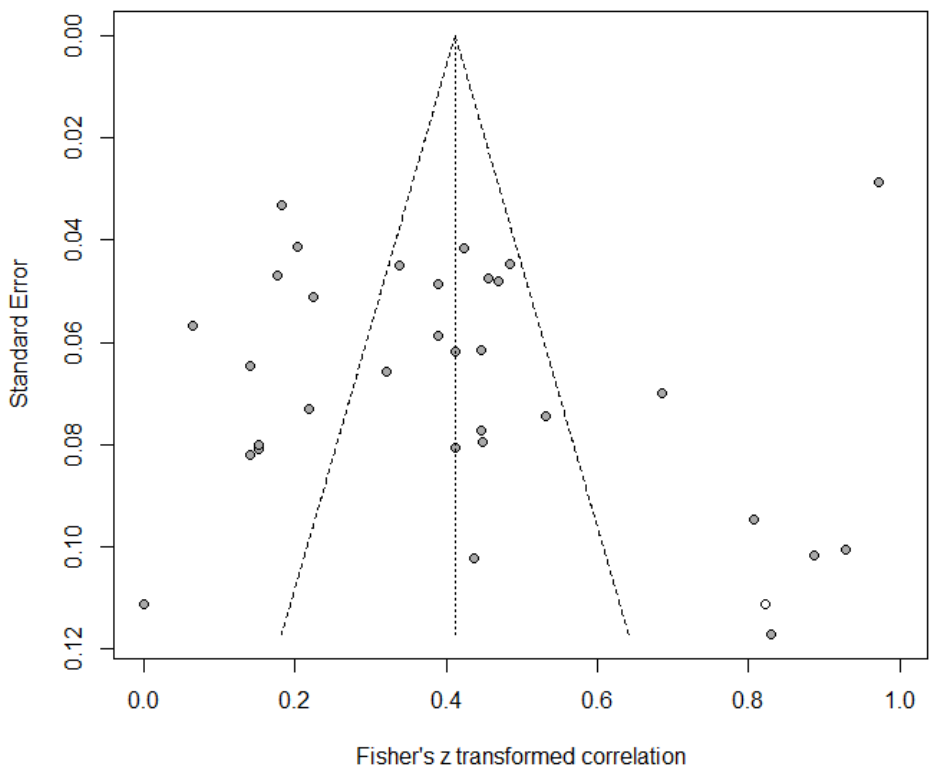
P-Curve



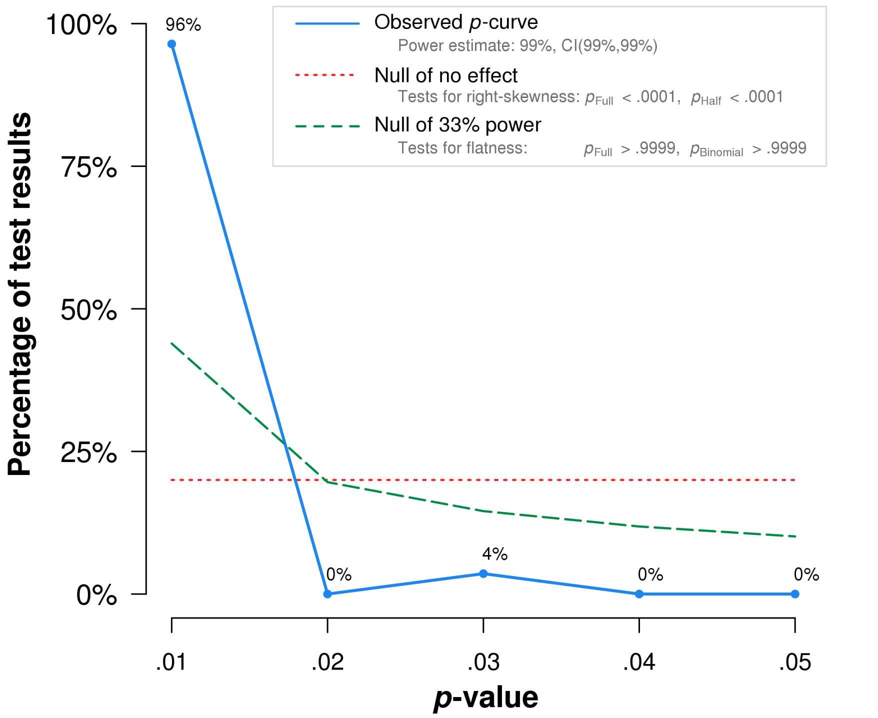
Note: The observed *p*-curve includes 34 statistically significant ($p < .05$) results, of which 33 are $p < .025$. There were 5 additional results entered but excluded from *p*-curve because they were $p > .05$.

BI–SN correlation

Funnel plot (with trim and fill)



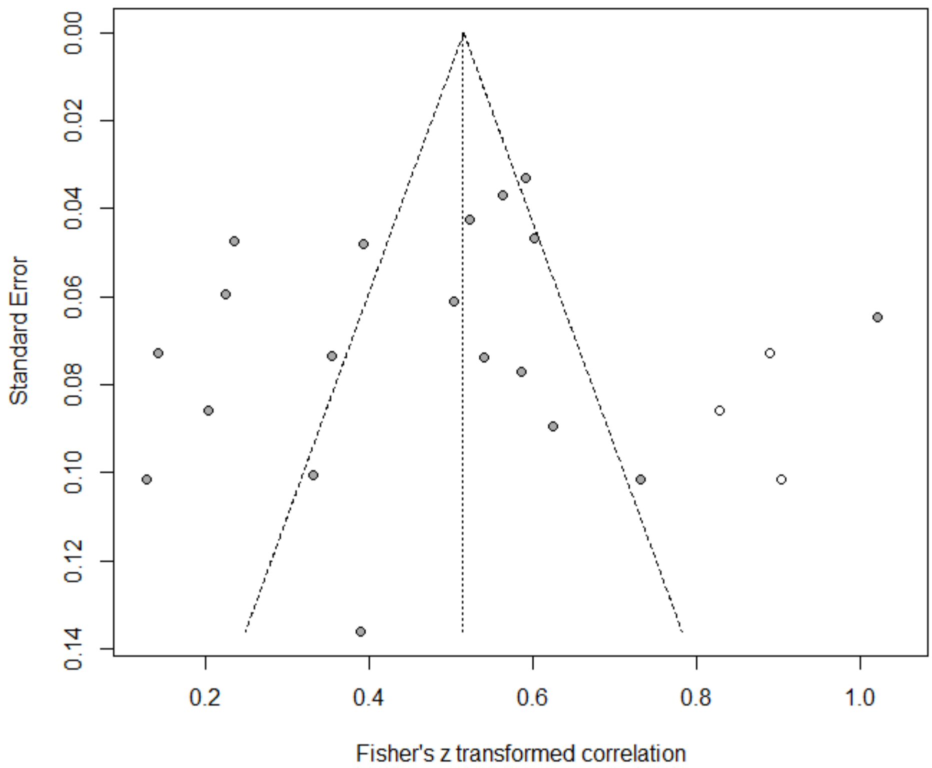
P-Curve



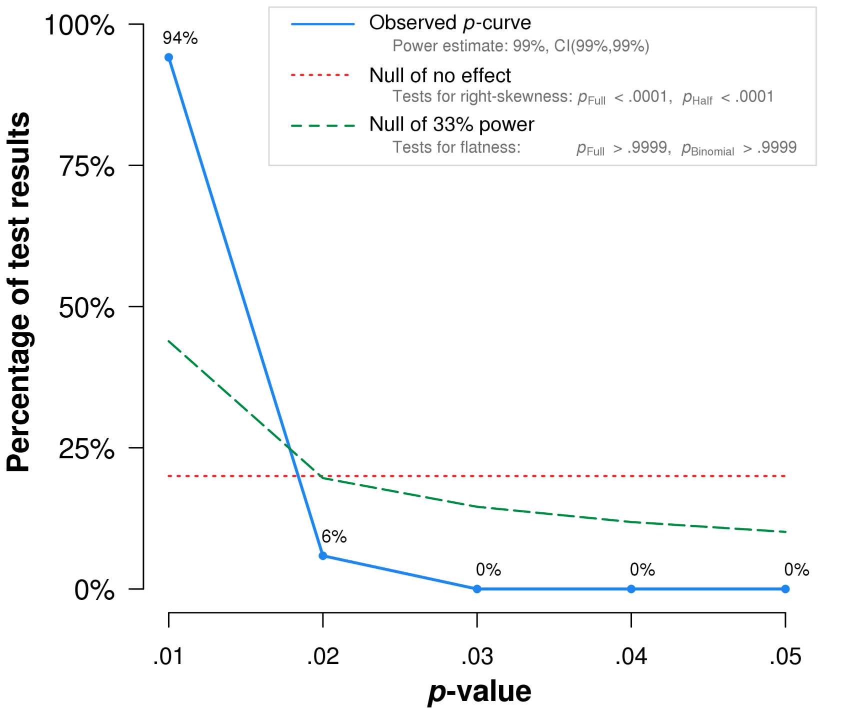
Note: The observed *p*-curve includes 28 statistically significant ($p < .05$) results, of which 27 are $p < .025$. There were 5 additional results entered but excluded from *p*-curve because they were $p > .05$.

BI–USE correlation

Funnel plot (with trim and fill)



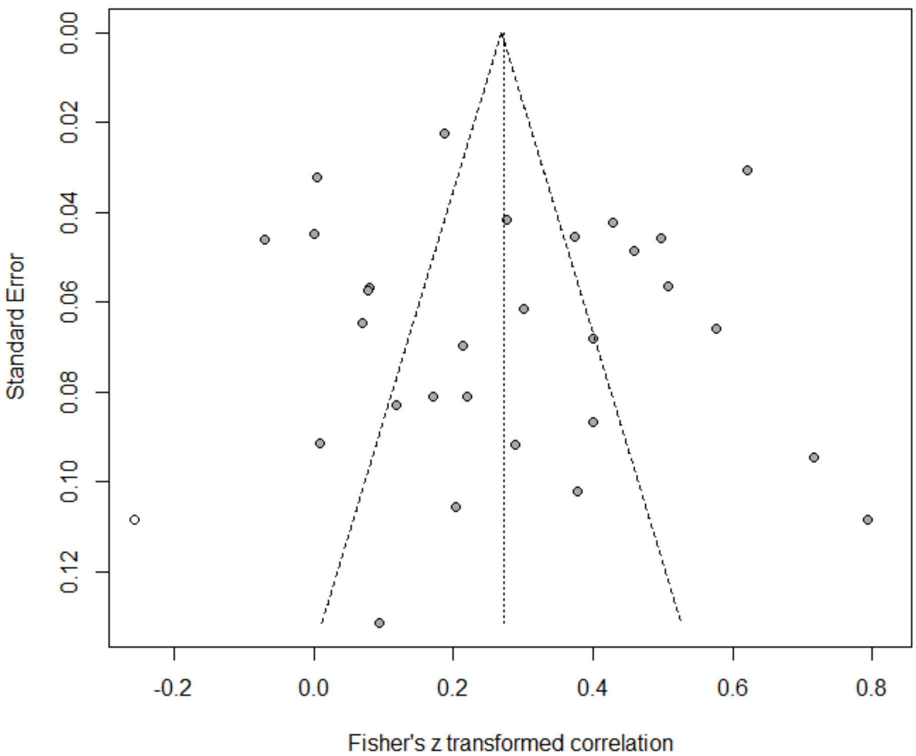
P-Curve



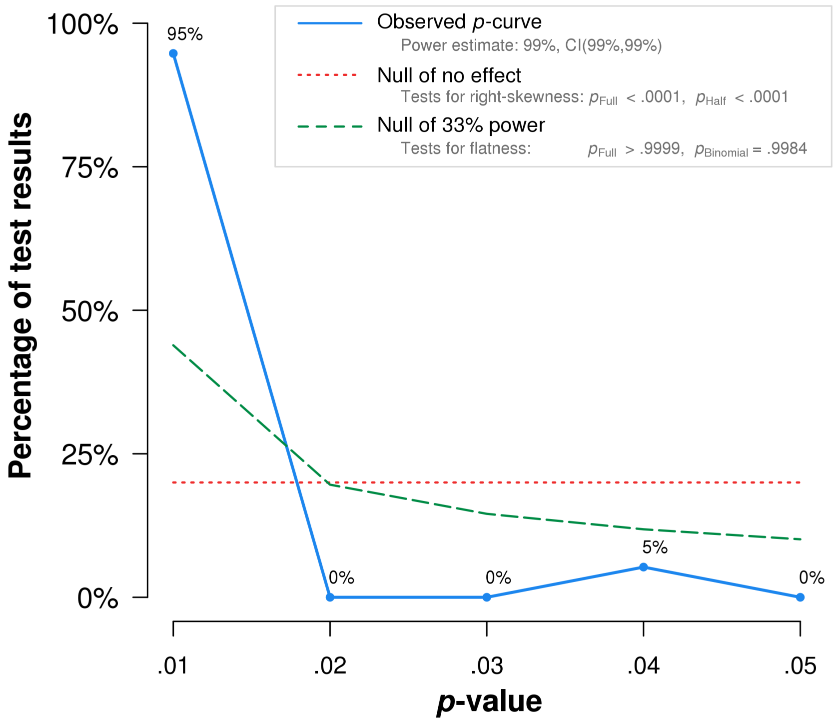
Note: The observed *p*-curve includes 17 statistically significant ($p < .05$) results, of which 17 are $p < .025$. There were 2 additional results entered but excluded from *p*-curve because they were $p > .05$.

CSE–FC correlation

Funnel plot (with trim and fill)



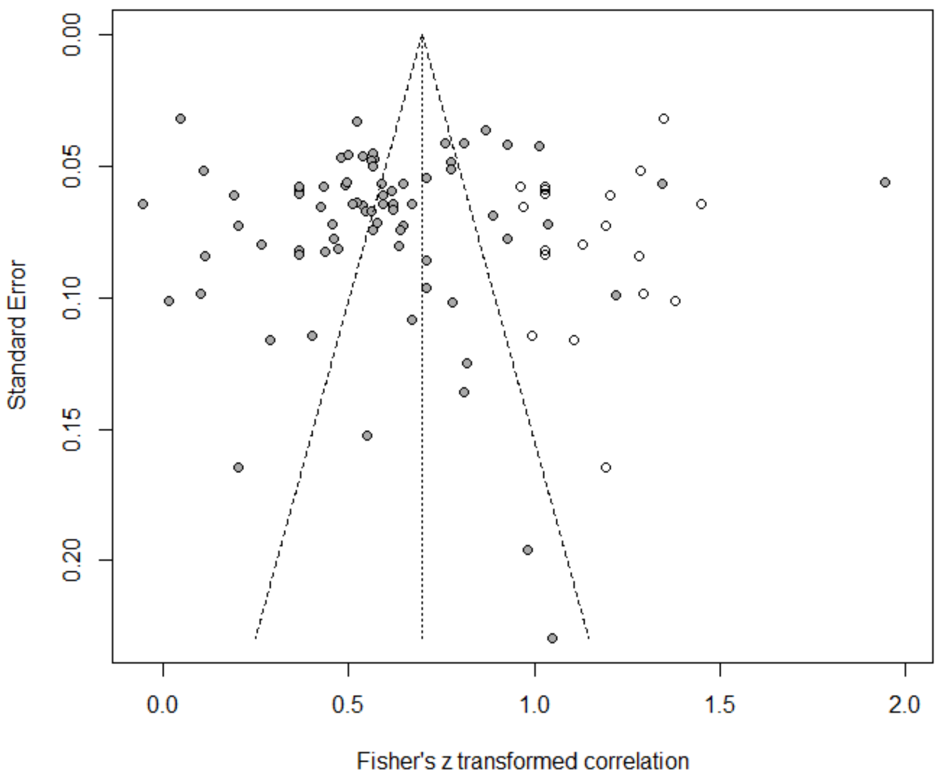
P-Curve



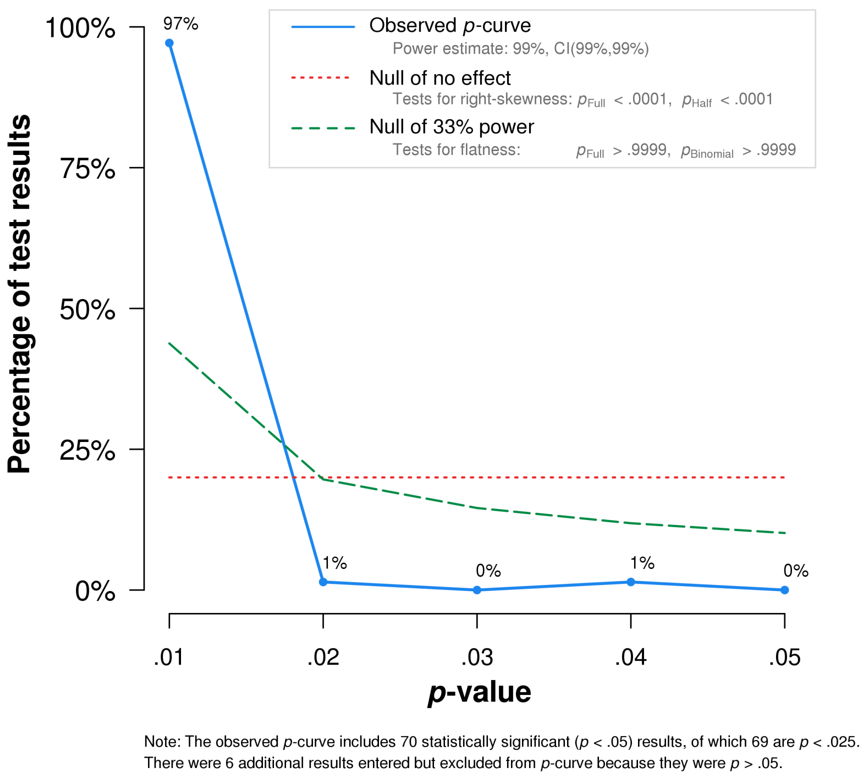
Note: The observed *p*-curve includes 19 statistically significant ($p < .05$) results, of which 18 are $p < .025$. There were 10 additional results entered but excluded from *p*-curve because they were $p > .05$.

PEU–ATT correlation

Funnel plot (with trim and fill)

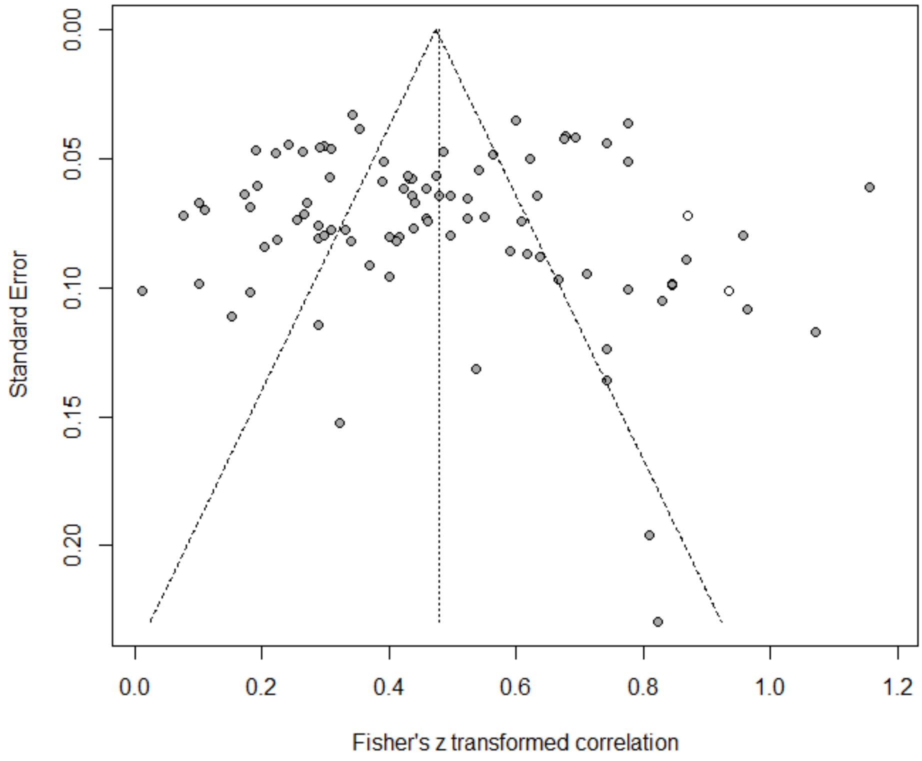


P-Curve

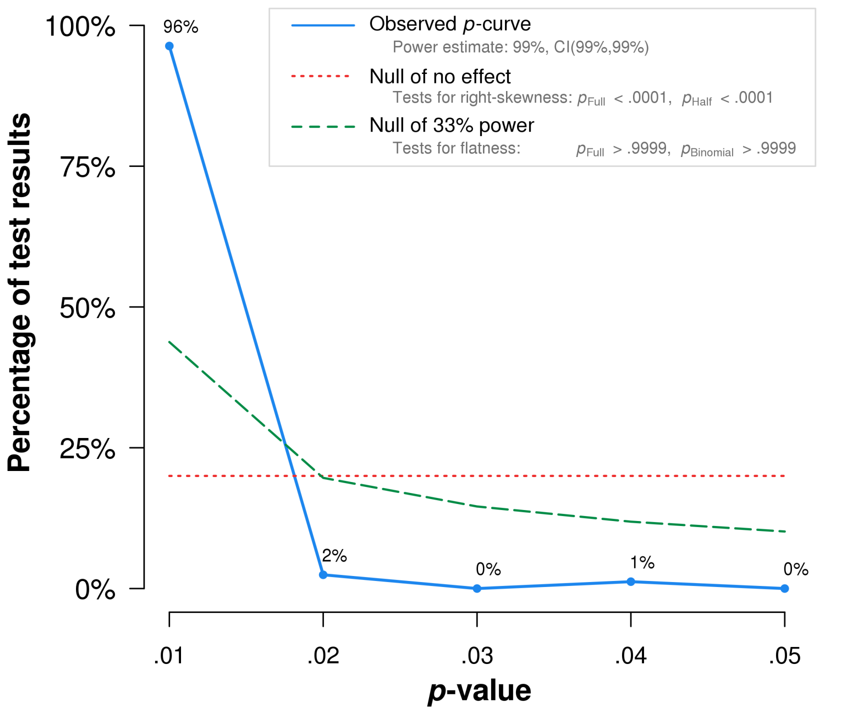


PEU–BI correlation

Funnel plot (with trim and fill)



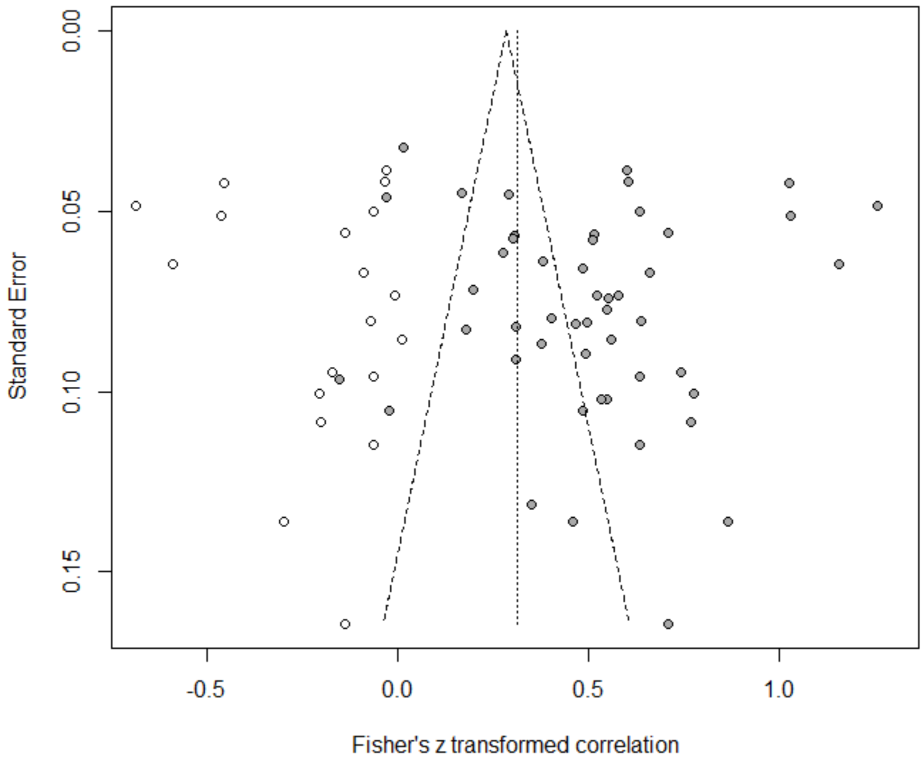
P-Curve



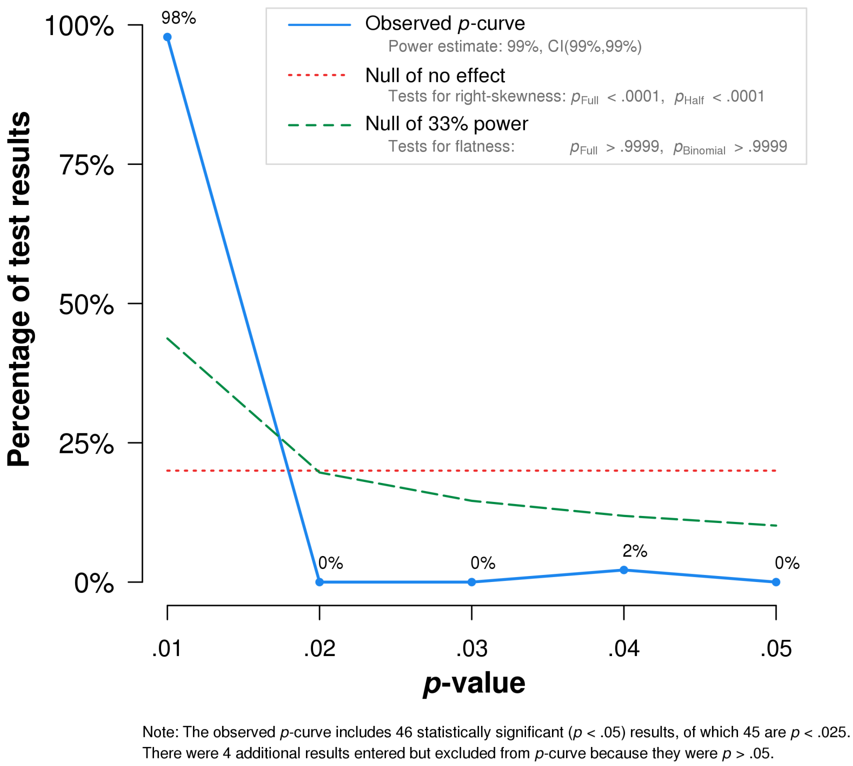
Note: The observed *p*-curve includes 82 statistically significant (p < .05) results, of which 81 are p < .025. There were 7 additional results entered but excluded from *p*-curve because they were p > .05.

PEU–CSE correlation

Funnel plot (with trim and fill)

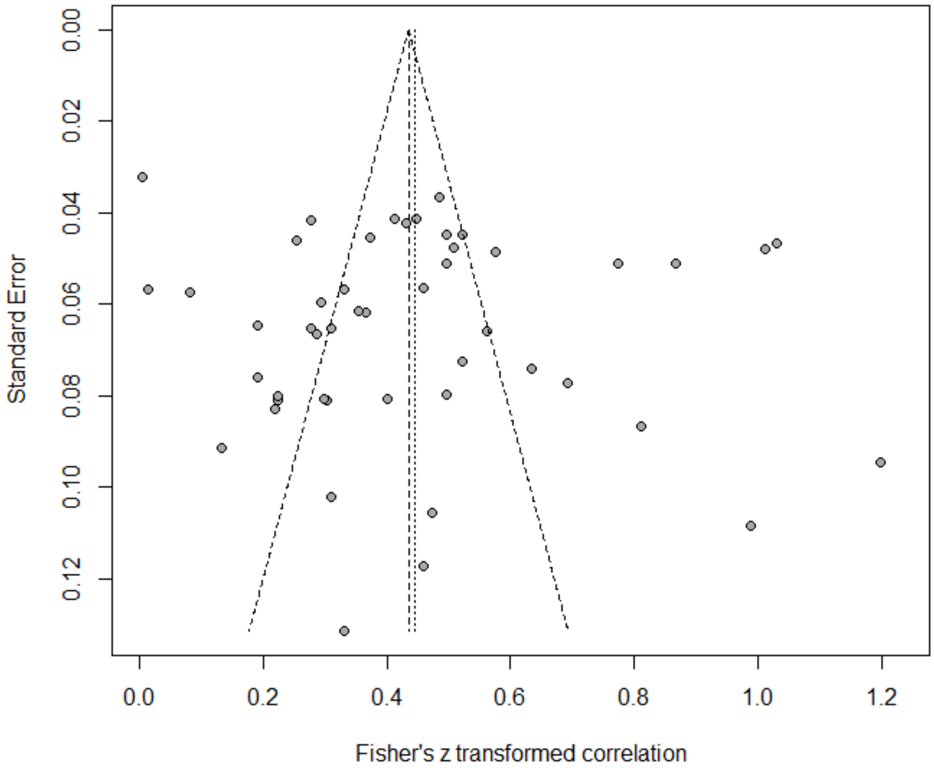


P-Curve

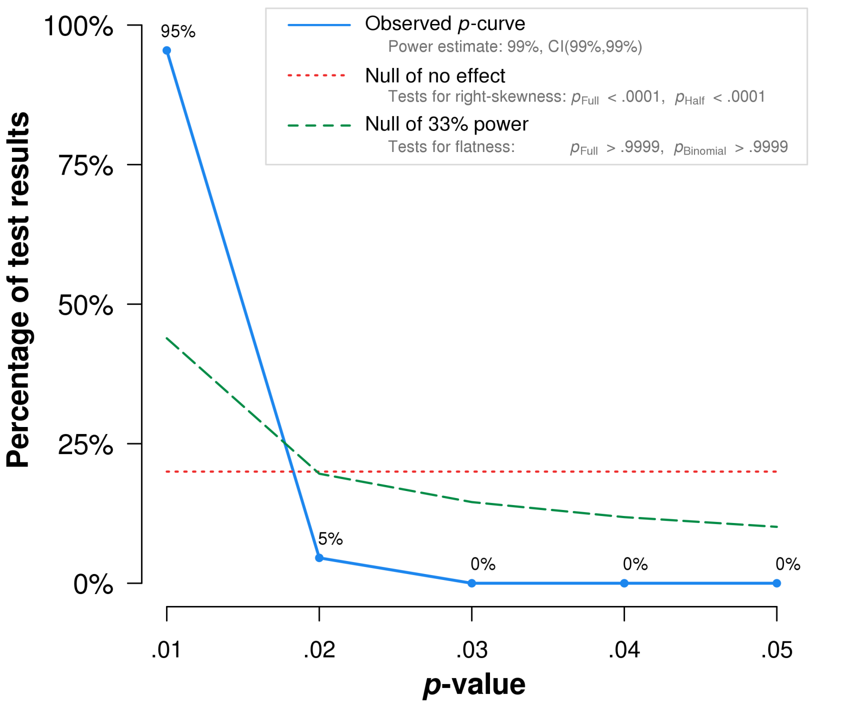


PEU–FC correlation

Funnel plot (with trim and fill)



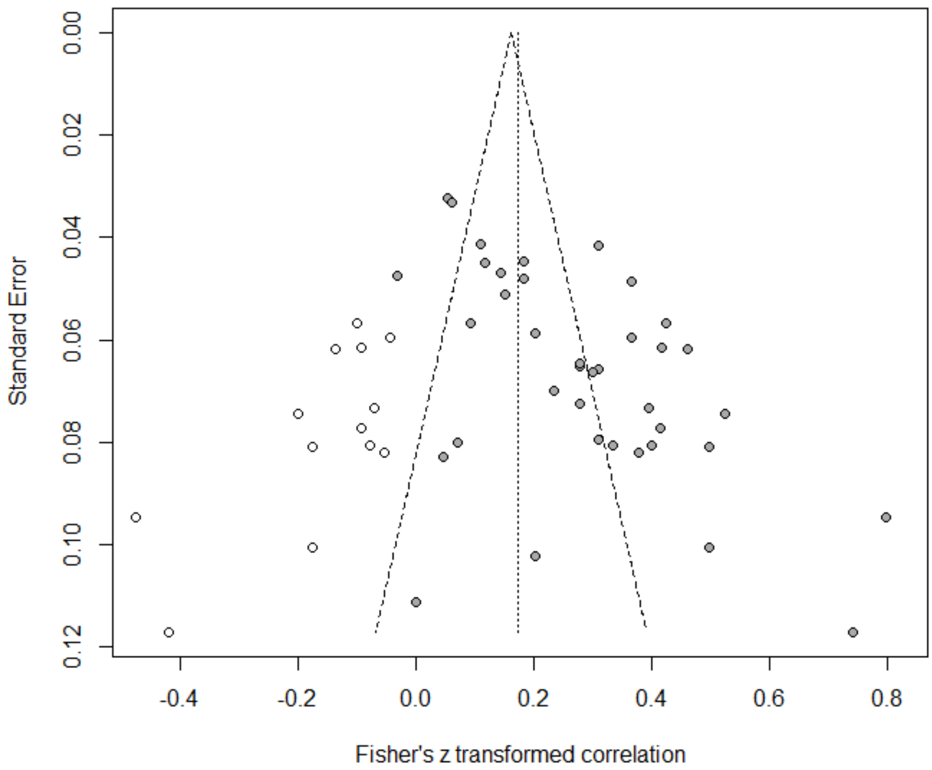
P-Curve



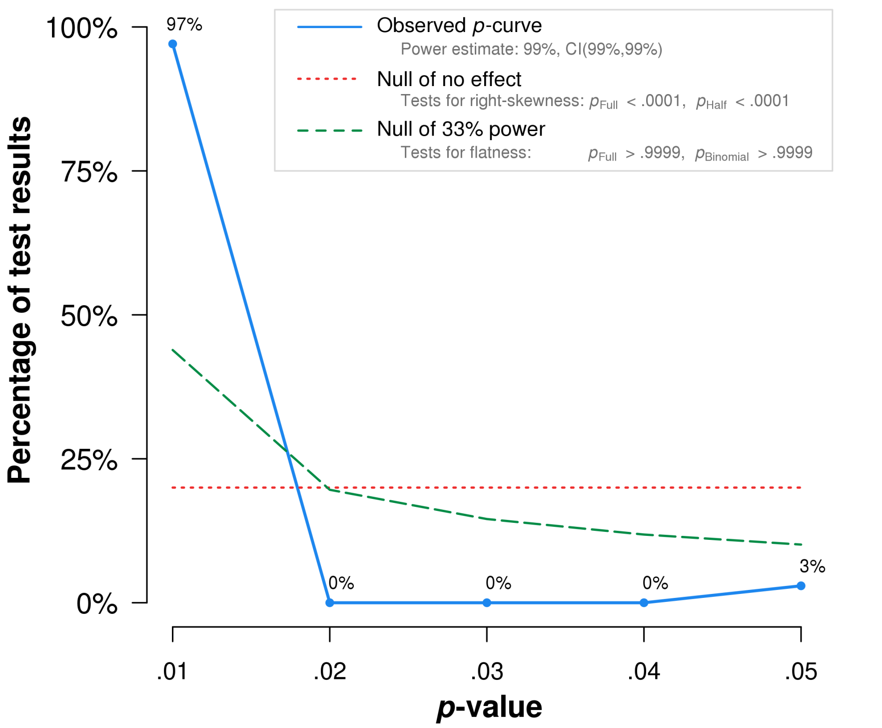
Note: The observed *p*-curve includes 44 statistically significant ($p < .05$) results, of which 44 are $p < .025$. There were 4 additional results entered but excluded from *p*-curve because they were $p > .05$.

PEU–SN correlation

Funnel plot (with trim and fill)



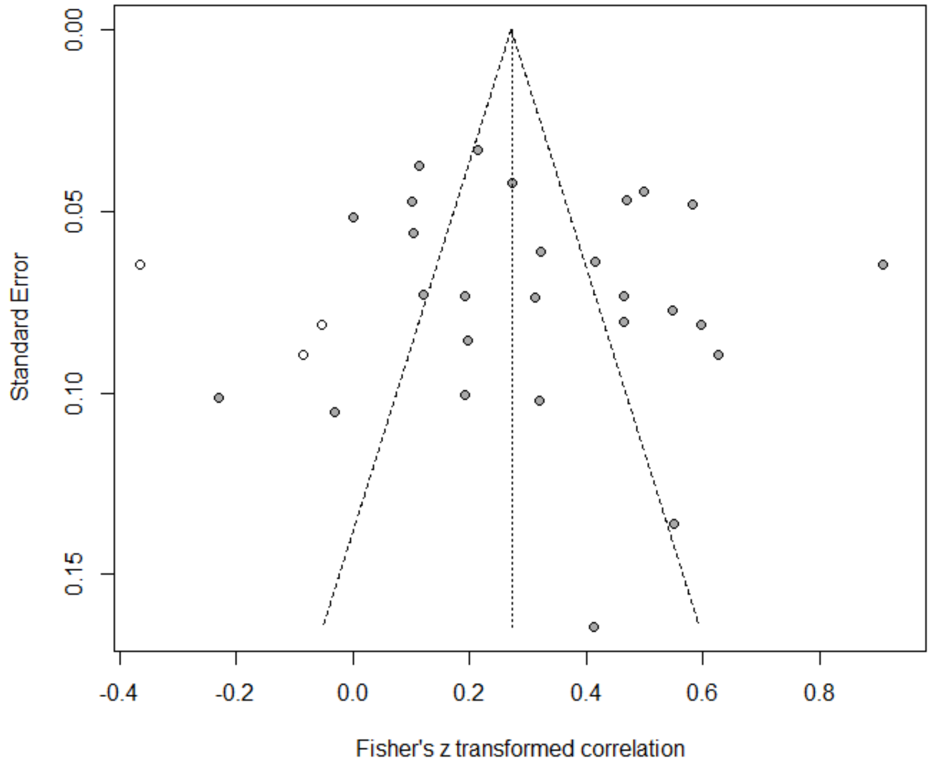
P-Curve



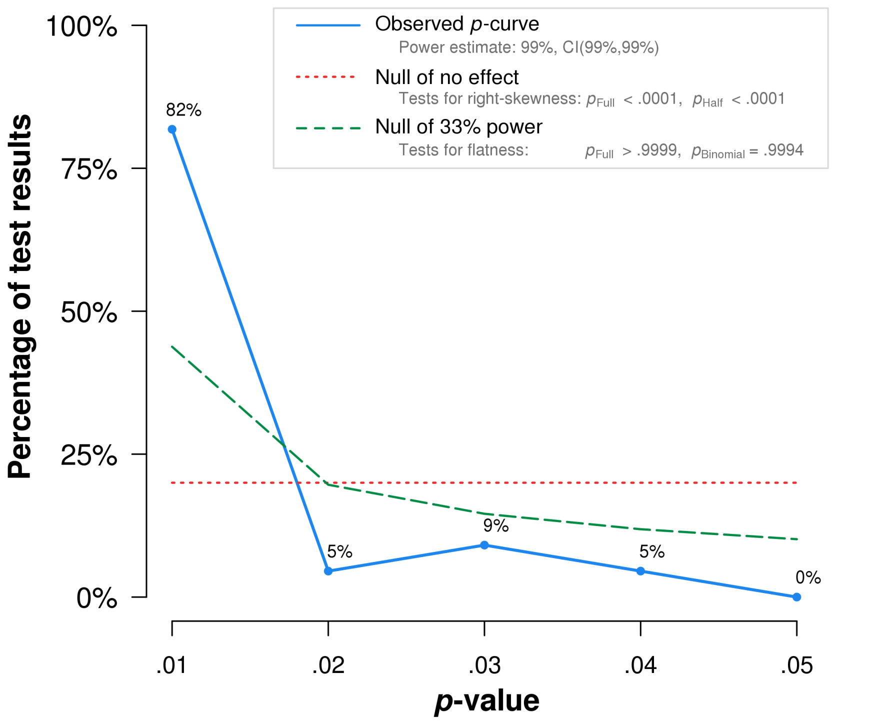
Note: The observed *p*-curve includes 34 statistically significant ($p < .05$) results, of which 33 are $p < .025$. There were 7 additional results entered but excluded from *p*-curve because they were $p > .05$.

PEU–USE correlation

Funnel plot (with trim and fill)



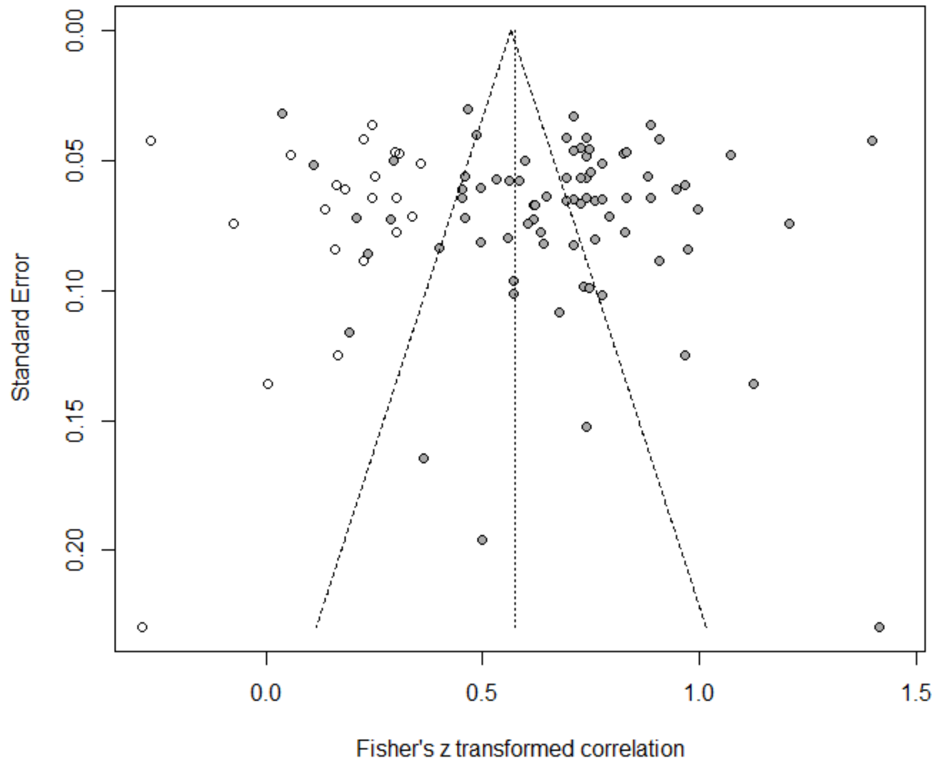
P-Curve



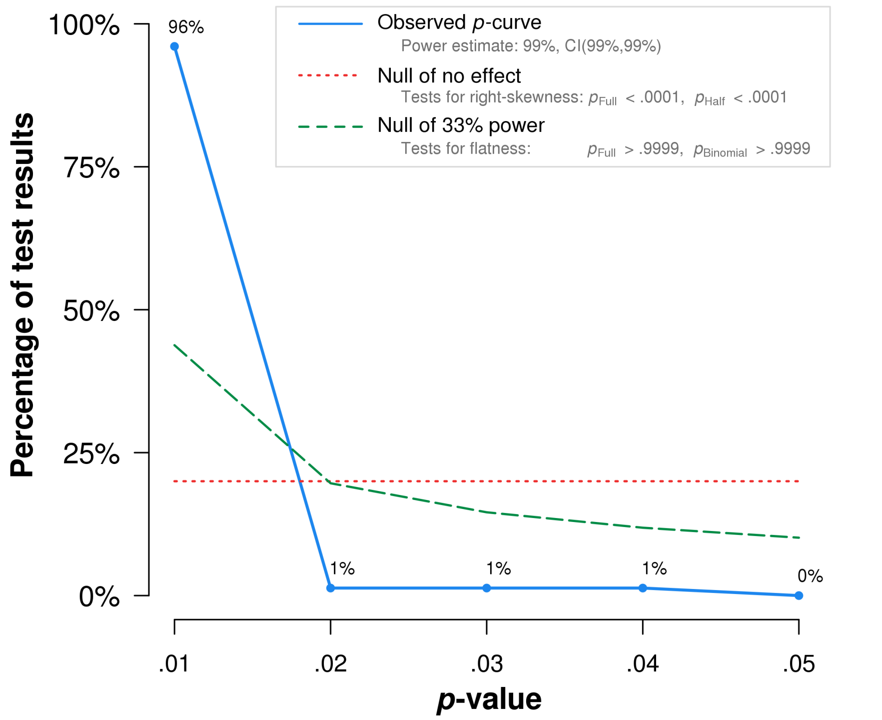
Note: The observed *p*-curve includes 22 statistically significant (*p* < .05) results, of which 21 are *p* < .025. There were 5 additional results entered but excluded from *p*-curve because they were *p* > .05.

PU–ATT correlation

Funnel plot (with trim and fill)



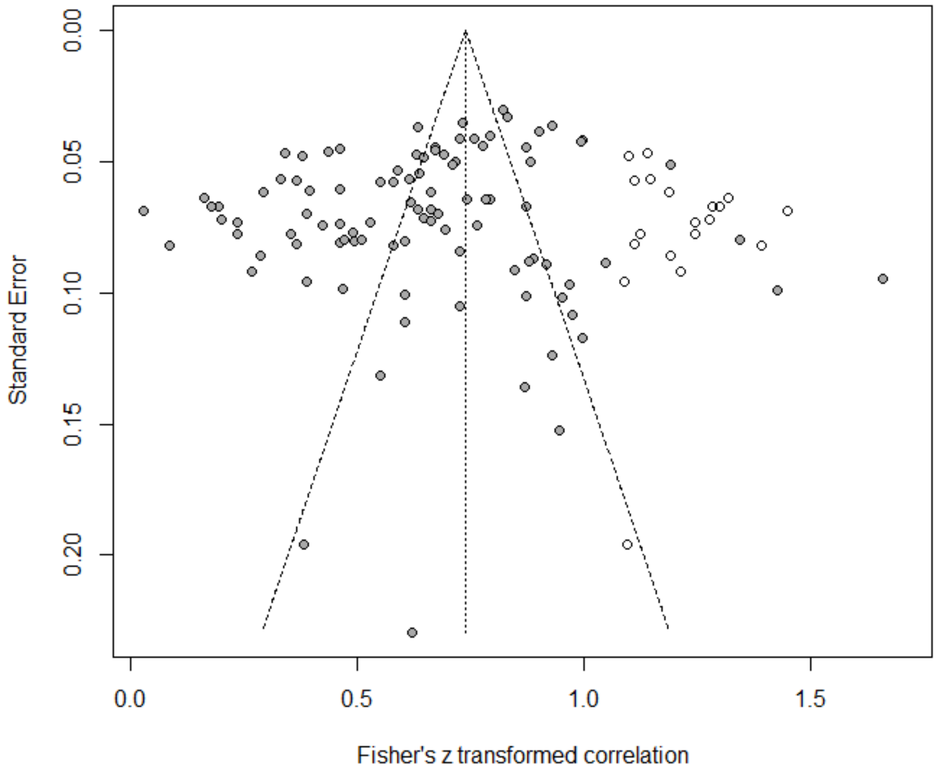
P-Curve



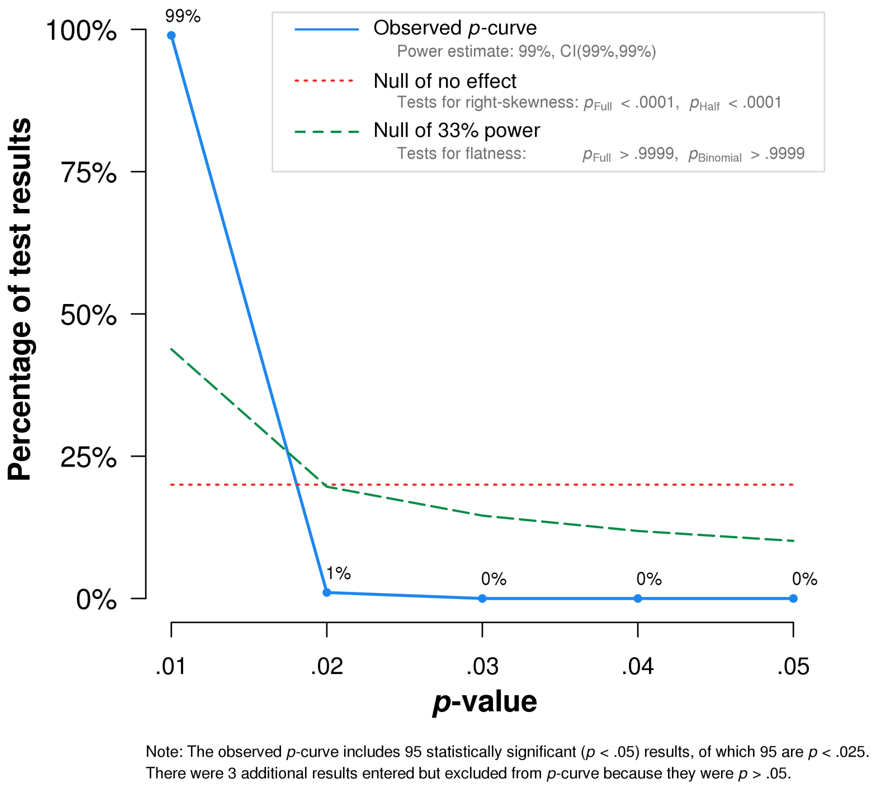
Note: The observed *p*-curve includes 76 statistically significant ($p < .05$) results, of which 74 are $p < .025$. There were 2 additional results entered but excluded from *p*-curve because they were $p > .05$.

PU–BI correlation

Funnel plot (with trim and fill)

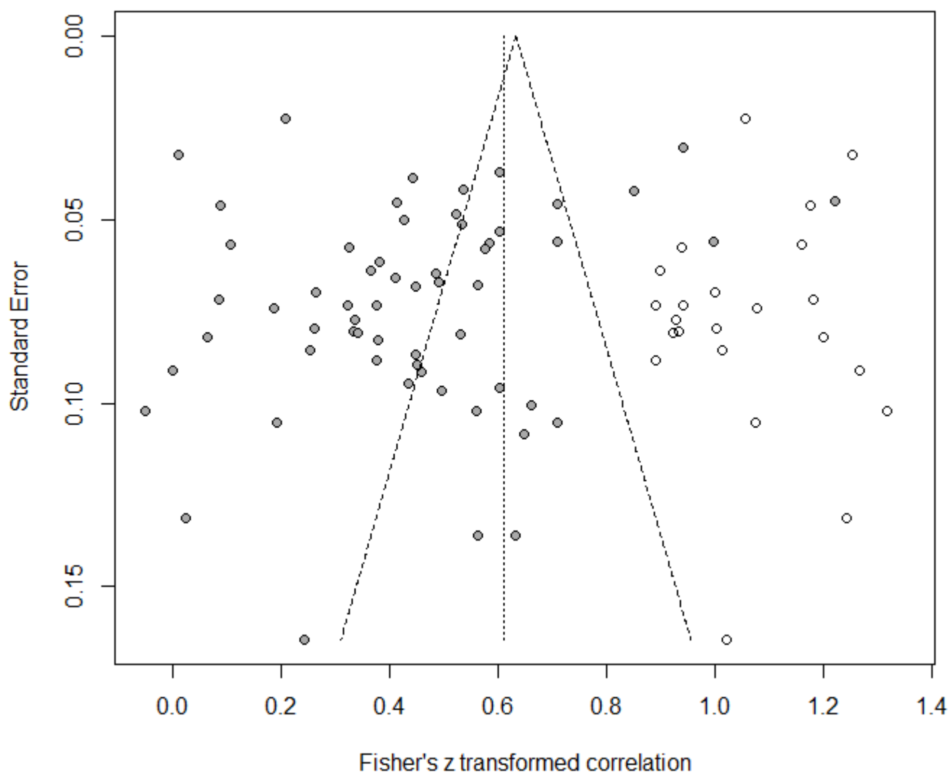


P-Curve

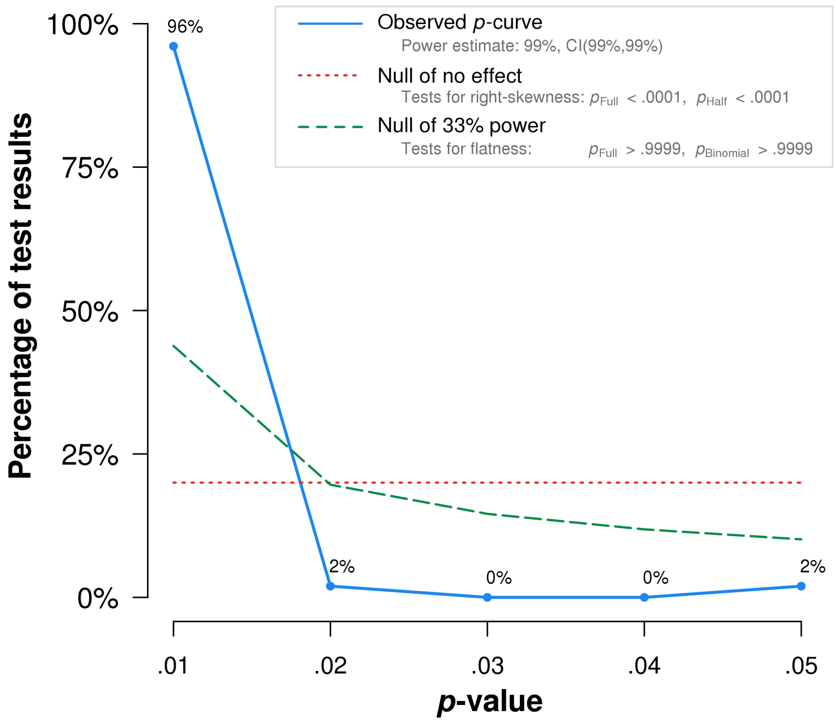


PU–CSE correlation

Funnel plot (with trim and fill)



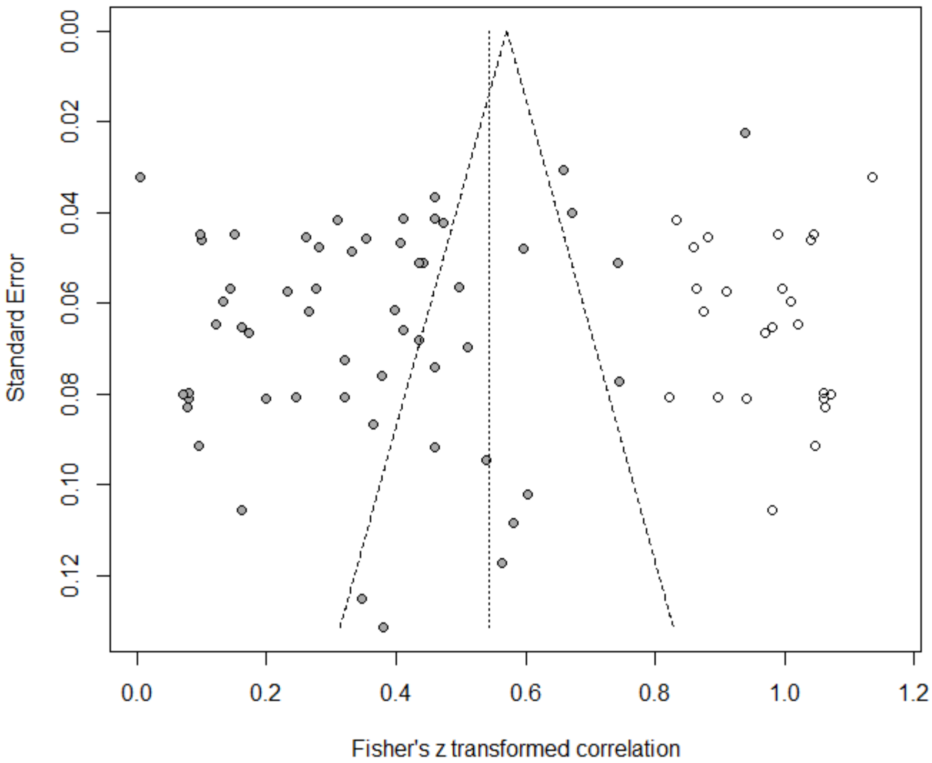
P-Curve



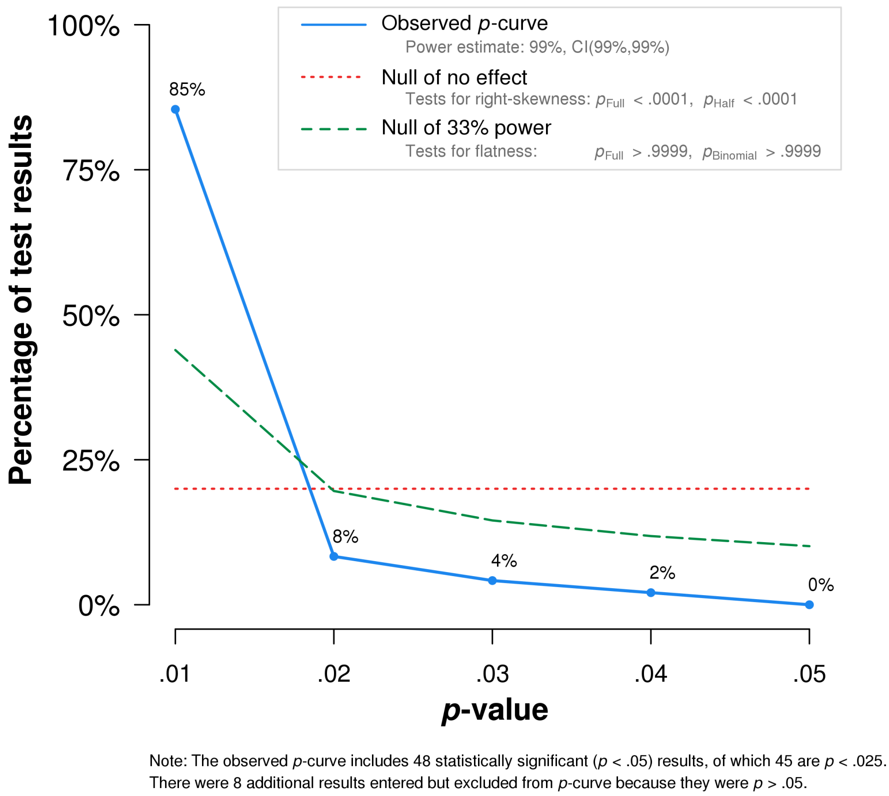
Note: The observed *p*-curve includes 51 statistically significant ($p < .05$) results, of which 50 are $p < .025$. There were 9 additional results entered but excluded from *p*-curve because they were $p > .05$.

PU–FC correlation

Funnel plot (with trim and fill)

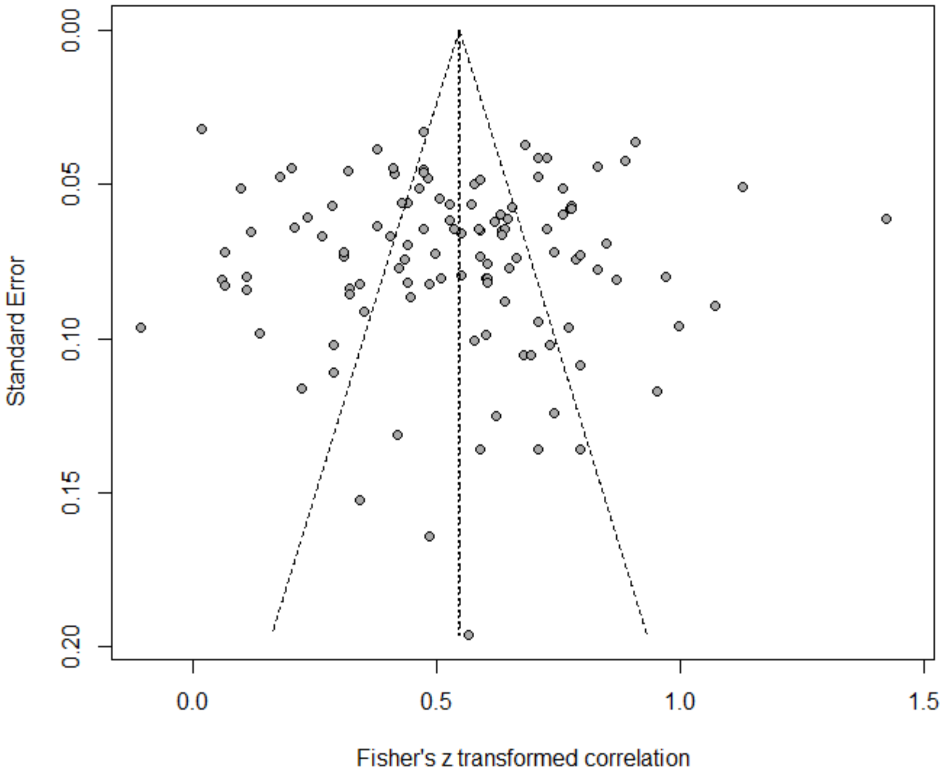


P-Curve

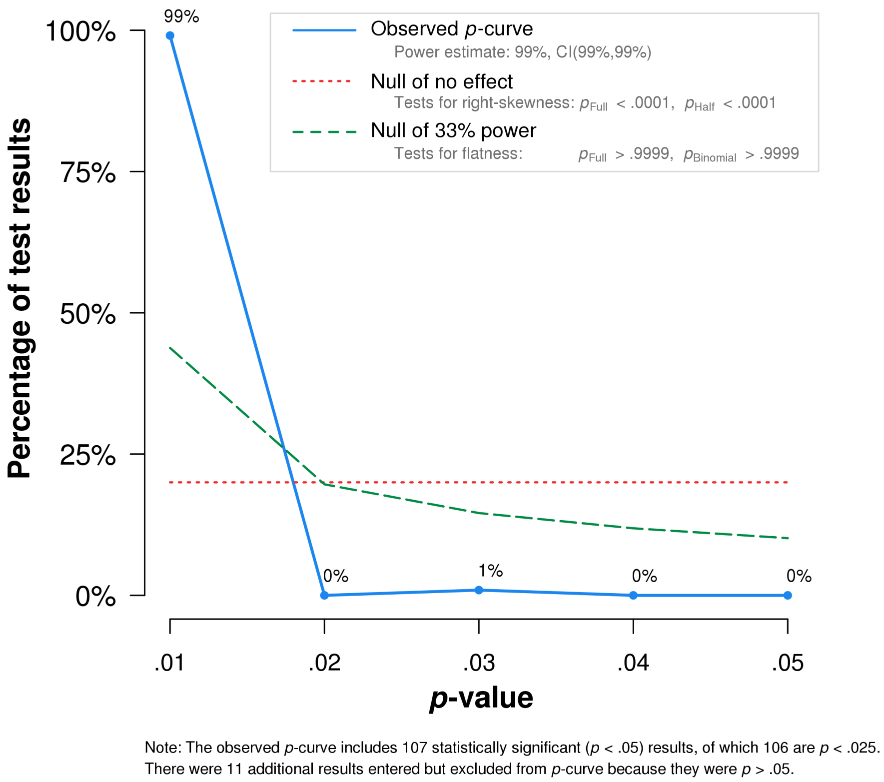


PU–PEU correlation

Funnel plot (with trim and fill)

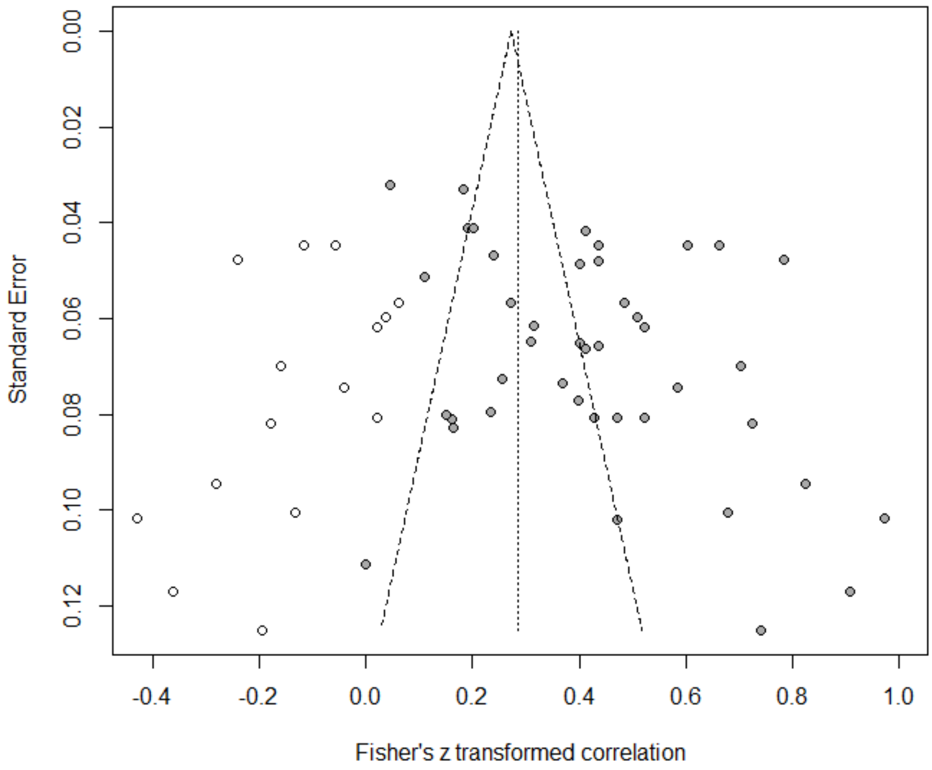


P-Curve

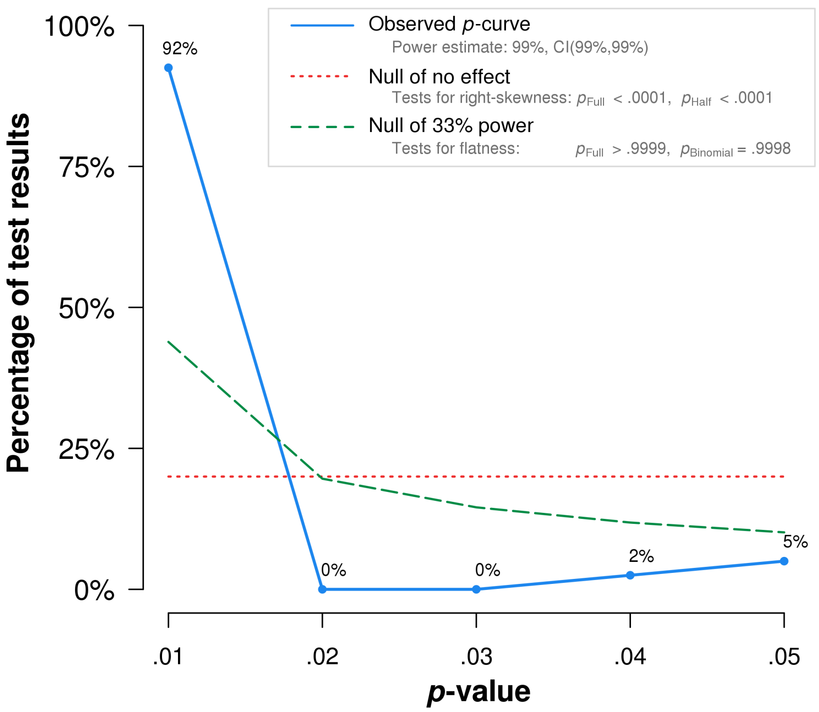


PU–SN correlation

Funnel plot (with trim and fill)



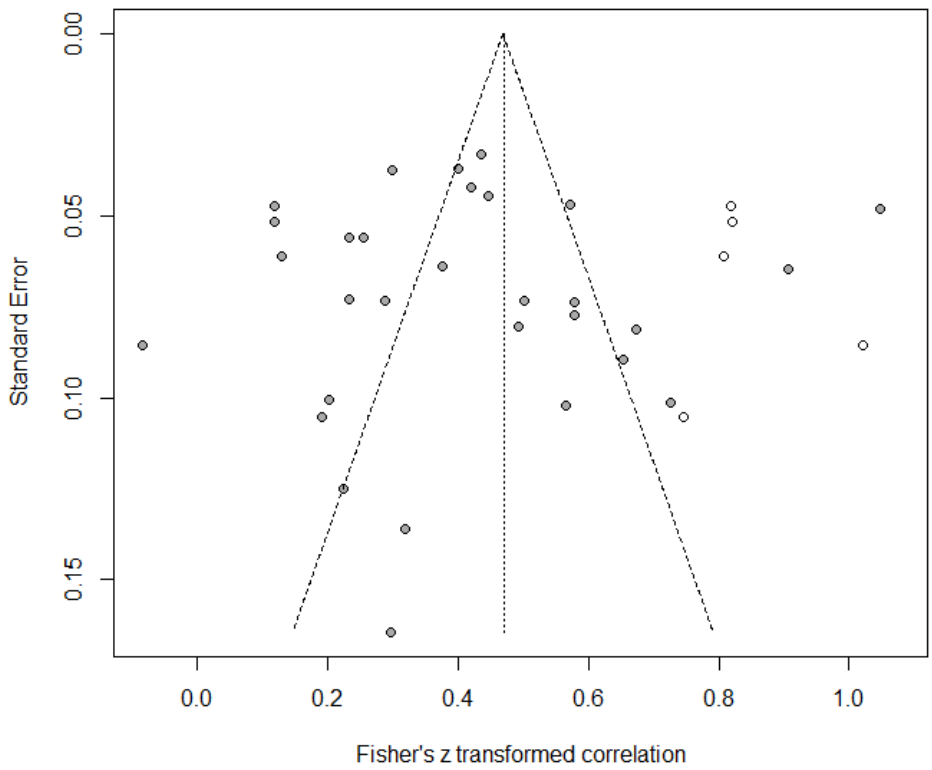
P-Curve



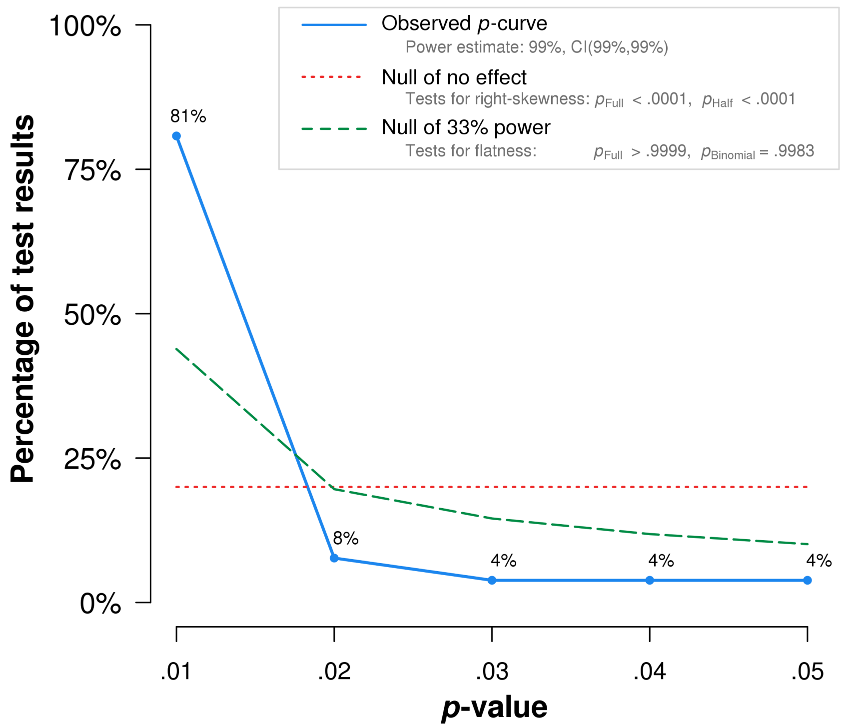
Note: The observed *p*-curve includes 40 statistically significant ($p < .05$) results, of which 37 are $p < .025$. There were 3 additional results entered but excluded from *p*-curve because they were $p > .05$.

PU–USE correlation

Funnel plot (with trim and fill)



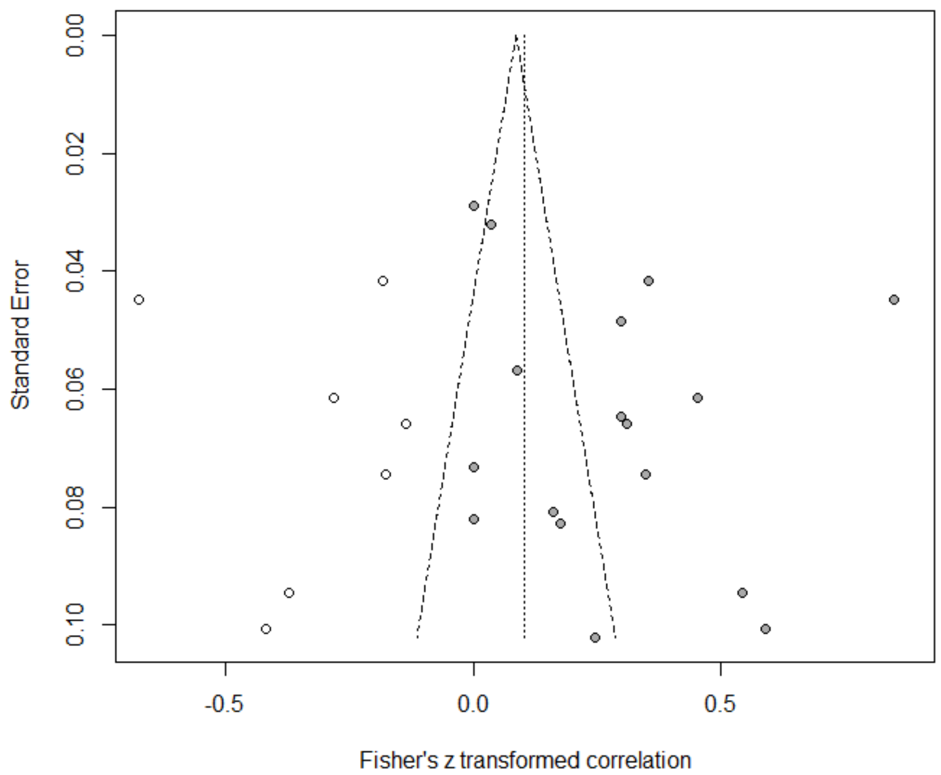
P-Curve



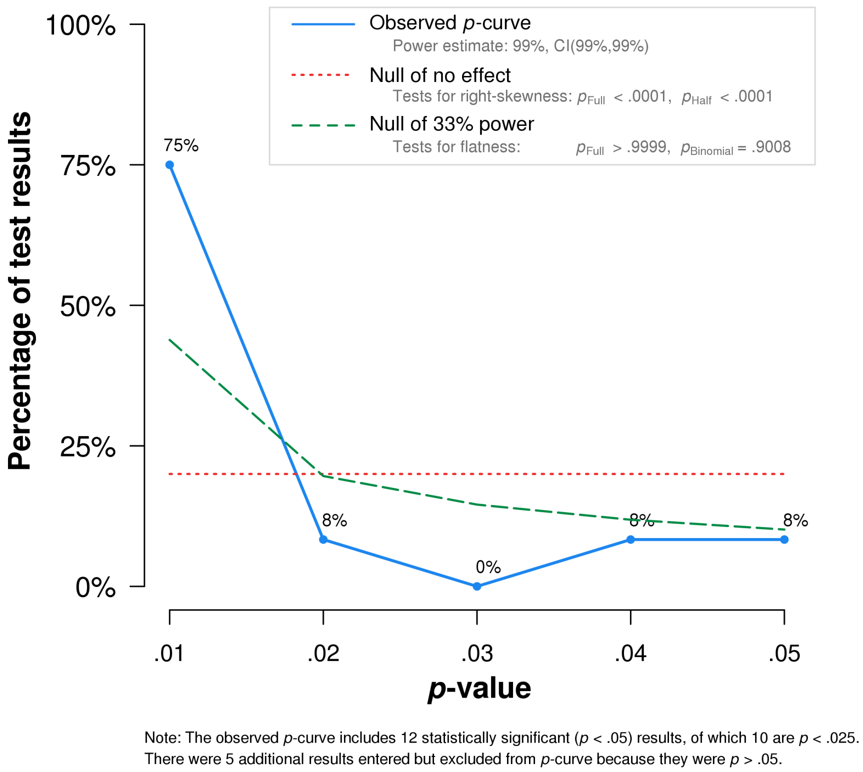
Note: The observed p-curve includes 26 statistically significant (p < .05) results, of which 24 are p < .025. There were 4 additional results entered but excluded from p-curve because they were p > .05.

SN–CSE correlation

Funnel plot (with trim and fill)

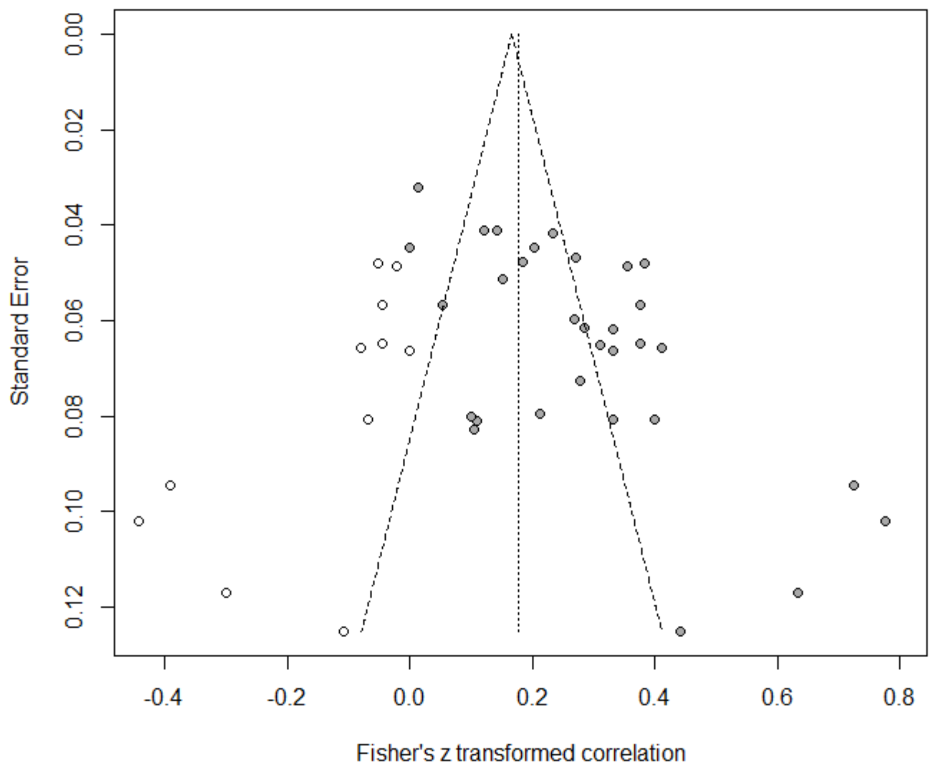


P-Curve

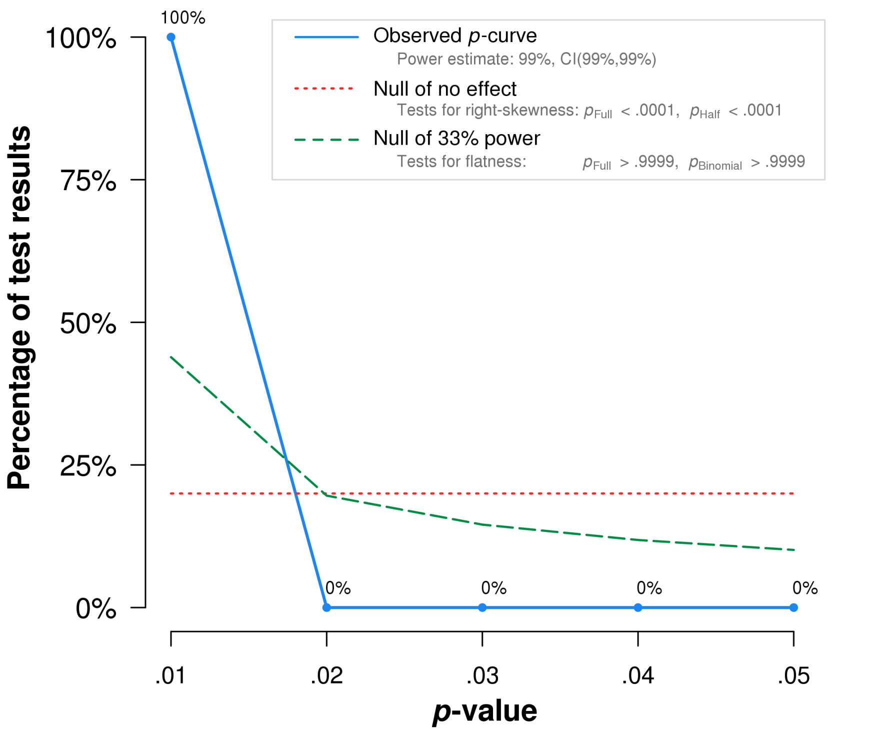


SN–FC correlation

Funnel plot (with trim and fill)



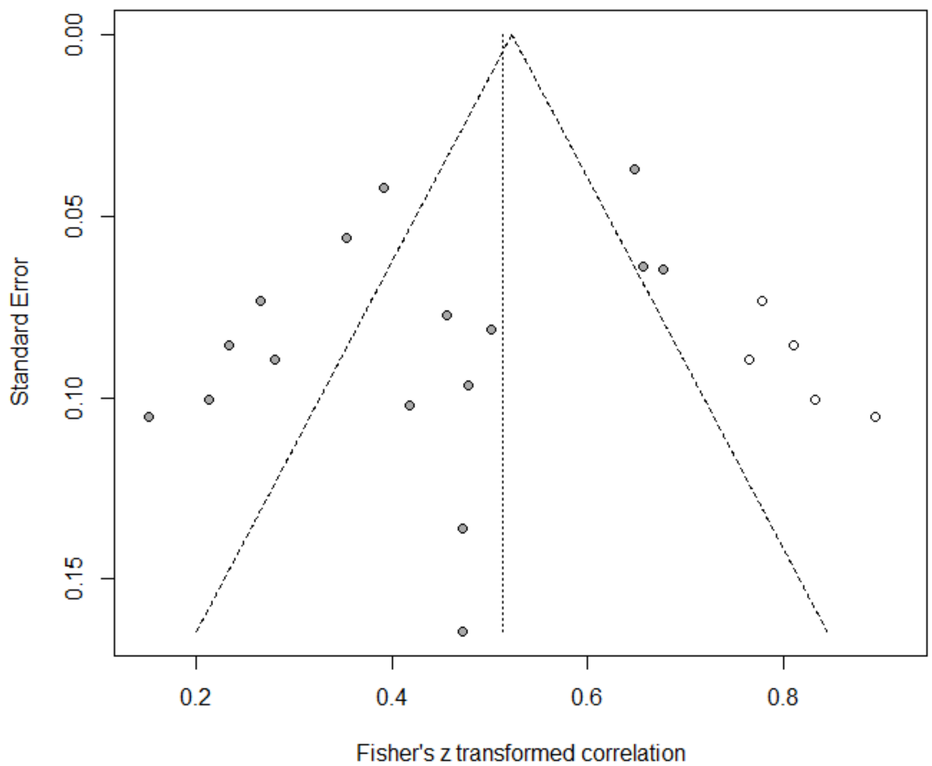
P-Curve



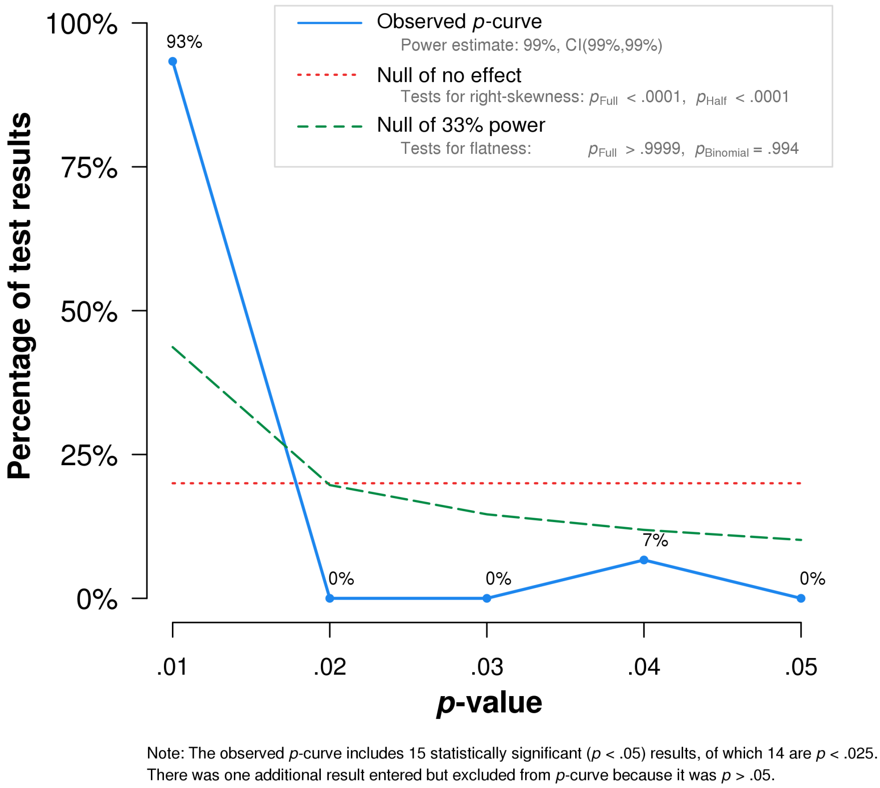
Note: The observed *p*-curve includes 26 statistically significant ($p < .05$) results, of which 26 are $p < .025$. There were 6 additional results entered but excluded from *p*-curve because they were $p > .05$.

USE–CSE correlation

Funnel plot (with trim and fill)

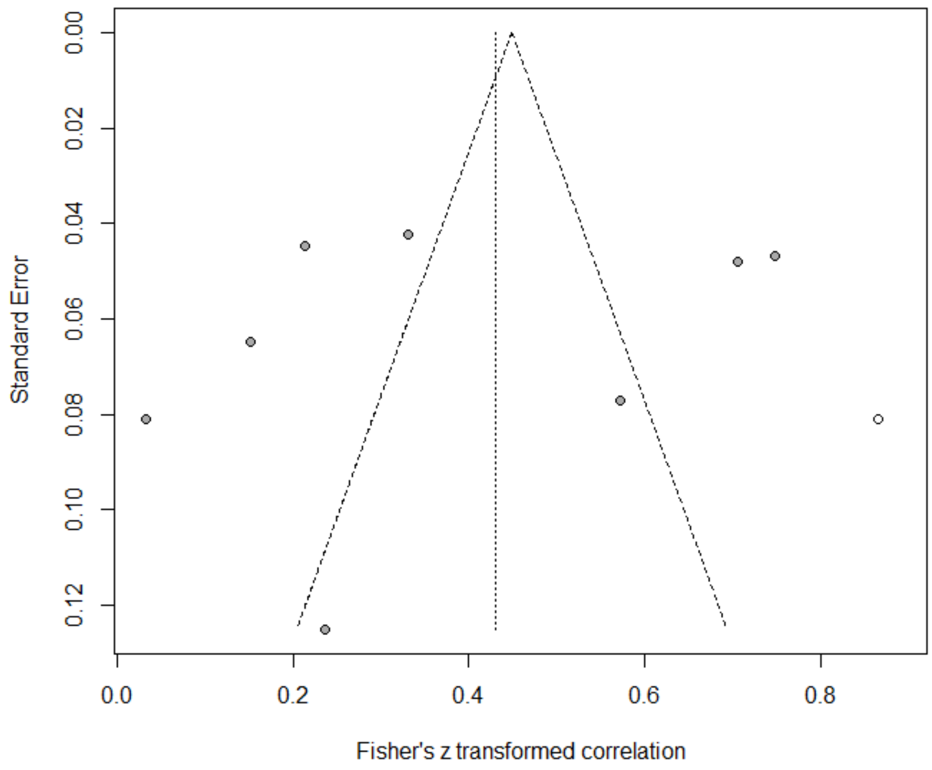


P-Curve

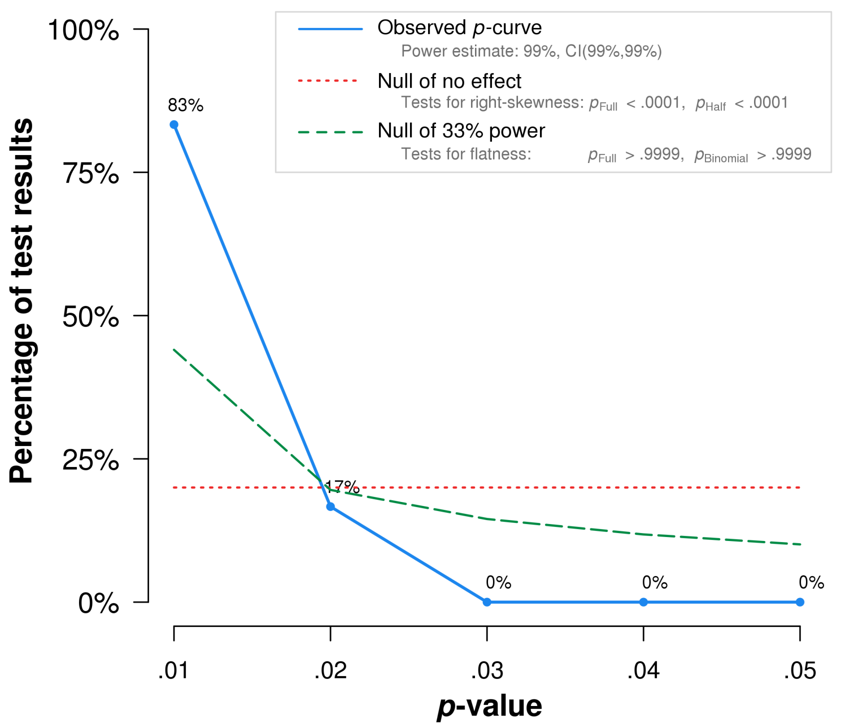


USE–FC correlation

Funnel plot (with trim and fill)



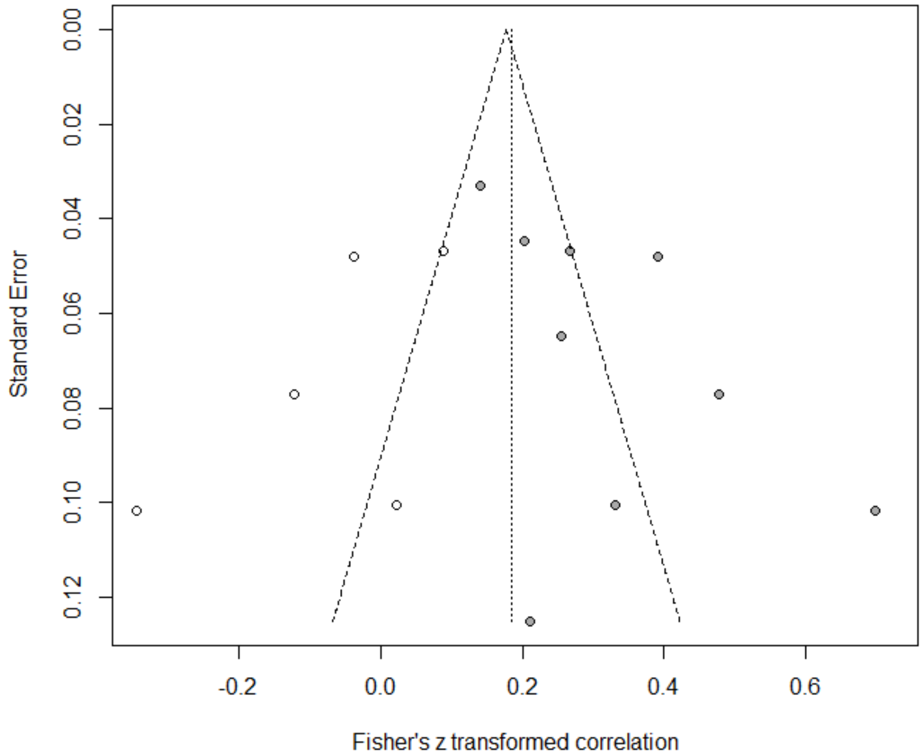
P-Curve



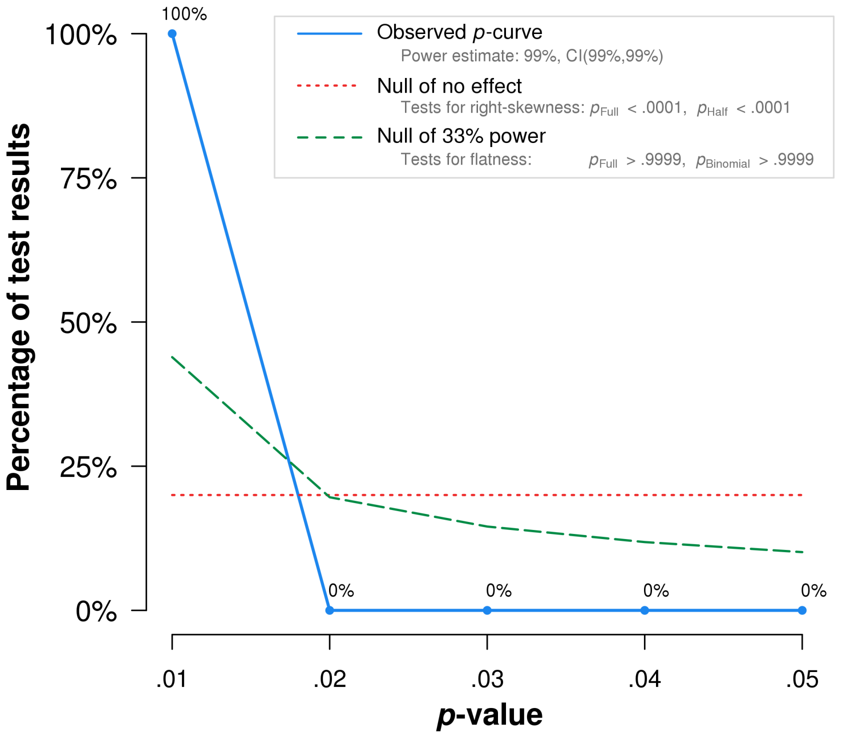
Note: The observed *p*-curve includes 6 statistically significant ($p < .05$) results, of which 6 are $p < .025$. There were 2 additional results entered but excluded from *p*-curve because they were $p > .05$.

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 *N*s

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. PU	207567	-					
3. ATT	101894	143736	-				
4. BI	93040	218068	105872	-			
5. USE	4131	9263	3170	5418	-		
6. SN	5872	16665	3419	12117	432	-	
7. FC	27256	44758	11038	34817	2532	1107	-
8. CSE	27527	38157	10955	18584	769	3855	5289

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

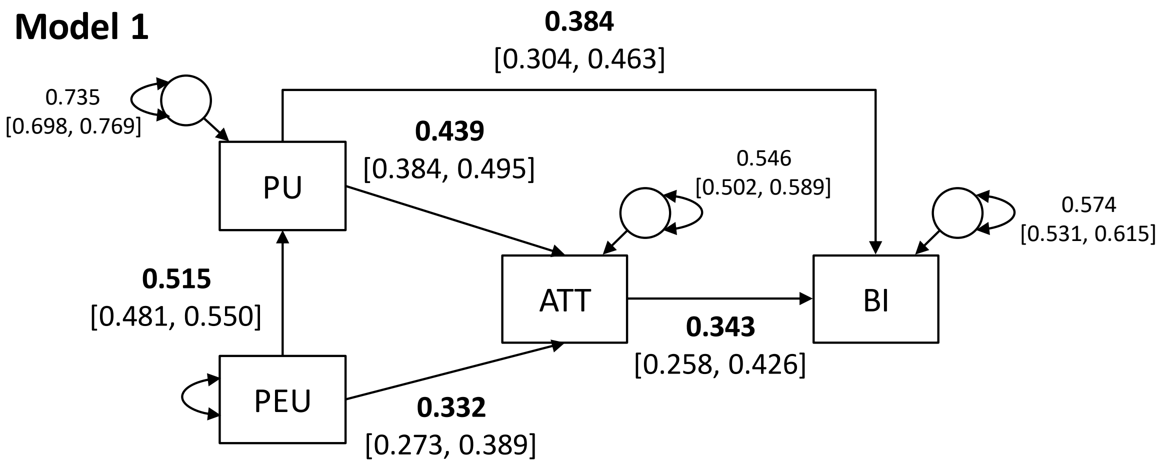
S5. Sensitivity analyses

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

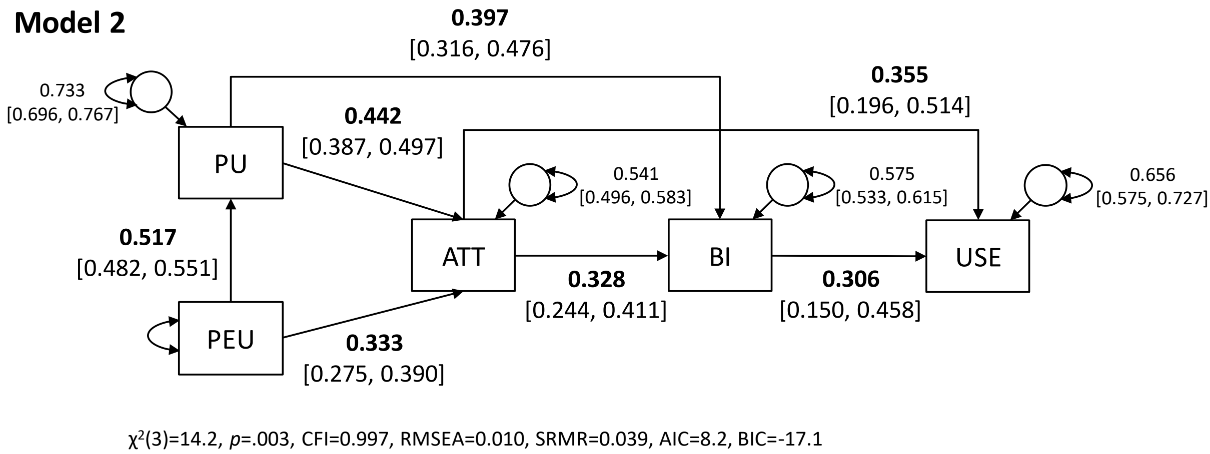
Heterogeneity tests of correlation matrices

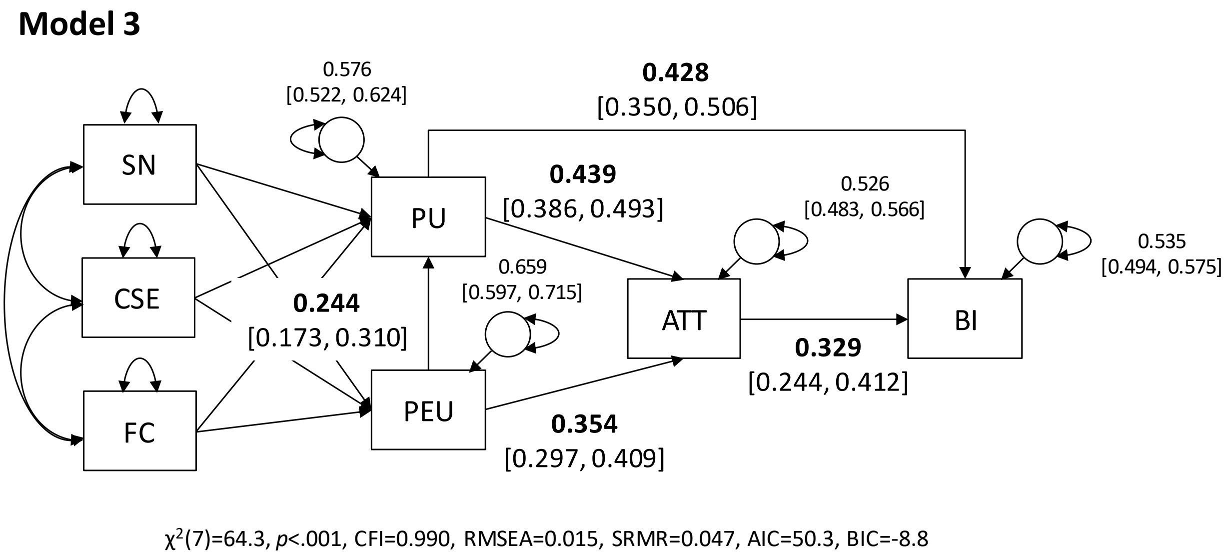
Model	*Q*	*df*	*p*	I^2
Model 1	13,027.5	447	< .001	92.3–96.3 %
Model 2	14,443.4	502	< .001	87.2–96.3 %
Model 3	30,319.3	911	< .001	84.0–96.2 %
Model 4	32,477.2	982	< .001	84.0–96.2 %



$\chi^2(1)$=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.





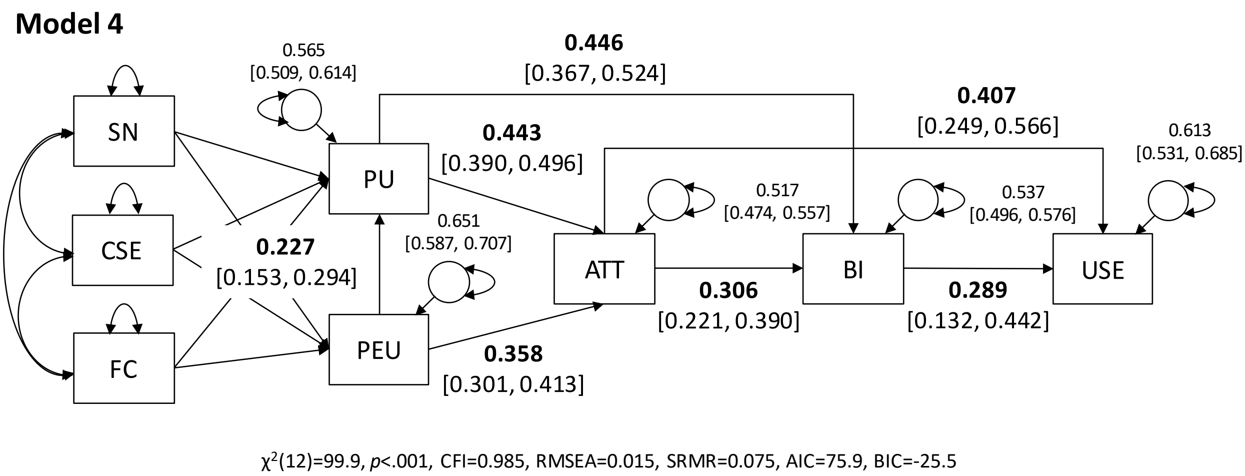


Figure S5-1. Structural equation models after unreliability corrections.

Table S5-2

Effects of external variables in Models 3 and 4

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

S6. References to TAM studies used in this meta-analysis

Ahmad, S. A., Abdullahi, I. M., & Usman, M. (2015). General Attitude and Acceptance of Holography in Teaching among Lecturers in Nigerian Colleges of Education. *IAFOR Journal of Education - Technologies & Education Special Edition*, 140-160. doi:10.22492/ije.3.se.09

Ahmad, T. B. T., Madarsha, K. B., Zainuddin, A. M., Ismail, N. A. H., & Nordin, M. S. (2010). Faculty's Acceptance of Computer Based Technology: Cross-Validation of an Extended Model. *Australasian Journal of Educational Technology, 26*(2), 268-279.

Alshahri, M. (2015). *A comparison of Saudi and United States faculty use of information and communication technology tools.* (3708753 Ed.D.), Montana State University, Ann Arbor. Retrieved from https://search.proquest.com/docview/1698495461

Anderson, S., & Groulx, J. (2013). *Elementary Student Teachers' Technology Use and Intentions for Technology Integration*. Paper presented at the Society for Information Technology & Teacher Education International Conference 2013, New Orleans, Louisiana, United States. https://www.learntechlib.org/p/48396

Anderson, S. E., Groulx, J. G., & Maninger, R. M. (2011). Relationships among Preservice Teachers' Technology-Related Abilities, Beliefs, and Intentions to Use Technology in Their Future Classrooms. *Journal of Educational Computing Research, 45*(3), 321-338. doi:10.2190/EC.45.3.d

Atif, A., Richards, D., Busch, P., & Bilgin, A. (2015). Assuring graduate competency: A technology acceptance model for course guide tools. *Journal of Computing in Higher Education, 27*(2), 94-113. doi:10.1007/s12528-015-9095-4

Attis, J. (2014). *An Investigation of the Variables That Predict Teacher E-Learning Acceptance.* Liberty University. Retrieved from http://digitalcommons.liberty.edu/doctoral/903

Aypay, A., Celik, H. C., Aypay, A., & Sever, M. (2012). Technology acceptance in education: A study of pre-service teachers in Turkey. *TOJET: The Turkish Online Journal of Educational Technology, 11*(4), 264-272.

Baytiyeh, H. (2014). Teachers left behind: Acceptance and use of technology in Lebanese public high schools. *International Journal of Information and Communication Technology Education, 10*(4), 16-29. doi:10.4018/ijicte.2014100102

Bourgonjon, J., De Grove, F., De Smet, C., Van Looy, J., Soetaert, R., & Valcke, M. (2013). Acceptance of game-based learning by secondary school teachers. *Computers & Education, 67*, 21-35. doi:10.1016/j.compedu.2013.02.010

Bøe, T. (2014). *Adoption of technology in higher education: Expanding the technology acceptance model.* Paper presented at the Norsk konferanse for organisasjoners bruk av IT, Oslo, Norway.

Chen, H.-R., & Tseng, H.-F. (2012). Factors that influence acceptance of web-based e-learning systems for the in-service education of junior high school teachers in Taiwan. *Evaluation and Program Planning, 35*(3), 398-406. doi:10.1016/j.evalprogplan.2011.11.007

Chen, R.-S. (2016). Preschool Teachers' Attitudes toward Internet Applications for Professional Development in Taiwan. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(10), 2671-2684. doi:10.12973/eurasia.2016.1300a

Cheung, E. Y. M., & Sachs, J. (2006). Test of the Technology Acceptance Model for a web-based information system in a Hong-Kong Chinese sample. *Psychological Reports, 99*(3), 691-703. doi:10.2466/PR0.99.7.691-703

Chiu, T. K. F. (2017). Introducing electronic textbooks as daily-use technology in schools: A top-down adoption process. *British Journal of Educational Technology, 48*(2), 524-537. doi:10.1111/bjet.12432

Chou, C.-M. (2012). Influence of teachers' perceived e-portfolio acceptance on teacher evaluation effectiveness in Taiwan. *Australasian Journal of Educational Technology, 28*(4), 719-739.

Cigdem, H., & Topcu, A. (2015). Predictors of instructors' behavioral intention to use learning management system: A Turkish vocational college example. *Computers in Human Behavior, 52*, 22-28. doi:10.1016/j.chb.2015.05.049

Cote, T., & Milliner, B. (2015). *Training ELF Teachers to Create a Blended Learning Environment: Encouraging CMS Adoption and Implementation.* Paper presented at the EUROCALL Conference 2015, Padova, Italy.

De Smet, C., Bourgonjon, J., De Wever, B., Schellens, T., & Valcke, M. (2012). Researching instructional use and the technology acceptation of learning management systems by secondary school teachers. *Computers & Education, 58*(2), 688-696. doi:10.1016/j.compedu.2011.09.013

Dreyer, C., & Nel, C. (2004). *Profiling Teacher Educators: Implications for Educational Technology Integration and Professional Development*. Paper presented at the EdMedia: World Conference on Educational Media and Technology 2004, Lugano, Switzerland. https://www.learntechlib.org/p/12497

Fathema, N., Shannon, D., & Ross, M. (2015). Expanding the Technology Acceptance Model (TAM) to examine Faculty use of Learning Management Systems (LMSs) in higher education institutions. *MERLOT Journal of Online Learning and Teaching, 11*(2), 210-232.

Fong, R. W.-t., Lee, J. C.-k., Chang, C.-y., Zhang, Z., Ngai, A. C.-y., & Lim, C. P. (2014). Digital teaching portfolio in higher education: Examining colleagues' perceptions to inform implementation strategies. *The Internet and Higher Education, 20*, 60-68. doi:10.1016/j.iheduc.2013.06.003

Garcia, A. V. M., & Gomez, M. C. S. (2014). Predictive model of the intention to adopt Blended Learning in a university setting. *Universitas Psychologica, 13*(2), 601-614.

Gyamfi, S. A. (2016). Identifying Ghanaian Pre-Service Teachers' Readiness for Computer Use: A Technology Acceptance Model Approach. *International Journal of Education and Development using Information and Communication Technology, 12*(2), 105-122.

Harris, K. M., Phelan, L., McBain, B., Archer, J., Drew, A. J., & James, C. (2016). Attitudes toward learning oral communication skills online: The importance of intrinsic interest and student-instructor differences. *Educational Technology Research and Development, 64*(4), 591-609. doi:10.1007/s11423-016-9435-8

Hew, T.-S., & Syed Abdul Kadir, S. L. (2016a). Predicting the acceptance of cloud-based virtual learning environment: The roles of Self Determination and Channel Expansion Theory. *Telematics and Informatics, 33*(4), 990-1013. doi:10.1016/j.tele.2016.01.004

Hew, T.-S., & Syed Abdul Kadir, S. L. (2016b). Behavioural intention in cloud-based VLE: An extension to Channel Expansion Theory. *Computers in Human Behavior, 64*, 9-20. doi:10.1016/j.chb.2016.05.075

Holden, H., & Rada, R. (2011). Understanding the Influence of Perceived Usability and Technology Self-Efficacy on Teachers' Technology Acceptance. *Journal of Research on Technology in Education, 43*(4), 343-367. doi:10.1080/15391523.2011.10782576

Huang, S.-H., & Hsu, W.-K. (2007). *A causal model for teacher intention to use web-based teaching platforms*. Paper presented at the Society for Information Technology & Teacher Education International Conference 2007, San Antonio, Texas, USA. https://www.learntechlib.org/p/25070

Huntington, H. (2011). *Digital media in education: Expanding the technology acceptance model.* The Rochester Institute of Technology, Rochester, NY. Retrieved from https://search.proquest.com/docview/905289364/abstract/4B7950D313BF468APQ

Huntington, H., & Worrell, T. (2013). Information communication technologies in the classroom: Expanding TAM to examine instructor acceptance and use. *Journal of Educational Multimedia and Hypermedia, 22*(2), 147-164.

Hur, J. W., Shen, Y. W., Kale, U., & Cullen, T. A. (2015). An exploration of pre-service teachers' intention to use mobile devices for teaching. *International Journal of Mobile and Blended Learning, 7*(3), 1-17. doi:10.4018/IJMBL.2015070101

Ibili, E., & Sahin, S. (2016). The Use of Cartoons in Elementary Classrooms: An Analysis of Teachers' Behavioral Intention in Terms of Gender. *Educational Research and Reviews, 11*(8), 508-516.

Juarez Collazo, N. A., Elen, J., & Clarebout, G. (2012). *Perceptions for Tool Use: In Search of a Tool Use Model*. Paper presented at the EdMedia: World Conference on Educational Media and Technology 2012, Denver, Colorado, USA. https://www.learntechlib.org/p/41181

Jung, H.-J. (2015). Fostering an English Teaching Environment: Factors Influencing English as a Foreign Language Teachers' Adoption of Mobile Learning. *Informatics in Education, 14*(2), 219-241.

Kabakci-Yurdakul, I., Ursavaş, O. F., & Becit-Isciturk, G. (2014). An Integrated Approach for Preservice Teachers' Acceptance and Use of Technology: UTAUT-PST Scale. *Eurasian Journal of Educational Research, 55*, 21-36. doi:10.14689/ejer.2014.55.2

Kannan, K., & Narayanan, K. (2015). Structural equation modelling approach for massive blended synchronous teacher training. *Journal of Educational Technology & Society, 18*(3), 1-15.

Kelly, H. (2014). A Path Analysis of Educator Perceptions of Open Educational Resources Using the Technology Acceptance Model. *International Review of Research in Open and Distance Learning, 15*(2), 26-42.

Kiraz, E., & Ozdemir, D. (2006). The Relationship between Educational Ideologies and Technology Acceptance in Pre-Service Teachers. *Educational Technology and Society, 9*(2), 152-165.

Kirmizi, O. (2014). Measuring Technology Acceptance Level of Turkish Pre-Service English Teachers by Using Technology Acceptance Model. *Educational Research and Reviews, 9*(23), 1323-1333.

Koutromanos, G., Styliaras, G., & Christodoulou, S. (2015). Student and In-Service Teachers' Acceptance of Spatial Hypermedia in Their Teaching: The Case of Hypersea. *Education and Information Technologies, 20*(3), 559-578.

Kreijns, K., Van Acker, F., Vermeulen, M., & van Buuren, H. (2013). What stimulates teachers to integrate ICT in their pedagogical practices? The use of digital learning materials in education. *Computers in Human Behavior, 29*(1), 217-225. doi:10.1016/j.chb.2012.08.008

Kusano, K., Frederiksen, S., Jones, L., Kobayashi, M., Mukoyama, Y., Yamagishi, T., . . . Ishizuka, H. (2013). The Effects of ICT Environment on Teachers' Attitudes and Technology Integration in Japan and the U.S. *Journal of Information Technology Education: Innovations in Practice, 12*, 29-43.

Lai, H.-C., Chang, C.-Y., Wen-Shiane, L., Fan, Y.-L., & Wu, Y.-T. (2013). The implementation of mobile learning in outdoor education: Application of QR codes. *British Journal of Educational Technology, 44*(2), E57-E62. doi:10.1111/j.1467-8535.2012.01343.x

Lay, J.-G., Chi, Y.-L., Hsieh, Y.-S., & Chen, Y.-W. (2013). What influences geography teachers' usage of geographic information systems? A structural equation analysis. *Computers & Education, 62*, 191-195. doi:10.1016/j.compedu.2012.10.014

Lee, C.-Y., & Chen, M.-J. (2016). Developing a questionnaire on technology-integrated mathematics instruction: A case study of the AMA training course in Xinjiang and Taiwan. *British Journal of Educational Technology, 47*(6), 1287-1303. doi:10.1111/bjet.12339

Li, K., Li, Y., & Franklin, T. (2016). Preservice teachers' intention to adopt technology in their future classrooms. *Journal of Educational Computing Research, 54*(7), 946-966.

Lin, S., Zimmer, J. C., & Lee, V. (2013). Podcasting acceptance on campus: The differing perspectives of teachers and students. *Computers & Education, 68*, 416-428. doi:10.1016/j.compedu.2013.06.003

Liu, S.-H. (2011). *Modeling pre-service teachers' knowledge of, attitudes toward, and intentions for technology integration*. Paper presented at the EdMedia: World Conference on Educational Media and Technology 2011, Lisbon, Portugal. https://www.learntechlib.org/p/38335

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

Luan, W. S., & Teo, T. (2011). Student Teachers' Acceptance of Computer Technology. In T. Teo (Ed.), *Technology Acceptance in Education: Research and Issues* (pp. 43-61). Rotterdam: Sense Publishers.

Ma, W. W.-k., Andersson, R., & Streith, K.-O. (2005). Examining user acceptance of computer technology: an empirical study of student teachers. *Journal of Computer Assisted Learning, 21*(6), 387-395. doi:10.1111/j.1365-2729.2005.00145.x

Mac Callum, K., Jeffrey, L., & Kinshuk. (2014). Factors Impacting Teachers' Adoption of Mobile Learning. *Journal of Information Technology Education: Research, 13*, 141-162.

Mamat, I., Mat Yusoff, A. S., Abdullah, W. S. W., & Abdul Razak, F. Z. (2015). Factors contributing pre-school trainees teachers adoption of virtual learning environment: Malaysian evidence. *TOJET: The Turkish Online Journal of Educational Technology, 14*(2), 73-79.

McGill, T., Klobas, J., & Renzi, S. (2011). LMS use and Instructor Performance: The Role of Task-technology Fit. *International Journal on E-Learning, 10*(1), 43-62.

Nair, I., & Das, V. M. (2012). Using Technology Acceptance Model to assess teachers' attitude towards use of technology as teaching tool: A SEM Approach. *International Journal of Computer Applications, 42*(2), 1-6.

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

Okazaki, S., & dos Santos, L. M. R. (2012). Understanding E-Learning Adoption in Brazil: Major Determinants and Gender Effects. *International Review of Research in Open and Distance Learning, 13*(4), 91-106.

Oshiro, D. T. (2015). *One hawai`i k-12 complex public school teachers' level of computer self-efficacy and their acceptance of and integration of technology in the classroom.* University of Southern California, Los Angeles, CA, US. Retrieved from https://search.proquest.com/docview/1559197928/abstract/A893157F988A4F03PQ

Park, N., Lee, K. M., & Cheong, P. H. (2007). University instructors' acceptance of electronic courseware: An application of the Technology Acceptance Model. *Journal of Computer-Mediated Communication, 13*(1), 163-186. doi:10.1111/j.1083-6101.2007.00391.x

Parkman, S. (2015). *Factors affecting Pre-Service Teachers' Acceptance of Technology-Rich Learning Environments in Abu Dhabi*. Paper presented at the Society for Information

Technology & Teacher Education International Conference 2015, Las Vegas, NV, United States. https://www.learntechlib.org/p/150468

Perkmen, S., Antonenko, P., & Caracuel, A. (2016). Validating a Measure of Teacher Intentions to Integrate Technology in Education in Turkey, Spain and the USA. *Journal of Technology and Teacher Education, 24*(2), 215-241.

Phua, P. L., Wong, S. L., & Abu, R. (2012). Factors Influencing the Behavioural Intention to use the Internet as a Teaching-Learning Tool in Home Economics. *Procedia - Social and Behavioral Sciences, 59*, 180-187. doi:10.1016/j.sbspro.2012.09.263

Pittalis, M., & Christou, C. (2011). *Extending the Technology Acceptance Model to assess secondary school teachers 'intention to use CABRI in Geometry Teaching'*. Paper presented at the Seventh Congress of the European Society for Research in Mathematics Education, University of Rzeszów, Poland.

Powers, J. R. (2014). *Lutheran School Teachers' Instructional Usage of the Interactive Whiteboard.* Florida Atlantic University, Boca Raton, FL. Retrieved from https://search.proquest.com/docview/1548007205/abstract/4B728C26E0B343A9PQ

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

Sadeghi, K., Saribagloo, J. A., Aghdam, S. H., & Mahmoudi, H. (2014). The impact of iranian teachers cultural values on computer technology acceptance. *TOJET: The Turkish Online Journal of Educational Technology, 13*(4), 124-136.

Salajan, F., Welch, A., Peterson, C., & Ray, C. (2011). *A Measurement of Faculty Perceptions and Usage of Learning Technologies through Authentic Testing and Qualitative Assessment*. Paper presented at the E-Learn: World Conference on E-

Learning in Corporate, Government, Healthcare, and Higher Education 2011, Honolulu, Hawaii, USA. https://www.learntechlib.org/p/39104

Salajan, F. D., Welch, A. G., Ray, C. M., & Peterson, C. (2015). The Role of Peer Influence and Perceived Quality of Teaching in Faculty Acceptance of Web-Based Learning Management Systems. *International Journal on E Learning, 14*(4), 487-524.

Sánchez-Gómez, M. C., Iglesias-Rodríguez, A., & Martín-García, A. V. (2016). *Methodological triangulation as a research strategy in educational innovation processes: case study of the b-learning methodology in the university context*. Paper presented at the Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality, Salamanca, Spain.

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2017). MLearning and pre-service teachers: An assessment of the behavioral intention using an expanded TAM model. *Computers in Human Behavior, 72*, 644-654. doi:10.1016/j.chb.2016.09.061

Shiue, Y.-M. (2007). Investigating the sources of teachers' instructional technology use through the decomposed theory of planned behavior. *Journal of Educational Computing Research, 36*(4), 425-453.

Shroff, R. H., Trent, J., & Ng, E. M. (2013). Using e-portfolios in a field experience placement: Examining student-teachers' attitudes towards learning in relationship to personal value, control and responsibility. *Australasian Journal of Educational Technology, 29*(2), 143-160.

Smith, J. A., & Sivo, S. A. (2012). Predicting continued use of online teacher professional development and the influence of social presence and sociability. *British Journal of Educational Technology, 43*(6), 871-882. doi:10.1111/j.1467-8535.2011.01223.x

Smith, L. A. (2014). *Pre-Service Teachers: A Study of Self-Theories of Intelligence and Attitudes about Web 2.0.* Western Kentucky University, Bowling Green, Kentucky. Retrieved from http://digitalcommons.wku.edu/diss/73/

Stols, G., & Kriek, J. (2011). Why Don't All Maths Teachers Use Dynamic Geometry Software in Their Classrooms? *Australasian Journal of Educational Technology, 27*(1), 137-151.

Sumak, B., & Sorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behavior, 64*, 602-620. doi:10.1016/j.chb.2016.07.037

Teo, T. (2008). Pre-service teachers' attitudes towards computer use: A Singapore survey. *Australasian Journal of Educational Technology, 24*(4), 413-424.

Teo, T. (2009a). The impact of subjective norm and facilitating conditions on pre-service teachers' attitude toward computer use: A structural equation modeling of an extended technology acceptance model. *Journal of Educational Computing Research, 40*(1), 89-109. doi:10.2190/EC.40.1.d

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

Teo, T. (2010a). The development, validation, and analysis of measurement invariance of the Technology Acceptance Measure for Preservice Teachers (TAMPST). *Educational and Psychological Measurement, 70*(6), 990-1006. doi:10.1177/0013164410378087

Teo, T. (2010b). Measuring the effect of gender on computer attitudes among pre-service teachers: A multiple indicators, multiple causes (MIMIC) modeling. *Campus-Wide Information Systems, 27*(4), 227-239.

Teo, T. (2010c). A path analysis of pre-service teachers' attitudes to computer use: Applying and extending the technology acceptance model in an educational context. *Interactive Learning Environments, 18*(1), 65-79. doi:10.1080/10494820802231327

Teo, T. (2010d). A structural equation modelling of factors influencing student teachers' satisfaction with e-learning. *British Journal of Educational Technology, 41*(6), E150-E152. doi:10.1111/j.1467-8535.2010.01110.x

Teo, T. (2010e). Validation of the Technology Acceptance Measure for Pre-Service Teachers (TAMPST) on a Malaysian Sample: A Cross-Cultural Study. *Multicultural Education and Technology Journal, 4*(3), 163-172.

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432-2440. doi:10.1016/j.compedu.2011.06.008

Teo, T. (2012a). Examining the intention to use technology among pre-service teachers: An integration of the technology acceptance model and theory of planned behavior. *Interactive Learning Environments, 20*(1), 3-18. doi:10.1080/10494821003714632

Teo, T. (2012b). Modelling the Influences of Beliefs on Pre-Service Teachers' Attitudes towards Computer Use. *European Journal of Educational Research, 1*(1), 13-22.

Teo, T. (2013). Influences of contextual variables on the intention to use technology in education: A latent variable modeling approach. *Campus-Wide Information Systems, 30*(2), 95-105.

Teo, T., Fan, X., & Du, J. (2015). Technology Acceptance among Pre-Service Teachers: Does Gender Matter? *Australasian Journal of Educational Technology, 31*(3), 235-251.

Teo, T., Khlaisang, J., Thammetar, T., Ruangrit, N., Satiman, A., & Sunphakitjumnong, K. (2014). A survey of pre-service teachers' acceptance of technology in Thailand. *Asia Pacific Education Review, 15*(4), 609-616. doi:10.1007/s12564-014-9348-3

Teo, T., Lee, C. B., & Chai, C. S. (2008). Understanding Pre-Service Teachers' Computer Attitudes: Applying and Extending the Technology Acceptance Model. *Journal of Computer Assisted Learning, 24*(2), 128-143.

Teo, T., Lee, C. B., Chai, C. S., & Choy, D. (2009). Modelling pre-service teachers' perceived usefulness of an ICT-based student-centred learning (SCL) curriculum: A Singapore study. *Asia Pacific Education Review, 10*(4), 535-545.

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

Teo, T., & Milutinović, V. (2015). Modelling the Intention to Use Technology for Teaching Mathematics among Pre-Service Teachers in Serbia. *Australasian Journal of Educational Technology, 31*(4), 363-380.

Teo, T., Milutinović, V., Zhou, M., & Banković, D. (2017). Traditional vs. innovative uses of computers among mathematics pre-service teachers in Serbia. *Interactive Learning Environments, 25*(7), 811-827. doi:10.1080/10494820.2016.1189943

Teo, T., & Noyes, J. (2010). Exploring Attitudes towards Computer Use among Pre-Service Teachers from Singapore and the UK: A Multi-Group Invariance Test of the Technology Acceptance Model (TAM). *Multicultural Education and Technology Journal, 4*(2), 126-135.

Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modeling approach. *Computers & Education, 57*(2), 1645-1653. doi:10.1016/j.compedu.2011.03.002

Teo, T., & Noyes, J. (2014). Explaining the intention to use technology among pre-service teachers: A multi-group analysis of the Unified Theory of Acceptance and Use of Technology. *Interactive Learning Environments, 22*(1), 51-66. doi:10.1080/10494820.2011.641674

Teo, T., Ruangrit, N., Khlaisang, J., Thammetar, T., & Sunphakitjumnong, K. (2014). Exploring E-Learning Acceptance among University Students in Thailand: A National Survey. *Journal of Educational Computing Research, 50*(4), 489-506. doi:10.2190/EC.50.4.c

Teo, T., & Tan, L. (2012). The Theory of Planned Behavior (TPB) and Pre-Service Teachers' Technology Acceptance: A Validation Study Using Structural Equation Modeling. *Journal of Technology and Teacher Education, 20*(1), 89-104.

Teo, T., Ursavaş, Ö. F., & Bahçekapili, E. (2011). Efficiency of the technology acceptance model to explain pre-service teachers' intention to use technology: A Turkish study. *Campus-Wide Information Systems, 28*(2), 93-101.

Teo, T., Ursavaş, Ö. F., & Bahçekapili, E. (2012). An assessment of pre-service teachers' technology acceptance in Turkey: A structural equation modeling approach. *The Asia-Pacific Education Researcher, 21*(1), 191-202.

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

Teo, T., & Wong, S. L. (2013). Modeling key drivers of e-learning satisfaction among student teachers. *Journal of Educational Computing Research, 48*(1), 71-95.

Teo, T., Wong, S. L., & Chai, C. S. (2008). A cross-cultural examination of the intention to use technology between Singaporean and Malaysian pre-service teachers: an application of the Technology Acceptance Model (TAM). *Educational Technology & Society, 11*(4), 265-280.

Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A structural equation modeling approach. *Journal of Computing in Higher Education, 26*(2), 124-142.

Teo, T., Zhou, M., & Noyes, J. (2016). Teachers and technology: development of an extended theory of planned behavior. *Educational Technology Research and Development, 64*(6), 1033-1052. doi:10.1007/s11423-016-9446-5

Tokel, S. T., & Isler, V. (2015). Acceptance of virtual worlds as learning space. *Innovations in Education and Teaching International, 52*(3), 254-264. doi:10.1080/14703297.2013.820139

Ulrich, J. W. (2009). *Test of a Structural Model to Investigate the Impact of Instructor Knowledge, Attitudes, and Contextual Constraints on Intent to Use Web 2.0 in Online Courses.* Western Carolina University, Cullowhee, NC. Retrieved from https://search.proquest.com/docview/305167385/abstract/609D233B80334A97PQ

Waheed, M. (2010). *Instructor's Intention to Accept Online Education: An Extended TAM Model*. Paper presented at the E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2010, Orlando, Florida, USA. https://www.learntechlib.org/p/35729

Wang, W.-T., & Wang, C.-C. (2009). An empirical study of instructor adoption of web-based learning systems. *Computers & Education, 53*(3), 761-774. doi:10.1016/j.compedu.2009.02.021

Watts, R. (2009). *Predicting Technology Use in K-12 Classrooms*. Paper presented at the Society for Information Technology & Teacher Education International Conference 2009, Charleston, SC, USA. https://www.learntechlib.org/p/31318

Wong, G. K. (2015). Understanding technology acceptance in pre-service teachers of primary mathematics in Hong Kong. *Australasian Journal of Educational Technology, 31*(6), 713-735.

Wong, G. K. (2016). The behavioral intentions of Hong Kong primary teachers in adopting educational technology. *Educational Technology Research and Development, 64*(2), 313-338. doi:10.1007/s11423-016-9426-9

Wong, K.-T., Osman, R. b., Goh, P. S. C., & Rahmat, M. K. (2013). Understanding Student Teachers' Behavioural Intention to Use Technology: Technology Acceptance Model (TAM) Validation and Testing. *International Journal of Instruction, 6*(1), 89-104.

Wong, K.-T., Teo, T., & Goh, P. S. C. (2014). Development of the interactive whiteboard acceptance scale (IWBAS): An initial study. *Educational Technology & Society, 17*(4), 268-277.

Wong, K.-T., Teo, T., & Goh, P. S. C. (2015). Understanding the intention to use interactive whiteboards: Model development and testing. *Interactive Learning Environments, 23*(6), 731-747. doi:10.1080/10494820.2013.806932

Wong, K.-T., Teo, T., & Russo, S. (2012). Influence of gender and computer teaching efficacy on computer acceptance among Malaysian student teachers: An extended technology acceptance model. *Australasian Journal of Educational Technology, 28*(7), 1190-1207.

Wong, K.-T., Teo, T., & Russo, S. (2013). Interactive whiteboard acceptance: Applicability of the UTAUT model to student teachers. *The Asia-Pacific Education Researcher, 22*(1), 1-10.

Wu, B., Hu, Y., Gu, X., & Lim, C. P. (2016). Professional Development of New Higher Education Teachers With Information and Communication Technology in Shanghai. *Journal of Educational Computing Research, 54*(4), 531-562. doi:10.1177/0735633115621922

Wu, C., & Liu, C.-F. (2015). Acceptance of ICT-Mediated Teaching/Learning Systems for Elementary School Teachers: Moderating Effect of Cognitive Styles. *Education and Information Technologies, 20*(2), 381-401.

Wu, W., Chang, H.-P., & Guo, C.-J. (2008). An empirical assessment of science teachers' intentions toward technology integration. *Journal of Computers in Mathematics and Science Teaching, 27*(4), 499-520.

Yeni, S., & Gecu-Parmaksiz, Z. (2016). Pre-Service Special Education Teachers Acceptance and Use of ICT: A Structural Equation Model. *Journal of Education and Training Studies, 4*(12), 118-125.

Yeung, A. S., Taylor, P. G., Hui, C., Lam-Chiang, A. C., & Low, E.-L. (2012). Mandatory use of technology in teaching: Who cares and so what? *British Journal of Educational Technology, 43*(6), 859-870. doi:10.1111/j.1467-8535.2011.01253.x

Yuen, A. H. K., & Ma, W. W. K. (2002). Gender Differences in Teacher Computer Acceptance. *Journal of Technology and Teacher Education, 10*(3), 365-382.

Yuen, A. H. K., & Ma, W. W. K. (2008). Exploring Teacher Acceptance of E-Learning Technology. *Asia Pacific Journal of Teacher Education, 36*(3), 229-243.

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

Zhang, W., & Xu, P. (2011). Do I Have to Learn Something New? Mental Models and the Acceptance of Replacement Technologies. *Behaviour and Information Technology, 30*(2), 201-211.

Zhou, M., Chan, K. K., & Teo, T. (2016). Modelling Mathematics Teachers' Intention to Use the Dynamic Geometry Environments in Macau: An SEM Approach. *Educational Technology & Society, 19*(3), 181-194.

S7. Additional references

Cheung, M. W.-L. (2015). *Meta-Analysis: A Structural Equation Modeling Approach*. Chichester, West Sussex: John Wiley & Sons, Ltd.

Cheung, M. W.-L., & Hafdahl, A. R. (2016). Special issue on meta-analytic structural equation modeling: introduction from the guest editors. *Research Synthesis Methods, 7*(2), 112-120. doi:10.1002/jrsm.1212

Kenny, D. A. (1979). *Correlation and Causality* (1 ed.). New York, NY: John Wiley & Sons Inc.

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4 ed.). New York, London: Guilford Press.

Loehlin, J. C. (2004). *Latent variable models: an introduction to factor, path, and structural equation analysis*. Mahwah, NJ: Lawrence Erlbaum.

Muthén, B., & Muthén, L. (1998-2015). *Mplus* (Version 7.3). Los Angeles, CA: Muthén & Muthén.

Peterson, R. A., & Brown, S. P. (2005). On the Use of Beta Coefficients in Meta-Analysis. *Journal of Applied Psychology, 90*(1), 175-181. doi:10.1037/0021-9010.90.1.175

Simonsohn, U., Nelson, L., & Simmons, J. (2017). *P-Curve App* (Version 4.052). Retrieved from http://www.p-curve.com/app4/

Viechtbauer, W. (2017). *metafor: Meta-Analysis Package for R* (Version 2.0-0). Retrieved from https://cran.r-project.org/web/packages/metafor/index.html

Wright, S. (1934). The method of path coefficients. *The Annals of Mathematical Statistics, 5*(3), 161-215.