Determinants of technology acceptance: Two modeling-based meta-analytic reviews

Abstract

Examining the determinants of technology acceptance has been a central interest across disciplines. The technology acceptance model (TAM) as well as its variants and extensions are the most popular theoretical framework in this line of research. Two modeling-based meta-analytical approaches, i.e., the meta-meta-analysis and the conventional meta-analysis, were used to test the correlations and path relationships among the variables of the TAM. It was found that the extended TAM prevails in the model fit testing, and that the results of pooled correlations and path coefficients estimated using the meta-meta-analysis and meta-analysis were consistent in general.

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

Examining the determinants of technology use or acceptance has been a central interest across disciplines. While many theoretical perspectives have been proposed to address this issue, the Technology Acceptance Model (TAM) (Davis, 1986) is one of the relevant theories that is widely used to explain user acceptance intention and behaviors. Davis and his associates (Davis, 1986, 1989; Davis, Bagozzi, & Warshaw, 1989) hypothesize that perceived usefulness (PU) and perceived ease of use (PEOU) form the user's beliefs on a technology and subsequently predict the user's attitude towards the technology, which further determines the intended and actual adoption of the technology. The original TAM has been later extended or revised by many scholars, who either add additional constructs as determinants of PEOU and PU (Karahanna & Straub, 1999; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003; J.-H. Wu, Chen, & Lin, 2007; Yen, Wu, Cheng, & Huang, 2010), or attitude (Park & Kim, 2014), or intended use (Gefen, Karahanna, & Straub, 2003; Karahanna, Agarwal, & Angst, 2006).

Since the publication of the TAM (Davis, 1986), it as well as its extensions have been applied to a variety of end-user technologies in empirical studies (for a review, see Legris, Ingham, & Collerette, 2003; Ma & Liu, 2004), which, however, have produced inconsistent results in terms of model configurations, and statistical significance, direction, and magnitude of hypothesized relationships (Ma & Liu, 2004; Moore & Benbasat, 1991). Furthermore, due to the its popularity and also the considerable amount of mixed findings, there have existed amazingly 23 meta-analyses and multiple systematic literature reviews (e.g., Dwivedi, Williams, & Rana, 2015; Lee, Kozar, & Larsen, 2003; Legris et al., 2003; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010) and two computation literature reviews relying on machine learning (Mortenson & Vidgen, 2016) and statistical modeling techniques (Hsiao & Yang, 2011) thus far. These extant meta-analyses have made important contributions to our understanding of the TAM, but the inconsistency associated with primary studies also has also been channeled into the meta-analyses on the TAM. There are substantial gaps in association with the TAM studies to be addressed and filled.

Consequently, the research purpose of this paper is two twofold: 1) examine the exact effect and magnitude of the theoretical relationships involving the TAM by synthesizing existing empirical primary as well as meta-analytical studies; 2) seek and conclude a parsimonious theoretical framework built on the TAM, which can sufficiently explain individual intentions of adopting technologies. To avoid fueling the confusing status quo of the TAM field, we opt for some new procedures, which have never been tried in the TAM literature, i.e., the meta-meta-analysis, and the still innovative procedure in communication, i.e., meta-analysis using structural equation modeling.

Literature review

The origin and extensions of the TAM

Many scholars (e.g., Schepers & Wetzels, 2007) have mentioned that TAM was inspired by the theory of reasoned action (TRA) and the theory of planned behavior (TPB). However, both the connections and differences among them are far more complex. On the assumption that behavior is under volitional control (Icek Ajzen, 2002; Bagozzi Richard & Kimmel Susan, 1995), the TRA (I. Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) posits a model conceptually applicable to all human activities. The TRA posits that intention mediates the effects of external and the internal beliefs on behaviors without losing sight of joint effects (Baron & Kenny, 1986). Expressed mathematically, the relationship is shown as $A \propto \sum b_i e_i$, where A is the attitude toward engaging in a behavior, b is the individual's belief of the probability that certain outcomes will ensue from the action, and e is their evaluation of those outcomes. Subjective norms (SN) is measured by what the individual thinks to be desirable by important referent others (n) weighted by the motivation to comply (m): $SN \propto \sum n_i m_i$ (I. Ajzen & Fishbein, 1980; Baron & Kenny, 1986; Fishbein & Ajzen, 1975). Icek Ajzen (1985) later extended the TRA to the TPB to predict not fully volitional behaviors by including the 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*): $PBC \propto \sum p_i c_i$. The TRA and the TPB combined have generated remarkably more than 100,000 citations according to Google Scholar.

Taylor and Todd (1995a) combined the TAM and the TPB. Following that, they (1995b) adapted the TPB to form the decomposed TPB, using such constructs as relative advantage, complexity, compatibility from the diffusion of innovation theory (Rogers, 1983). Venkatesh and Davis (2000) proposed the TAM2 by identifying several determinants of perceived usefulness—that is, subjective norm, image, job relevance, output quality, result demonstrability, and perceived ease of use—and two moderators—that is, *experience* and *voluntariness*. Van Raaij and Schepers (2008) extends TAM2 by including subjective norm, personal innovativeness on 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) through 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 PC utilization the innovation diffusion theory, and the social cognitive theory) comprising related 32 constructs. In UTAUT, individual intentions to accept technologies are determined by performance expectancy, effort expectance, social influence, user behavior is predicted by facilitating conditions, and all of the four predictions are moderated by age, gender, experience and voluntariness of use. The UTAUT has been also extended by later scholars through the addition of new predictors such as social support (Lin & Anol, 2008; Sykes, Venkatesh, & Gosain, 2009) and perceived playfulness (H.-Y. Wang & Wang, 2010). Seemingly noting the weakness of previous proposed models, Venkatesh and Bala (2008) further developed an integrated model named the TAM3, by combining TAM2 (Venkatesh & Davis, 2000) and the model of the determinants of perceived ease of use [early stage of anchors including computer self-efficacy, computer anxiety, and computer playfulness, and perceptions of external control (or facilitating conditions), and later adjustment comprised of perceived enjoyment and objective usability] (Venkatesh, 2000). Furthermore, Venkatesh, Thong, and Xu (2012) proposed UTAUT2 incorporates three constructs into UTAUT: hedonic motivation, price value, and habit. Nevertheless, Dwivedi et al. (2015) also found that only performance expectancy of UTAUT is the important predictor of technology use. Van Raaij and Schepers (2008) and Bagozzi (2007) also criticized the UTAUT for its complexity and incoherent integration, and suggested new extensions or revisions to the TAM.

As one of the coauthors of the TAM (Davis et al., 1989), Bagozzi is, nevertheless, the prominent scholar who has 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) believes that little theoretical insight is provided into the prediction and moderation mechanisms embodied in the TAM and its variation as well as extensions. Bagozzi

(2007) instead proposed the technology user acceptance decision making core by classifying previously proposed determinants of PU, PEOU and intentions into the corresponding process of decision making core in addition to a self-regulation mechanism in between.

The criticism against the TAM and its extensions with respect to "little theoretical insight" may not be true. In origin, the TAM and its numerous extensions including UTAUT, the TRA, and the TPB, as well as social cognitive theories (Bandura, 1986) are all applications of value-expectancy theories (VET) (e.g., Atkinson, 1957; Edwards, 1954; Fishbein, 1963; Fishbein & Raven, 1962; Kahneman & Tversky, 1979; Morgenstern & Von Neumann, 1953; Rosenberg, 1956). Therefore, not surprisingly, they have much in common (Bish, Sutton, & Golombok, 2000). In addition, Abdullah and Ward (2016) identified a total of 152 external determinants of PU and PEOU tested in their meta-analysis comprised of 107 studies, and argued that only five external factors (Self-Efficacy, Subjective Norm, Enjoyment, Computer Anxiety and Prior Experience) are more relevant. What is more, some of the five factors may not be applicable across use settings (e.g., Enjoyment, and Computer Anxiety may not be relevant for the adoption of e-health products, e-government and such other organizational settings). Therefore, even fewer number of variables among the five external factors are generally necessary.

The findings on various predictions involved in the TAM in its extensions in the both primary studies are inconsistent and contradictory at worse. This calls into question the validity of the theoretical underpinnings of the TAM and its extensions in particular. Specifically, what necessary constructs are needed for a parsimonious theory, and what relationships and magnitudes are among them? Such questions can be addressed using the meta-analysis, which is a means of quantitatively determining the real effect and effect size based on findings from previous research on a certain topic (Glass, Smith, & McGaw, 1981; John Edward Hunter, Schmidt, & Jackson, 1982; Rosenthal, 1991b). Despite its necessity and importance, most meta-analyses in the field of communication have looked at 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 merely examined the bivariate correlation in actual studies but rather addressed more complex theoretical relationships through incorporating either covariates, moderators, or mediators (Wilson, Polanin, & Lipsey, 2016). The complex chains of events (Becker, 2009) can only be addressed with a totally different modeling technique of meta-analysis. Therefore, the meta-analysis using structural equation modeling is superior to separate univariate correlation-based (e.g., John E. Hunter & Schmidt, 1990) meta-analysis in this regard.

Previous meta-analysis of TAM

As mentioned above, there have been around 20 published meta-analyses reporting effect sizes on the TAM or its extensions. Such an astonishing number of meta-analytical reviews on the same topic seem to be far more sufficient. It provides rich information in exploring the “true” theoretical relationships. Such a massive number of published meta-analyses on the TAM as well as its extensions offers a new possibility of re-examining the predictive relationship based on the effect sizes reported in the prior meta-analyses employing an innovative procedure called meta-meta-analysis (Cafri, Kromrey, & Brannick, 2010; Cleophas & Zwinderman, 2017; Kazrin, Durac, & Agteros, 1979).

Notwithstanding a great number of meta-analytical studies, many of them also suffer from a variety of limitations. Consequently, there have been considerable research gaps, which need to be filled. Most of these meta-analytical studies examined the univariate relationships predicted in the TAM. Moreover, Two univariate meta-analysis on UTAUT (Khechine, Lakhal, & Ndjambou, 2016;

Taiwo & Downe, 2013) did not conduct moderator analysis [Khechine et al. (2016) attributed this to too few available number of included studies after the significant heterogeneity tests]. Some (Chauhan & Jaiswal, 2017b; King & He, 2006) directly meta-analyzed path coefficients, which do not satisfy the requirement of effect size (cf. Ferguson, 2009). Two model-based meta-analyses (Hamari & Keronen, 2017b; Schepers & Wetzels, 2007) used the correlation matrix in place of the covariance matrix as input. The consequence incurred due to using such a procedure was discussed in Mike W-L Cheung and Chan (2005).

Since all the predictions are derived from established theories, we are hence interested in examining the magnitude, instead of the presence, of the effects of predictions. The present study aims to answer the following research questions:

1. What is the magnitude of predictor effect size of intentional use of technology?
2. What kinds of significant relationships among predictors and outcomes are present?

Study 1: A modeling-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", "The unified theory of acceptance and use of technology" in Web of Science with only SCI and SSCI listed English language journals. The first round of the search started in July 2018, still yielding 12,427 potentially eligible studies. We then made several steps of screening of these articles.

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, i.e., PU, PEOU and intentions; and (c) reporting complete zero-order correlations among independent variables and dependent variables. After a series of filtered searches, we obtained 787 eligible articles (cumulative $N = 296{,}121$).

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, Mullen, and Salas (1995) in order to retain the correlation metric and the associated variances and covariances among the correlations for use in Stage 2 of MASEM (cf. Wilson et al., 2016).

Coding

Nine undergraduate students were recruited to independently code studies according to the codebook. We selected 30% of the studies to check inter-coder reliability on the major variables, such as effect size, sample size, technology characteristics (hedonic, both hedonic and utilitarian, and utilitarian) and user types (consumer vs. business), between pairs of coders, which was estimated via the "irr" package of R 3.4. The results of the inter-coder reliability estimation using Krippendorff's α ranged between .81 and .92. Partial discrepancies were resolved through discussion.

Procedures

Overall, there were two steps in the present two-stage meta-analytic structural equation modeling (MASEM) approach. The heterogeneity is estimated using a homogeneity statistic *Q* (Brockwell & Gordon, 2001; Hedges, 1981; Higgins & Thompson, 2002; Schmid, Koch, & LaVange, 1991) in stage 1 (cf. Mike W.-L. Cheung, 2014; M. W. L. Cheung, 2015b; Jak, 2015). In the absence of homogeneity, the random effects model (as opposed to a fixed effects model, which assumes that the true effect is the same for all studies), which allows the true effect to vary across studies, is used (Brockwell & Gordon, 2001; Council, 1992; Schmid et al., 1991). In addition, the original correlations instead of Fisher's Z or other corrected correlations were used in the random-effects modeling [Although Fisher-z score may be used in pooling correlation matrices, using original correlation matrices is a better choice in MASEM according to some (M. W. L. Cheung & Hong, 2017; Wilson et al., 2016)]. Subsequently, the path models based on the pooled correlation matrix are estimated using the weighted least squares (WLS) estimation (with 5,000 parametric bootstrap replicates) of the metaSEM package (M. W.-L. Cheung, 2015) in stage 2. In addition, the moderator analysis was performed using sub-group analysis (for details, see Jak & Cheung, 2018).

Results

Estimation of the pooled correlation matrix

Majority of the primary studies tested the intention of using a technology rather than the actual use as the ultimate dependent variable. Consequently, the following models excluding actual use were tested. Moreover, we tested two models, i.e., the original TAM, and an extended TAM (adding social influence predicting use intentions), on account of the theoretical significance, data availability and data quality (the correlation matrix has to satisfy the requirement of positive-definite). In addition, some predictions were slightly changed in order to keep the positive definite matrix.

In stage 1, the pooled correlation matrix is estimated through the fixed-effects model and the random-effects model. The model fit indices indicate that the random-effects models fit the data better than the fixed-effects models (all the model fit indices of the fixed-effects models did not pass the cut-off threshold recommended by Hu and Bentler (1999). In addition, the likelihood ratio test also favors the random-effects model: $-2LL$= 58171.231, $likelihood_{difference}$ = 58616.43, $df_{difference}$ =20, p <.001). In addition, the Q test was significant (Q (df=740)=7369.102, p < .001) and the values of I^2 , which indicates the proportion of the between-study variance relative to the total variance for the effect size of interest, were above 0.8. That is, there is significant amount of between-study variance for each effect, so the random-effect is more appropriate.

The random-effects meta-analysis in the first stage of the MASEM found that the magnitudes of all the correlations among the original TAM as well as the extended TAM 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 magnitude of effect sizes (see Table 1 for details). In general, attitude towards use has strong correlations with all other variables.

The estimation of path analysis

Subsequently, two path analyses were performed in the second stage of the MASEM. The extended TAM was better than the original TAM through the loglikelihood ratio test ($-2LL$=216.695, $likelihood_{difference}$ =150.626, $df_{difference}$ =3, p <.001), so the extended TAM was retained and further explained subsequently. The fit statistics show that the extended TAM exhibits very good fit to the meta-analytic data according to the recommendations of Hu and Bentler (1999) (for details, see Table 2). The path coefficients and the R^2s for the endogenous variables were presented in Table 2 and Figure 1. Corresponding to the research questions, the perceived ease of use has an about medium effect on attitude towards use ($\beta = .285, p < .001$), but has a lower indirect effect on use intention ($\beta = .159$); likewise, the perceived usefulness has a nearly strong effect on attitude towards use ($\beta = .494, p < .001$), but has a lower indirect effect on use intentions ($\beta = .279$); attitude has a strong effect on intention ($\beta = .561, p < .001$); social influence has an about medium effect on intentions ($\beta = .277, p < .001$). The R^2 values of attitude and intention are .462 and .487, respectively, which means that 46.2% of the variance of attitude and 48.7% of the variance of intention can be explained by the model.

Sub-group moderator analysis

After the path model has been tested, we further conducted sub-group analysis by the study-level moderators, specifically, technology characteristics and user types. The procedures (cf. Jak & Cheung, 2018) were the same as above, but the pooled effect sizes and path models were estimated by the sub-groups. As for technology characteristics, there were no significant differences in effects among hedonic, both hedonic and utilitarian, and utilitarian technologies through the chi-square difference test (χ^2(24)= -3.991, , p = 1). That is, the model with equality constraints fits the data better (χ^2(3)= 66.069, , p = 0, RMSEA = 0.015, RMSEA lower 95% CI = 0.011, RMSEA upper 95% CI = 0.019, SRMR = 0.060, TLI = 0.989, CFI = 0.988). In addition, there were no significant differences in path coefficients between the business and consumer users (χ^2(2.554)= 12, , *p* = .998). The model with equality constraints fits the data better (χ^2(18)=83.877 , *p* = 0, RMSEA = 0.017, RMSEA lower 95% CI = 0.013, RMSEA upper 95% CI = 0.021, SRMR = 0.053, TLI = 0.986, CFI = 0.987).

Discussion

A strong effect of attitude towards use on use intention demonstrates that a positive attitude is a good indication of use intentions. The effects of the perceived ease of use and the perceived usefulness on use intention are fully mediated by attitude. Consequently, the full mediation effects of attitude between the perceived ease of use and the perceived usefulness and use intentions are real. Moreover, the indirect effects (also total effect) of the perceived ease of use and the perceived usefulness on use intention were much lower than their direct effects on attitude towards technology use. This also implies that the perceived ease of use and the perceived usefulness are more important determinants of attitude towards use vis-à-vis use intentions.

Social influence, or subjective norms, only exerts a direct (medium sized) effect on use intentions. As explained in the section of literature review, the perceived ease of use and the perceived usefulness actually belong to the behavioral beliefs. Therefore, all of the above-mentioned findings conform to the primary hypotheses of TRA and TAM. The tested path model confirms the predictions of the extended TAM, but in fact, it is a variant of the TRA. Moreover, all the effects tested through sub-group analysis were uniform across use settings (consumer vs. business) and technological characteristics (hedonic, hedonic and utilitarian, and utilitarian technologies).

Study 2: A modeling-based meta-meta-analysis

Method

Selection Criteria

We searched for the following keywords such as “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 JCR (journal citation reports of Web of Science) and non-JCR included journal articles. This search yielded 23 meta-analytical studies, 21 of which are rigorous ones with quantitative effect sizes and related information reported. 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. 47 variables and 1,807 pairs were identified after some necessary merge and renaming (e.g. performance expectance and effort expectance were renamed to perceived usefulness and perceived ease of use, respectively). In order to compare the results between the two approaches, we kept the same variables and pairs as Study 1. The average number of primary studies included in the meta-analysis for the correlations among the six variables was 45, and the accumulative sample size of included primary studies was 304,821.

Procedures

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

Results

The pooled correlation matrix was estimated using both fixed-effects and random-effects meta-analysis on stage 1. Both the results of likelihood ratio test (*-2LL*=1807.293, $likelihood_{difference}$ =1833.359, $df_{difference}$ =10, *p* <.001) and the model fit indices of the two modeling approaches favors the fixed-effects model (Sample size = 538, χ^2 (df=10)= 8.796, *p* = 0.552, RMSEA = 0, SRMR = 0, TLI = 1, CFI = 1, AIC = -11.204, BIC = -54.086). As shown in Table 1, the estimated correlations using the meta-meta-analysis approach had very similar results to the meta-analysis method. A T-test procedure also confirmed the intuition (t (15.738)= 0.296, p = 0.771, $mean_{meta\text{-}analysis}$=0.462, $mean_{meta\text{-}meta\text{-}analysis}$ = 0.447).

The extended TAM model tested in Study 2 did not have very satisfactory model fit in general (RMSEA = .183, SRMR = .059, TLI = .788, CFI = .937) through the path analysis on Stage 2, and yet all of the path coefficients were significant (see Table 2). Nevertheless, 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 (9.321) = -0.160, p = 0.876, $mean_{meta\text{-}analysis}$=0.342, $mean_{meta\text{-}meta\text{-}analysis}$ = 0.359). Therefore, the extended TAM is viable in light of the results of the two approaches.

Discussion

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

General discussion

The effect sizes estimated using the two approaches are consistent. All of the effect sizes are not only significant, but also nontrivial. If we keep the two decimal points of the estimations shown in Table 1, the magnitudes of correlations between attitude and all other factors are strong (above .5), while the rest of the effect sizes are moderate (above .3). This demonstrates that attitude indeed plays a pivotal role in the TAM.

As reviewed above, numerous scholars have proposed plenty of extensions to the TAM. Most of them add in more predictors of either perceived usefulness or perceived ease of use, but remove the mediating variable of attitude. While the present paper sticks with the original TAM, it removes the variable of actual use (behavior) from the model in that it is not easy to be measured in real studies and had unsatisfactory connections with predictors. This paper, through both meta-analysis and meta-meta-analysis, extends the original TAM by merely incorporating one of the important factors of the TRA, i.e., social influence (or subjective norms). Such a model not only satisfies the parsimony principle but also has better explanatory power than the original TAM. The original TAM is too simple to explain sufficient amount of the variance of use intentions, and yet many extensions of the TAM are either too complex, or too tautological (e.g., performance expectancy and perceived usefulness). If a phenomenon can be explained adequately by means of fewer hypotheses, it is superfluous to propose more according to the Ockham razor or parsimony principle (Sober, 1981). Furthermore, the extended TAM model is supposed to be applicable across use settings, technology characteristics and cultural contexts. Therefore, this paper has made significant theoretical contributions to the TAM research.

The paper may also have practical implications. For the promoter of technological products or services, they do not have to be stunned by the lion share of predictors. As shown and re-shown in our studies, a parsimonious model integrating the factors primarily from the TAM base and the TRA has been more than enough and useful. As pointed out above, all of the effect sizes of attitude with other variables in the TAM are strong. The path analysis of the extended TAM also shows that attitude towards the technology use fully mediates the effects of perceived usefulness and perceive ease of use on use intentions. Therefore, cultivating a positive attitude is crucial. The indirect effects of perceived usefulness and perceive ease of use on use intentions are not trivial. The two factors are still the core interests offered and promoted to users. In addition, they should attach importance to social influence. Therefore, this implies that viral marketing relying on social network or affiliate marketing (cf. Boughton, 2005) may be the effective marketing strategy to promote technological products or services.

Although there have been many meta-analytical studies on the TAM, the present one has included the much more number of primary studies than any other published meta-analysis. More importantly, this paper has made significant methodological contributions in the field of communication. It is the first study conducting the meta-meta-analysis in communication thus far. It is still one of the few number of papers that performs the modeling-based meta-analysis in communication. As explained earlier, the modeling-based meta-analysis is superior to the conventional univariate meta-analysis, which merely focuses on a certain effect size alone, in that it is able to test mediation, moderation and other complex relationships among the variables of interest. The method of meta-meta-analysis only needs fewer number of studies, so it is an economical, but powerful and promising approach of integrating primary research findings.

This paper has limitations. Although this paper consists of a large scale of meta-analytical study and a met-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, selecting the journal articles, which were published in relatively prestigious journals, is necessary. Moreover, the estimation results of the meta-meta-analysis, which is based on 21 meta-analytical studies that also includes 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 the effect size by either reliability or covariates (moderators) before Stage 2. While John E. Hunter and Schmidt (1990) and others advocate the correction for unreliability, many (M. W. L. Cheung, 2015a, pp. 243-244; Michel, Viswesvaran, & Thomas, 2011; Rosenthal, 1991a) oppose such a practice. We did not correct for the influence of study-level moderators in that the metaSEM package of R still does not provide such a facility. Instead, we tested the effect of study-level moderators using the approach of sub-group analysis. Nonetheless, with intensive customized programming, using the effect size adjusted by study-level moderators could be done in the future.

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Table 1 Pooled correlations based on the random-effects TAM extended model and meta-meta-analysis

	Random-effects meta-analysis			Fixed-effects meta-meta-analysis	
	Estimate	I^2	Pr(>|z|)	Estimate	Pr(>|z|)
Correlation 1	0.578	0.941	0.000	0.628	0.000
Correlation 2	0.490	0.894	0.000	0.442	0.000
Correlation 3	0.575	0.946	0.000	0.613	0.000
Correlation 4	0.382	0.893	0.000	0.363	0.000
Correlation 5	0.436	0.876	0.000	0.430	0.000
Correlation 6	0.537	0.923	0.000	0.566	0.000

Correlation 7	0.419	0.904	0.000	0.381	0.000
Correlation 8	0.495	0.917	0.000	0.492	0.000
Correlation 9	0.311	0.826	0.000	0.208	0.000
Correlation 10	0.395	0.887	0.000	0.347	0.000
Tau2_1_1	0.030		0.000		
Tau2_2_2	0.021		0.000		
Tau2_3_3	0.031		0.000		
Tau2_4_4	0.025		0.000		
Tau2_5_5	0.020		0.000		
Tau2_6_6	0.028		0.000		
Tau2_7_7	0.030		0.000		
Tau2_8_8	0.028		0.000		
Tau2_9_9	0.017		0.000		
Tau2_10_10	0.025		0.000		

Note: Correlation 1, Correlation 2, Correlation 4, Correlation 4, Correlation 5, Correlation 6 , Correlation 7, Correlation 8, Correlation 9, and Correlation 10 indicate the following correlations in sequence: attitude with intention, attitude with perceived ease of use, attitude with perceived usefulness, attitude with social influence, intention with perceived ease of use, intention with perceived usefulness, intention with social influence, perceived ease of use with perceived usefulness, perceived ease of use with social influence, and perceived usefulness with social influence respectively; Taus are their respective between-study variances

Table 2 Model estimates of the TAM extended model using meta-analysis

DV	IV	Effects	Meta-analysis Estimate	Meta-meta-analysis Estimate
attitude	Perceived ease of use	direct effect	0.285***	0.223***
attitude	Perceived usefulness	direct effect	0.494***	0.581***

intention	Perceived ease of use	indirect effect	0.159***	0.139***
intention	Perceived usefulness	indirect effect	0.279***	0.361***
intention	attitude	direct effect	0.561***	0.621***
intention	Social influence	direct effect	0.277***	0.229***
attitude R^2			0.462	0.518
intention R^2			0.487	0.526

Note: the model fit of the extended model using meta-analysis (Sample size = 17863, Chi-square of target model = 66.069, DF of target model = 3, p value of target model = 0, RMSEA = 0.034, RMSEA lower 95% CI = 0.027, RMSEA upper 95% CI = 0.042, SRMR = 0.049, TLI = 0.953, CFI = 0.986, AIC = 60.069, BIC = 36.698)

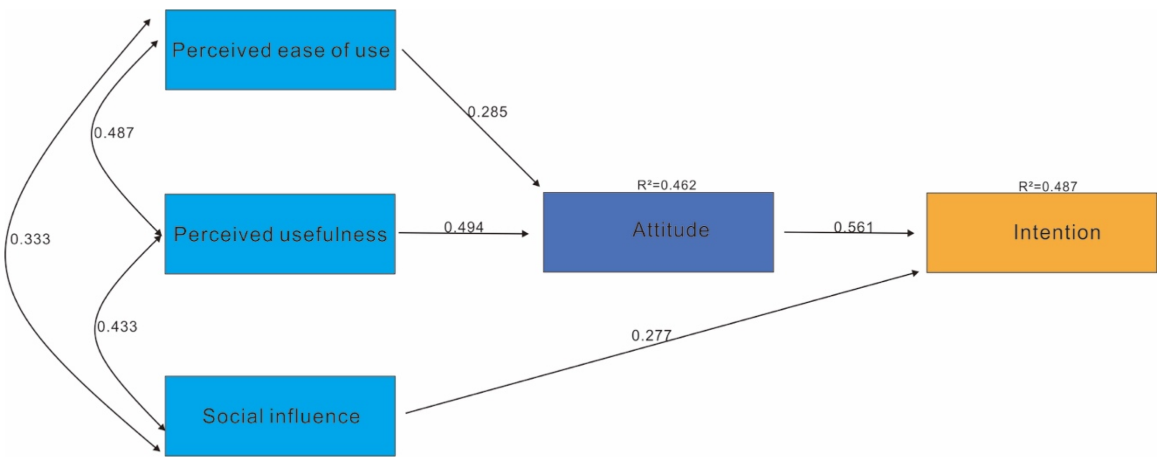

Figure 1 The extended TAM and the estimates