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Determinants of Technology Acceptance: Two Model-Based Meta-Analytic Reviews

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Abstract

Examining the determinants of technology acceptance has been a central interest across disciplines. The technology acceptance model (TAM) and its variants and extensions are the most popular theoretical frameworks in this line of research. Two model-based meta-analytical approaches, that is, meta-meta-analysis and conventional meta-analysis, are used to pool the correlations and to test the path relationships among the variables of the TAM. We find that the extended TAM, which we term the TAM Plus, prevails in the model fit testing and that the results of the pooled correlations and path coefficients estimated using the meta-meta-analysis and meta-analysis are generally consistent.

Keywords

TAM, meta-analysis, meta-meta-analysis, modeling, technology acceptance

Examining the determinants of technology use or acceptance has been a central interest across disciplines. Although many theoretical perspectives have been proposed to address this issue, the technology acceptance model (TAM) (Davis, 1986) is the theory most widely used to explain user acceptance intentions and behaviors. Davis and his associates (Davis, 1986, 1989; Davis et al., 1989) hypothesize that perceived usefulness (PU) and perceived ease of use (PEOU) form users' beliefs regarding a technology and subsequently predict their attitude toward this technology, which further

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determines their intended and actual adoption of this technology. The original TAM has been extended or revised by many scholars who have added additional constructs such as determinants of PEOU and PU (Karahanna & Straub, 1999; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003; Wu et al., 2007; Yen et al., 2010), attitudes (Park & Kim, 2014), and intended use (Gefen et al., 2003; Karahanna et al., 2006).

Since it was published, the TAM (Davis, 1986) and its extensions have been empirically applied to a variety of end-user technologies ranging from mobile technologies (Khayyat & Heshmati, 2013) to gaming (Yoon et al., 2013) (for a review, see Legris et al., 2003; Ma & Liu, 2004). However, these studies have produced inconsistent results in terms of model configurations and the statistical significance, direction, and magnitude of hypothesized relationships (Ma & Liu, 2004; Moore & Benbasat, 1991). Furthermore, due to the TAM's popularity and the considerable number of mixed findings, the TAM is examined in at least 23 meta-analyses, multiple systematic literature reviews (e.g., Lee et al., 2003; Legris et al., 2003; Turner et al., 2010; Williams et al., 2015), and two computational literature reviews relying on machine learning (Mortenson & Vidgen, 2016) and statistical modeling techniques (Hsiao & Yang, 2011). These extant meta-analyses have made important contributions to our understanding of the TAM, but the inconsistency of primary studies is channeled into meta-analyses on the TAM. Some primary studies found very high correlations between predictors and the major outcome variable, that is, behavioral intentions, while some meta-analyses had contradictory findings on the same predictions. For instance, some scholars (Khor, 2014; Yen et al., 2010) found very strong correlations (i.e., larger than .9) between PU and intentions and between PEOU and intentions, but meta-analyses by Rana et al. (2015) and Šumak et al. (2017) found a trivial effect size (a correlation of approximately .10 between the variable PEOU and intentions). Šumak et al. (2017) observed a small effect size (approximately .30) concerning the correlation between the variable PU and intentions. Therefore, there are substantial gaps in TAM studies that must be addressed and filled.

Consequently, the research purpose of this article is twofold: (a) to examine the exact effects and magnitudes of the theoretical relationships involving the TAM by synthesizing existing empirical primary and meta-analytical studies and (b) to seek and establish a parsimonious theoretical framework built on the TAM that can sufficiently explain individual intentions to adopt technologies. To avoid adding to the confusing status quo of the TAM field, we opt for new procedures that have never been applied in the TAM literature, that is, meta-meta-analysis and the innovative procedure of meta-analysis using structural equation modeling (MASEM).

Literature Review

The Origin and Extensions of the TAM

Many scholars (e.g., C. A. Lin, 2009; Schepers & Wetzels, 2007; Venkatesh, 2000) have mentioned that the TAM was inspired by the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) because the core TAM predictors in the TAM (i.e., the variables PEOU and PU) are actually more general behavioral beliefs in the TRA (Karahanna & Straub, 1999; Venkatesh, 2000). The TRA posits that intentions mediate the effects of external and internal beliefs on behaviors. Expressed mathematically, the relationship between internal beliefs and attitudes is $A \propto \sum b_i e_i$, where A is an individual's attitude toward engaging in a behavior, b is an individual's belief regarding the probability that certain outcomes will ensue from the action, and e is an individual's evaluation of those outcomes. Moreover, external beliefs, that is, subjective norms (frequently called social influence [SI] in other models), are measured by what an individual thinks is desirable in reference to others (n), which is weighted by the motivation to comply (m): $SN \propto \sum n_i m_i$ (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). Ajzen (1985) later extended the TRA to the theory of planned behavior (TPB) by including perceived behavioral control (PBC), which is measured by the strength of each control belief (c) weighted by the perceived power of the control factor (p): $\text{PBC} \propto \sum p_i c_i$. Fishbein and Ajzen (2010) later proposed an integrative model (IM) integrating the TRA, the TPB, and the social cognitive theory (SCT). The IM is very similar to the TPB, notwithstanding some nomenclatural differences (e.g., it changes PBC to self-efficacy and divides norms into injunctive and descriptive ones).

Taylor and Todd (1995a) combined the TAM and the TPB and later (Taylor & Todd, 1995b) adapted the TPB to form the decomposed TPB using constructs such as relative advantage, complexity, and compatibility from the diffusion of innovation theory (Rogers, 1983). Venkatesh and Davis (2000) proposed the TAM2 by removing attitude (mediator) and identifying several determinants of PU—subjective norms, image, job relevance, output quality, result demonstrability, and PEOU—and two moderators: *experience* and *voluntariness*. Van Raaij and Schepers (2008) extended the TAM2 by including subjective norms, personal innovativeness in IT, and computer anxiety. Venkatesh et al. (2003) further expanded the TAM2 to formulate a unified model called the Unified Theory of Acceptance and Use of Technology (UTAUT) by summarizing eight closely related models (i.e., the TRA, the TAM, the motivational model, the TPB, a model combining the TAM and the TPB, the model of personal computer (PC) utilization, innovation diffusion theory, and SCT) comprising 32 related constructs. According to the UTAUT, individual intentions to accept technologies are determined by performance expectancy, effort expectancy, and SI; user behavior is predicted by facilitating conditions; and all four predictions are moderated by age, gender, experience, and voluntariness of use. The UTAUT has been extended by later scholars through the addition of new predictors such as social support (C.-P. Lin & Anol, 2008; Sykes et al., 2009) and perceived playfulness (Wang & Wang, 2010). Seemingly noting the weaknesses of previously proposed models, Venkatesh and Bala (2008) further developed an integrated model named TAM3 by combining TAM2 (Venkatesh & Davis, 2000) and the model of the determinants of PEOU (the early-stage anchors included computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control [or facilitating conditions], and the later adjustment comprised perceived enjoyment and objective usability) (Venkatesh, 2000). Furthermore, Venkatesh et al. (2012) proposed the UTAUT2 by incorporating three constructs into the UTAUT: hedonic motivations, price value, and habits (for a summary of differences among related theories, see Table 1).

As one of the coauthors of the TAM (Davis et al., 1989), Bagozzi has nevertheless harshly criticized the foundation and advances of the TAM (see Bagozzi, 2007). Bagozzi (2007) lamented that the study of TAM "is at the threshold of crisis, if not chaos, in regard to explaining technology acceptance." Bagozzi (2007) believed that research has provided little theoretical insight into the prediction and moderation mechanisms embodied in the TAM and its variations and extensions. Although harsh, these comments may be reasonable if we trace the origins of these models. The TAM and its parallels, including the UTAUT, the TRA, the TPB, and SCT (Bandura, 1986), are all applications of expectancy-value theory (EVT) (e.g., Atkinson, 1957; Edwards, 1954; Fishbein, 1963; Fishbein & Raven, 1962; Kahneman & Tversky, 1979; Morgenstern & Von Neumann, 1953; M. J. Rosenberg, 1956). Therefore, not surprisingly, these models have much in common (Bish et al., 2000; Fishbein & Ajzen, 2011), that is, many seemingly disparate constructs actually share the same meanings.

The original TAM suggests that the effect of external variables on intention is mediated by key beliefs (i.e., PEOU and PU; Davis et al., 1989). Although a number of external variables have been tested in prior studies, the literature reveals "no clear pattern with respect to the choice of the external variables considered" (Legris et al., 2003). Abdullah and Ward (2016) identified 152 external determinants of the PU and PEOU in their meta-analysis of 107 studies, and they argued that only five external factors (self-efficacy, subjective norms, enjoyment, computer anxiety, and prior experience) are crucial. Many of the proposed models reviewed above (Van Raaij & Schepers, 2008; Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) introduced many external predictors of either PEOU or PU. However, these factors may not be applicable across study settings. For instance, enjoyment and computer anxiety may not be relevant for the adoption of e-health products, e-government or similar organizational uses, and enjoyment or flow (or presence), instead of self-efficacy, may be important for the selection of games. Therefore, even fewer variables among the above-mentioned external factors are generally necessary, and not many theories are as universal as the literature suggests they are. In addition, Williams et al. (2015) found that only performance expectancy in the UTAUT is an important predictor of technology use. Van Raaij and Schepers (2008) and Bagozzi (2007) also criticized the UTAUT for its complexity and incoherent integration.

In summary, the findings of various predictions in the TAM, its extensions, and its variants in primary studies are inconsistent and contradictory. This lack of clarity calls into question the validity of the theoretical underpinnings of the TAM and its various manifestations. Specifically, what necessary constructs are needed for a parsimonious theory, and what relationships and magnitudes exist among them? These questions can be addressed using meta-analysis, which is a means of quantitatively determining real effects and effect sizes based on the findings of previous research on a certain topic (Glass et al., 1981; Hunter et al., 1986; Rosenthal, 1991b). Most meta-analyses have examined relatively straightforward questions, such as whether a particular manipulation is effective or whether a particular predictor relates to an outcome (cf. Becker, 2009). However, few primary studies have examined bivariate correlations in actual

Table 1. Differences and Commonalities Among the Theories.

Construct	TRA	TPB	TAM	TAM2	TAM3	UTAUT	UTAUT2	IM
Attitude	Attitude	Attitude	Attitude					attitude
Subjective norm	Subjective norm[a]	Subjective norm		Subjective norm	Subjective norm	Social influence	Social influence	Perceived norm
Behavioral beliefs	Behavioral beliefs	Behavioral beliefs	Perceived ease of use	Perceived ease of use	Perceived ease of use	Effort expectancy	Effort expectancy	Behavioral beliefs
Outcome evaluation	Outcome evaluation	Outcome evaluation	Perceived usefulness	Perceived usefulness	Perceived usefulness	Performance expectancy	Performance expectancy	Outcome evaluation
PBC-internal		Perceived behavioral control			Self-efficacy			Self-efficacy
PBC-external					Facilitating conditions	Facilitating conditions	Facilitating conditions	

Note. TRA = theory of reasoned action; TPB = theory of planned behavior; TAM = technology acceptance model; UTAUT = Unified Theory of Acceptance and Use of Technology; IM = integrative model; PBC = perceived behavioral control.
[a]In TRA, TPB, and IM, subjective norms are determined by the interaction of normative beliefs and motivation to comply.

studies. Most studies have instead addressed more complex theoretical relationships by incorporating covariates, moderators, or mediators (Wilson et al., 2016). Complex chains of events (Becker, 2009) can be addressed only with the completely different modeling technique of meta-analysis. Therefore, MASEM is superior to separate univariate correlation-based meta-analyses (e.g., Hunter & Schmidt, 1990) in this regard.

Previous Meta-Analysis of the TAM

As mentioned above, approximately 20 meta-analyses have been published on effect sizes in the TAM or its extensions. These studies provide rich information for exploring "true" theoretical relationships. Moreover, this massive number of published meta-analyses on the TAM and its extensions offer a new possibility to re-examine predictive relationships based on effect sizes reported in prior meta-analyses employing an innovative procedure called meta-meta-analysis or second-order meta-analysis, which uses the estimated effect size of each meta-analysis with the effect size being the unit of analysis (Cafri et al., 2010; Cleophas & Zwinderman, 2017; Cooper & Koenka, 2012; Kazrin et al., 1979).

Of this vast number of meta-analytical studies, many suffer from a variety of limitations, leaving considerable research gaps that must be filled. Most of these studies examined the univariate relationships that are predicted in the TAM. Moreover, two univariate meta-analyses on the UTAUT (Khechine et al., 2016; Taiwo & Downe, 2013) did not conduct moderator analysis (Khechine et al. (2016) attributed this to too few studies being available for inclusion after significant heterogeneity tests were performed). Some studies (Chauhan & Jaiswal, 2017; King & He, 2006) directly meta-analyzed path coefficients, which do not satisfy the requirements of the effect size (cf. Ferguson, 2009). In addition, some studies (Hamari & Keronen, 2017; Schepers & Wetzels, 2007) did not test the influences of the study-level moderators (for an overview of the previous meta-analyses, see the table at https://figshare.com/s/5ca1a12c56a783376d36).

As all predictions are derived from established theories, we are interested in examining the magnitudes instead of the presence of the effects of predictions. We aim to answer the following research questions:

RQ1: What is the magnitude of the predicted effect size of the intentional use of technology?

RQ2: Are there any significant relationships among the predictor and outcome variables?

Study 1: A Model-Based Meta-Analysis

Method

Selection criteria. A cursory search for "technology acceptance model" on Google Scholar yielded more than three million results. To make the study manageable, we tried various combinations of the following keywords, namely "technology acceptance model" and "the unified theory of acceptance and use of technology" in the Web of Science with only Science Citation Index (SCI) and Social Science Citation Index (SSCI) listed English language journals. The first round of the search started in July 2018 and yielded 12,051 potentially eligible studies. We then implemented several screening steps for these articles following the procedure in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher et al., 2009) (see Figure 1).

The selection criteria for the studies to be included in this systematic review were as follows: (a) quantitative primary studies with effect sizes; (b) articles with at least the core theoretical variables of the TAM, that is, PU, PEOU, attitude, and intentions; and (c) articles reporting complete zero-order correlations among the independent variables and dependent variables. After a series of filtered searches, we obtained 786 eligible articles (cumulative N = 296,121), 81.93% of which are closely related to communication technology (for the explanation of its meaning, see Jackson, 1996).

Unit of analysis. The unit of analysis is the effect size, which is the correlation (Pearson's or other types of correlations that are appropriate for other measurement levels). In the following analyses, the original correlation will not be transformed into Fisher's z, a popular procedure termed *the* Rosenthal (1991b) *approach* by Johnson et al. (1995), to retain the correlation metric and the associated variances and covariances among the correlations for use in Stage 2 of the two-stage MASEM (cf. Wilson et al., 2016).

Classification of constructs. The original TAM consists of five constructs: PEOU, PU, attitude toward use, intention to use, and actual use (Chauhan & Jaiswal, 2017). However, the majority of the primary TAM studies tested the intentions to use a technology rather than actual use as the ultimate dependent variable (606 studies vs. 61 studies[1]). Consequently, the following models excluding actual use were tested. Moreover, only a few theories are actually more applicable across study characteristics according to the literature review above, so we tested six competing models, that is, the original TAM and five extension models by combining the original TAM and the TRA (i.e., adding SI for predicting use intentions) on account of the theoretical significance, data availability, and data quality (the correlation matrix has to satisfy the requirement of being positive-definite). In light of this rationale, many constructs from other theories are neglected. We then inspected the underlying meanings of the variables in the included studies and allocated the variables to the five construct categories, that is, intentions, attitudes, PEOU, PU, and SI (or subjective norms), on a "close fit" basis (for the descriptions of a theory coding scheme, see Michie & Prestwich, 2010).

Searching for moderators. Differences in study characteristics may introduce variability among the true effects. Therefore, once heterogeneity is detected, moderator analysis is imperative (Li et al., 2017). Although Venkatesh (2000) maintained that the TAM is robust across time, settings, populations, and technologies, many potential moderators

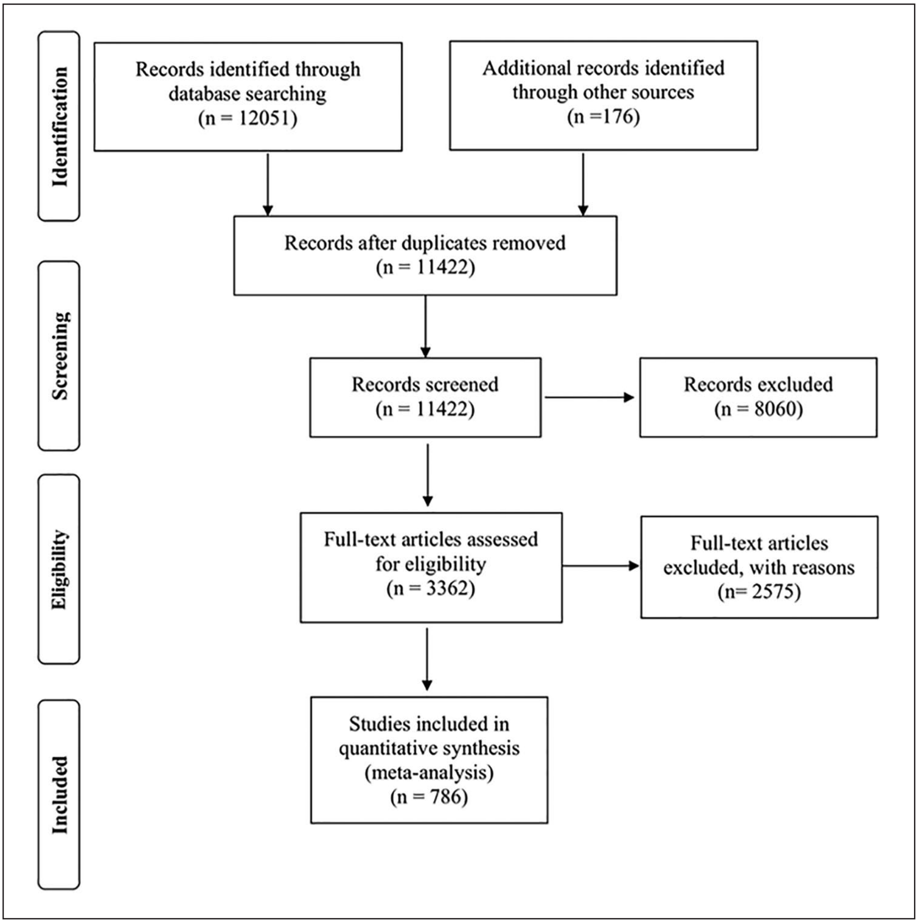

Figure 1. PRISMA 2009 flow diagram.
Note. PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

that account for variations in effect sizes in the TAM have been examined in previous meta-analyses. The most studied moderators are respondent types (or user types) (tested in eight previous meta-analyses), study's country of origin (tested in five previous meta-analyses), technology types (tested in five previous meta-analyses), and system types (or technology characteristics) (tested in four previous meta-analyses[2]) according to our research. Consequently, we choose the four above-mentioned moderators plus one, that is, the year when a technology was invented, as suggested by an anonymous reviewer.

Coding. Nine undergraduate students were recruited to independently code the studies according to the codebook. We selected 30% of the studies with which to check the intercoder reliabilities of the major variables, such as the effect size, sample size, technology characteristics (hedonic, both hedonic and utilitarian, and utilitarian), and user types (consumer vs. business) between pairs of coders, which were estimated via the "irr" package of R 3.4. Four graduate students additionally cross-checked the agreement of the three moderators, that is, study's country of origin, technology types, and the year when a technology was invented. The results of the intercoder reliability estimation using Krippendorff's α (for a review of the use of intercoder reliability indices, see Feng, 2015) ranged between .76 and .98. Partial discrepancies were resolved through discussion.

Procedures. There were two steps in the MASEM approach. Heterogeneity was estimated using a homogeneity statistic, Q (Brockwell & Gordon, 2001; Hedges, 1981; Higgins & Thompson, 2002; Schmid et al., 1991), in Stage 1 (Cheung, 2015a; Jak, 2015). In the absence of homogeneity, a random-effects (RE) model, as opposed to a fixed-effects (FE) model (which assumes that the true effect is the same for all studies) was used to allow the true effect to vary across studies (Brockwell & Gordon, 2001; National Research Council, 1992; Schmid et al., 1991). In addition, the original correlations instead of Fisher's z or other corrected correlations were used in the RE modeling. (Although the Fisher z score may be used in pooling correlation matrices, using original correlation matrices is a better choice in MASEM according to some (Wilson et al., 2016).) Subsequently, the path models based on the pooled correlation matrix were estimated using weighted least squares (with 5,000 parametric bootstrap replicates) in the metaSEM package (Cheung, 2015b) in Stage 2. In addition, moderator analysis was performed using subgroup analysis (for details, see Jak & Cheung, 2018b).

Handling missing correlations. There are three major approaches to handling missing correlations, that is, listwise deletion, pairwise deletion, and imputation (Allison, 2003). (For a review of the pros and cons concerning the three approaches, see Peugh & Enders, 2004.) Because listwise deletion curtails the sample size from 786 to 83 and pairwise deletion results in nonpositive-definite matrices, which cannot be used in MASEM (Cheung, 2015a), we adopted the approach to fixing the variances without SEs (NaN) as zeros proposed by Jak and her colleagues (Jak, 2015; Jak & Cheung, 2018a; Jak et al., 2013) to handle missing correlations. With this approach, we are able to retain all of the 786 studies for the two stages of tests.

Moreover, we also did the subgroup test to compare the differences of the two approaches (listwise deletion vs. Jak's method) and found that there were no significant differences in the results between the two approaches, χ^2 (13, N = 323,598) = 8.011, p = .843. Moreover, the model with equality constraints fit the data much better than the free model (without equality constraints) (see the table at figshare.com/s/5ca1a12c56a783376d36). Since there are no significant differences in the results from the two approaches, we subsequently report the results based on Jak's method for the sake of better generalizability.

Table 2. Pooled Correlations Based on the Random-Effects TAM Extended Model and Meta-Meta-Analysis.

Variable	ATT	INT	PEOU	PU	SI
ATT		.584 (.937)	.488 (.92)	.39 (.932)	.409 (.931)
INT	.577 (.037) (397,334)		.573 (.924)	.447 (.931)	.498 (.942)
PEOU	.488 (.029) (171,303)	.452 (.028) (86,746)		.543 (.938)	.321 (.926)
PU	.565 (.031) (429,689)	.546 (.026) (212,934)	.501 (.032) (137,303)		.413 (.909)
SI	.388 (.036) (78,864)	.417 (.035) (95,800)	.324 (.033) (35,765)	.42 (.026) (70,745)	

Note. The values below the diagonal represent random-effects estimates, τ^2 and fail-safe *N*, respectively, while the values above the diagonal represent fixed-effects estimates and I^2 values. All probability values of the zs are less than .001. ATT = attitude; TAM = technology acceptance model; INT = intention; PEOU = perceived ease of use; PU = perceived usefulness; SI = social influence.

Results

Estimation of the pooled correlation matrix. In Stage 1, the pooled correlation matrix was estimated through the FE model and the RE model. As missing correlations are not allowed in the FE model, the listwise deletion was performed for the FE model. Nevertheless, the RE model was estimated, keeping all of the 786 studies following the procedure of Jak's method. The model fit indices indicated that RE models fit the data better than FE models. All model fit indices of the FE models did not pass the cutoff threshold recommended by Hu and Bentler (1999). In addition, the Q test was significant, Q (df = 3,365) = 43,095, $p < .001$, and the values of I^2, which indicate the proportion of the between-study variance relative to the total variance for the effect size of interest, were above .9. In summary, there was a significant amount of between-study variance for each effect, so the RE model was more appropriate.

The RE meta-analysis in the first stage of the MASEM found that the magnitudes of all correlations among the original TAM and the extended TAMs were at least moderate (greater than .3) according to Cohen (1988, pp. 77–81), who suggested that correlation coefficients of .10 are "small," those of .30 are "medium," and those of .50 are "large" in terms of the magnitude of the effect sizes (see Table 2 for details). In general, attitudes toward use had strong correlations with the immediate predictors in TAM.

The file drawer problem, or publication bias, was estimated by calculating the fail-safe *N* (M. S. Rosenberg, 2005), which is the number of additional studies required to overturn the effect sizes stated. As shown in Table 2, the large digits of fail-safe *N*s indicate that the magnitudes of these effect sizes are unlikely to be "washed out" by the effects of missing studies. That is, there is no concern of publication bias.

Table 3. Model Estimates of the TAM Extended Model Using Meta-Analysis.

DV	IV	Effect	Meta-analysis estimate	Meta-meta-analysis estimate
Attitude	PEOU	Direct effect	.333***	.209***
Attitude	PU	Direct effect	.391***	.411***
PU	PEOU	Direct effect	.407***	.419***
PU	SI	Direct effect	.275***	.290***
Intentions	Attitude	Direct effect	.425***	.383***
Intentions	PU	Direct effect	.222***	.254***
Intentions	SI	Direct effect	.219***	.170***
Intentions	PU	Indirect effect	.166***	.158***
Intentions	PEOU	Indirect effect	.141***	.080***
Attitude R^2			.395***	.300***
Intention R^2			.478***	.410***
PU R^2			.323***	.320***

Note. TAM = technology acceptance model; DV = dependent variable; IV = independent variable; PEOU = perceived ease of use; PU = perceived usefulness; SI = social influence.

The estimation of path analysis. Subsequently, six path analyses were performed in the second stage of the MASEM. The model, which extends the original TAM by additionally including the predictions from SI to PU and intentions, was better than the original TAM and five alternative models (for the detailed results of model comparisons, see figshare.com/s/5ca1a12c56a783376d36), so the extended TAM was retained and subsequently further explained. The fit statistics showed that the extended TAM exhibited a very good fit to the meta-analytic data according to the recommendations of Hu and Bentler (1999). The path coefficients, the R^2 values for the endogenous variables, and model fit indices are presented in Table 3, Figure 2, and the online Appendices at figshare.com/s/5ca1a12c56a783376d36, respectively.

Corresponding to the research questions, PEOU had a medium effect on PU $(\beta = .407, p < .001)$, whereas SI had a nearly medium effect on PU $(\beta = .275, p < .001)$. Both PEOU and PU had medium effects on attitudes toward use $(\beta = .333, p < .001;$ $\beta = .391, p < .001)$. Attitudes also had a medium effect on intentions $(\beta = .425, p < .001)$.

Both PU and SI had weak direct effects on intentions, $\beta = .222, p < .001;$ $\beta = .219, p < .001$. PEOU had a lower indirect effect (the problems associated with the testing procedure of mediation effect proposed by Baron and Kenny (1986) are widely discussed in the literature [for an overview, see MacKinnon et al., 2007]), so the procedures suggested by Preacher and Hayes (2004) were adopted on use intentions $(\beta = .141, \text{confidence interval [CI]} = [.124, .158])$. PU also had a lower indirect effect on use intentions $(\beta = .166, \text{CI} = [.147, .187])$.

The R^2 values of PU, attitudes, and intentions were .323, .395, and .478, respectively, which means that 32.3%, 39.5%, and 47.8% of the variances of the three outcome variables could be explained by the predictors.

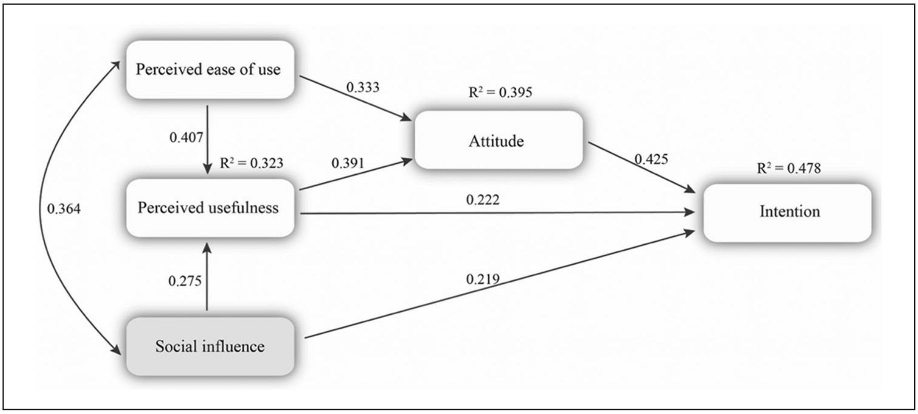

Figure 2. Extended technology acceptance model (TAM) model with estimates.
Note. The boxes in white represent the original TAM.

Subgroup moderator analysis. After the path model was tested, we further conducted subgroup analysis using the study-level moderators, specifically, technology characteristics (hedonic, both hedonic and utilitarian, and utilitarian) and user types (consumers vs. business), study's country of origin (three categories, that is, Asia, North America, and Europe were used in reference to similar previous meta-analyses), technology types (four categories, that is, communications systems, general-purpose systems, office systems, which was not tested after the removal of missing values in this category, and specialized systems were used in reference to Lee et al., 2003). We also tested the moderation effect of the year when a technology was invented. (The variable of years was turned into a nominal one with three categories by the median split.[3] Any value below the median was placed in the category "earlier," and every value above it was labeled "recent.") The procedures (see Jak & Cheung, 2018b) were the same as above, but the pooled effect sizes and path models were re-estimated by the subgroups. None of the moderators exerted significant effects on the above-mentioned predictions involved. All of the estimation results and model fit indices of the subgroup moderator analyses were stored at figshare.com/s/5ca1a12c56a783376d36 to save space.

Study 2: A Model-Based Meta-Meta-Analysis

Method

Selection criteria. We searched for the keywords "technology acceptance model, meta-analysis," "technology acceptance, meta-analysis," "TAM, meta-analysis," "UTAUT," and "technology acceptance model, meta-analysis" on Google Scholar, which contains both journal citation report (JCR of the Web of Science) and non-JCR journal articles. This search yielded 23 meta-analytical studies, 21 of which were rigorous and reported quantitative effect sizes and related information. Furthermore, 18 of them provided the complete correlation matrices pertaining to the tested models.

Four postgraduate students supervised by the first author conducted the coding work. Forty-seven variables and 1,807 pairs were identified after some necessary merging and renaming (e.g., performance expectancy and effort expectancy were renamed to PU and PEOU, respectively). To compare the results between the two approaches, we kept the same variables and pairs as in Study 1.

Procedures. The same procedures as Study 1 were employed in Study 2.

Results

The pooled correlation matrix was estimated using both FE and RE meta-analyses in Stage 1 (see the table at figshare.com/s/5ca1a12c56a783376d36). The results of the log-likelihood (LL) ratio test favors the RE model ($-2LL = -76.148$, $likelihood_{difference} = 105.118$, $df_{difference} = 6$, $p < .001$). The RE correlations using the meta-meta-analysis approach were very similar to the results of the meta-analysis method. A t test procedure also confirmed the result, $t\,(17.301) = 1.437$, $p = .169$, $mean_{meta\text{-}analysis} = .468$, and $mean_{meta\text{-}meta\text{-}analysis} = .409$.

The same extended TAM model as Study 1 had a satisfactory model fit (root mean square error of approximation [RMSEA] = .040, standardized root mean square residual [SRMR] = .050, Tucker–Lewis index [TLI] = .969, and comparative fit index [CFI] = .994) according to Hu and Bentler (1999) through the path analysis in Stage 2. All of the path coefficients were significant (see Table 3). Furthermore, we found that the path coefficients of the extended TAM estimated using the meta-analysis and meta-meta-analysis approaches did not differ significantly, $t\,(11.755) = .385$, $p = .707$, $mean_{meta\text{-}analysis} = .305$, and $mean_{meta\text{-}meta\text{-}analysis} = .324$. Therefore, the extended TAM is viable in light of the results of the two approaches.

Discussion

In Study 1, we discovered a strong effect of attitudes toward use on use intentions; this finding demonstrates that a positive attitude is a good indication of use intentions. The effects of PEOU and PU on use intentions are mediated by attitudes. Consequently, the mediation effects of attitudes between the variables PEOU and the PU and use intentions are real and inconsequential (this is in contrast to such models as TAM2, TAM3, and UTAUT proposed by Venkatesh, in which attitude is removed). Moreover, the indirect effects (as well as the total effects) of the variables PEOU and the PU on use intentions are much lower than their direct effects on attitude toward technology use. This finding also implies that the PEOU and the PU are more important determinants of attitudes toward use vis-à-vis use intentions.

SI, or subjective norms, exerts only a (medium-sized) direct effect on use intentions. As explained in the literature review section, the variables PEOU and the PU actually belong to behavioral beliefs. Therefore, all of the above-mentioned findings conform to the primary hypotheses of the TRA and TAM. The tested path model confirms the predictions of the extended TAM. Moreover, all effects tested through subgroup analyses are uniform across study-level moderators.

In Study 2, the results of pooled correlations and path coefficients estimated using the meta-meta-analysis are consistent with those of the meta-analysis. The meta-meta-analysis technique is nothing but meta-analysis. Nevertheless, with a much smaller sample size (including meta-analytical studies), meta-meta-analysis is able to address the same research questions as conventional meta-analysis.

Although there have been many meta-analytical studies on the TAM, the present one includes a much greater number of primary studies than any other published meta-analysis. More importantly, the findings of this article have noteworthy theoretical, practical, and methodological implications, which will be elaborated on below.

As reviewed above, numerous scholars have proposed extensions to the TAM. Most of them add more predictors of either PU or PEOU but remove the mediating variable of attitudes. This article removes the variable of actual use (behaviors) from the original TAM because this behavior variable is not easily measured in real studies and has unsatisfactory connections with predictors (Ajzen, 1991; Fishbein, 2000; Fishbein & Cappella, 2006; Webb & Sheeran, 2006). This article, through both meta-analysis and meta-meta-analysis, extends the original TAM merely by incorporating one of the important factors of the TRA, that is, SI (or subjective norms). Such a model, which is simpler than the TAM2 and other extensions, satisfies the parsimony principle and has better explanatory power than the original TAM. The original TAM is too simple to explain a sufficient amount of the variance of use intentions, yet many extensions of the TAM are either too complicated or tautological (e.g., performance expectancy and PU). If a phenomenon can be explained adequately by means of fewer hypotheses, it is superfluous to propose more hypotheses, according to Occam's razor or the parsimony principle (Sober, 1981). Similar arguments were raised by Fishbein and Ajzen (2010, p. 282), who suggested that five criteria should be met by any proposed addition of new predictors. Furthermore, the extended TAM model is supposed to be applicable across user types, technology characteristics, study's country of origin, technology type, and the year of technology invention. To demonstrate the uniqueness of this extended TAM, we term our finalized model the TAM Plus. Therefore, this article offers significant theoretical contributions to TAM research.

The article may also have practical implications. Promoters of technological products or services do not have to be stunned by a large number of predictors. As shown and reshown in our studies, a parsimonious model integrating the factors primarily from the base TAM and the TRA is sufficient and useful. As stated above, all of the effect sizes of attitudes with other variables in the TAM are generally strong. The path analysis of the extended TAM also shows that attitudes toward technology use mediate the effects of PU and PEOU on use intentions. Therefore, cultivating a positive attitude is crucial to intentions to use. The indirect effects of PU and PEOU on use intentions are not trivial. The two factors are still the core interests offered and promoted to users. In addition, importance should be attached to SI. Viral marketing relying on social networks or affiliate marketing (see Boughton, 2005) may be an effective marketing strategy to promote technological products or services.

In addition, as mentioned above, we did not include actual behavior in the model for many reasons, one of which is the unsatisfactory connection between predictors and actual use. Many scholars (e.g., Ajzen, 1991; Venkatesh, 2000) suggest that intentions (or motivation), nonmotivational factors such as the availability of necessary opportunities, resources, and abilities (for a review on Motivation–Opportunity–Ability [MOA], see MacInnis et al., 1991; MacInnis & Jaworski, 1989) (PBC in TPB), environmental factors (see Fishbein, 2000; Fishbein & Cappella, 2006), and even the interactions between motivation and ability factors (Ajzen, 1991) determine actual behavior. This notion may have practical implications. The formation of use motivation and positive attitudes might entail consistent advertising and publication relations campaigns, while strengthening nonmotivational factors, such as encouraging trial use of products and opening experience stores (Jones, 2010), may make people more determined to eventually adopt a technology.

Moreover, this article offers significant methodological contributions. It is one of the few papers to perform meta-meta-analysis and model-based meta-analysis in the social sciences. As explained earlier, model-based meta-analysis is superior to conventional univariate meta-analysis (which focuses on a certain effect size alone) because it is able to test mediation, moderation, and other complex relationships among variables of interest. Meta-meta-analysis requires fewer studies; thus, it is an economical but powerful and promising approach for integrating primary research findings.

This article has limitations. Although this article consists of a large number of meta-analytical studies and a meta-meta-analysis, many primary studies on the TAM and other related theories in relation to technology diffusion were left out if they were not published in SSCI or SCI listed journals. As explained above, there have been millions of studies in this line of research. Consequently, it is necessary to select journal articles published in more prestigious journals. Moreover, the estimation results of the meta-meta-analysis, which is based on 21 meta-analytical studies that also include many non-SSCI or non-SCI listed journal articles, are generally in accordance with those of our meta-analytical study.

In addition, we did not correct for effect sizes using either reliability or covariates (moderators) before Stage 2. While Hunter and Schmidt (1990) and others advocate correcting for unreliability[4] (by dividing the uncorrected correlation by the square root of the reliabilities of the variables), many researchers (Cheung, 2015a; Michel et al., 2011; Rosenthal, 1991a) oppose such a practice in that the correction for unreliability may cause serious consequences, for example, underestimating conditional sampling covariance matrix of the estimated corrected correlation (Cheung, 2015a, pp. 243–244). However, for nonmodeling or univariate meta-analytical studies, corrections for unreliability, restriction of range, and other such artifacts (see Hunter & Schmidt, 1990) are strongly recommended. We also did not correct for the influence of the study-level moderators since the metaSEM package of R does not provide this ability. Instead, we tested the effects of study-level moderators using subgroup analysis. Nonetheless, with intensive customized programming, future research could use the effect size adjusted by study-level moderators.

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Notes

1. The number of studies testing the relationship between intentions and actual use is 69, which is much lower than the number of studies examining the relationship between the primary TAM predictors (PEOU and PU) and intentions (606). For the ratio accounted for by each correlation, see https://figshare.com/s/5ca1a12c56a783376d36.
2. Sixteen different moderators were tested in the previous 12 meta-analyses with a moderator analysis of the TAM.
3. The metaSEM package of R cannot handle continuous moderators for the moment.
4. The average reliabilities of PEOU, PU, SI, attitude, and intentions in the primary studies were .887 (N = 713), .909 (N = 741), .880 (N = 307), .876 (N = 292), and .881 (N = 791), respectively.

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