

A meta-analysis of the technology acceptance model

William R. King^{a,*}, Jun He^b

^a *Katz Graduate School of Business, University of Pittsburgh, Pittsburgh, PA 15260, USA*

^b *School of Management, University of Michigan-Dearborn, Dearborn, MI 48126, USA*

Received 9 September 2005; received in revised form 8 March 2006; accepted 13 May 2006

Available online 2 August 2006

Abstract

A statistical meta-analysis of the technology acceptance model (TAM) as applied in various fields was conducted using 88 published studies that provided sufficient data to be credible. The results show TAM to be a valid and robust model that has been widely used, but which potentially has wider applicability. A moderator analysis involving user types and usage types was performed to investigate conditions under which TAM may have different effects. The study confirmed the value of using students as surrogates for professionals in some TAM studies, and perhaps more generally. It also revealed the power of meta-analysis as a rigorous alternative to qualitative and narrative literature review methods.

© 2006 Elsevier B.V. All rights reserved.

Keywords: Technology acceptance model; TAM; Meta-analysis; Perceived usefulness; Ease of use; Behavioral intention

One of the continuing issues of IS is that of identifying factors that cause people to accept and make use of systems developed and implemented by others. Over the decades, various theories and approaches have been put forth to address this problem. For instance, in 1971, King and Cleland [49] proposed analyst–user “teamwork” during the design development process as a means of overcoming the reluctance of users to actually use IS developed for them. Schultz and Slevin [82] proposed that distinction had to be made between *technical* and *organizational* validity to understand why systems that met all technical performance standards still were not universally used or understood. Prototyping [39,96] and other methodological innovations

have also been created and used in an attempt to address the problem, but often without success.

In 1989, Davis [13] proposed the technology acceptance model (TAM) to explain the potential user’s behavioral intention to use a technological innovation. TAM is based on the theory of reasoned action (TRA) [25], a psychological theory that seeks to explain behavior. TAM involved two primary predictors—perceived ease of use (EU) and perceived usefulness (U) and the dependent variable behavioral intention (BI), which TRA assumed to be closely linked to actual behavior.

TAM has come to be one of the most widely used models in IS, in part because of its understandability and simplicity. However, it is imperfect, and all TAM relationships are not borne out in all studies; there is wide variation in the predicted effects in various studies with different types of users and systems [55].

A compilation of the 88 TAM empirical studies that we considered to be the relevant universe shows that the number of studies rose substantially, from a publication

* Corresponding author. Tel.: +1 412 648 1587;

fax: +1 412 648 1693.

E-mail addresses: billking@katz.pitt.edu (W.R. King),

junhe@katz.pitt.edu (J. He).

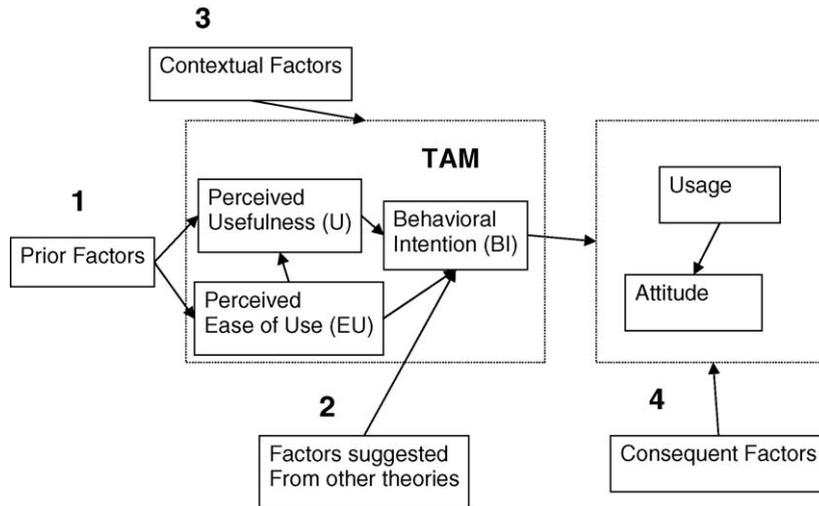


Fig. 1. TAM and four categories of modifications.

rate of 4 per year in 1998–2001 to a rate of 10 per year in 2002–2003.

Fig. 1 shows TAM as the “core” of a broader evolutionary structure that has experienced four major categories of modifications:

- (1) The inclusion of external precursors (prior factors) such as situational involvement [46], prior usage or experience [69,103], and personal computer self-efficacy [15].
- (2) The incorporation of factors suggested by other theories that are intended to increase TAMs predictive power; these include subjective norm [33], expectation [104], task-technology fit [20], risk [22,72], and trust [26,27].
- (3) The inclusion of contextual factors such as gender, culture [42,88], and technology characteristics [74] that may have moderator effects.
- (4) The inclusion of consequence measures such as attitude [14], perceptual usage [38,67,90], and actual usage [16].

1. Summarizing TAM research

Meta-analysis, as used here, is a statistical literature synthesis method that provides the opportunity to view the research context by combining and analyzing the quantitative results of many empirical studies [31]. It is a rigorous alternative to qualitative and narrative literature reviews [80,108]. In the social and behavioral sciences, meta-analysis is the most commonly used quantitative method [34]. Some leading journals have encouraged the use of this methodology [e.g., 21].

TAM has been the instrument in many empirical studies [102] and the statistics needed for a meta-analysis – effect size (in most cases the Pearson-moment correlation r) and sample size – are often reported in the articles. Meta-analysis allows various results to be combined, taking account of the relative sample and effect sizes, thereby allowing both insignificant and significant effects to be analyzed. The overall result is then undoubtedly more accurate and more credible because of the overarching span of the analysis.

Meta-analysis has been advocated by many researchers as better than literature reviews [e.g., 43, 79]. Meta-analysis is much less judgmental and subjective. However, it is not free from limitations: publication bias (significant results are more likely to be published) and sampling bias (only quantitative studies that report effect sizes can be included), etc. [50].

1.1. Prior TAM summaries

The most comprehensive narrative review of the TAM literature may be that provided by Venkatesh and colleagues, who selectively reviewed studies centered around eight models that have been developed to explain user acceptance of new technology; a total of 32 constructs were identified there; the authors proposed a unified theory of acceptance and use of technology (UTAUT) and developed hypotheses for testing it [104].

Since there are inconsistencies in TAM results, a meta-analysis is more likely to appropriately integrate the positive and the negative. We found two previous TAM meta-analyses. Legris et al. reviewed 22 empirical TAM studies to investigate the structural relationships

among key TAM constructs; they argued that “the correlation coefficients between the components observed must be available.” Unfortunately, only 3 of the 22 studies reported these matrices and therefore the meta-analysis included only those, thereby limiting “the presentation of the findings to the general conclusion.” In another meta-analysis, Ma and Liu [64] avoided the use of correlation matrices and included 26 empirical papers; they examined the zero-order correlations between three key constructs: EU, U, and technology acceptance (TA). They found that the sampled studies employed similar instruments of EU and U and “the differences in measurement items between studies tend to be the result of adapting TAM to different technologies.” However, they did not investigate any moderator effects and their focus on correlations (r 's) may be of less interest to researchers and practitioners who want to understand the structural relationships (β 's) among constructs.

There was another inadequate attempt at TAM meta-analysis: Deng et al. [17] retrieved their needed statistics, such as the effect sizes (structural coefficients and t -values) and the research context (type of application and user experiences) from 21 empirical studies. Because of the observed heterogeneity among them, which included modified instruments, various applications, different dependent variables, and different user experience with the application, the authors concluded that it was “difficult to compare studies and draw conclusions

concerning the relative efficacy of PU and PEU across applications.”

2. Methodology of our study

The papers included in the analysis were identified using “TAM” and “Technology Acceptance Model” as keywords and specifying “article” as the document type in the social science citation index (SSCI) in the fall of 2004. The initial search produced 178 papers. The elimination of irrelevant papers (such as those referring to tamoxifen in pharmacology, transfer appropriate monitoring in experimental psychology and Tam as a family name) produced a total of 134 papers.

This search was supplemented with one using the Business Source Premier (EBSCO Host database) which identified 11 additional papers, some published prior to 1992, the oldest papers in SSCI, and some from journals not covered by the SSCI database. Of these, six were found to be relevant for a total relevant count of 140.

Then 52 were eliminated because they were not empirical studies, or did not involve a direct statistical test of TAM, or were not available either online or through the University of Pittsburgh's Research Library. The resulting 88 papers provided TAM data and analyses for the meta-analysis.

Table 1 shows the distribution of the 140 papers in the 22 journals that published two or more TAM papers

Table 1
Journals that have published most TAM research articles

Rank	Journal	Count of papers (total = 140)
1	Information & Management	23
2	International Journal of Human-Computer Studies	9
3	MIS Quarterly	9
4	Information Systems Research	8
5	Journal of Computer Information Systems	8
6	Journal of Management Information Systems	7
7	Decision Sciences	6
8	Management Science	5
9	Behaviour & Information Technology	4
10	Decision Support Systems	4
11	Interacting With Computers	3
12	International Journal of Electronic Commerce	3
13	Internet Research-Electronic Networking Applications and Policy	3
14	Journal of Information Technology	3
15	Computers in Human Behavior	2
16	European Journal of Information Systems	2
17	IEEE Transactions on Engineering Management	2
18	Information and Software Technology	2
19	Information Systems Journal	2
20	International Journal of Information Management	2
21	International Journal of Service Industry Management	2
22	Journal of Organizational Computing and Electronic Commerce	2
	Other	29

(29 journals published one TAM paper). *Information & Management* publishes far and away the most TAM studies.

Coding rules were developed to ensure that all studies were treated consistently. These dealt with the identification and coding of correlations, path coefficients, and possible multiple effects:

Correlations

- data reported by the paper, or
- calculated from path coefficients (only for linear regression-based studies), or
- using the original covariance or correlation matrix to calculate the data of interest (only for LISREL-based studies).

Path coefficients (standardized):

- data reported by the paper, or
- calculated from correlations (only for linear regression-based studies), or
- using the original covariance or correlation matrix to calculate the data of interest (only for two LISREL-based studies), or
- models being converted into the core TAM (EU, U, and BI), if there were no confounding factors.

Multiple effects:

If a study had more than one effect size regarding a particular relationship, the effects were combined by conservative averaging. In fact, the multiple effect sizes reported in several papers of this variety were very close to each other and the differences were trivial.

3. Analysis

This meta-analysis was conducted on a “random effects” basis. The assumption underlying this was that the samples in individual studies are taken from populations that had varying effect sizes. This appeared to be a more descriptive assumption than the alternative (a “fixed effects” model that assumed that there was a single true effect in the “super population” from which

the populations were drawn) [24]. The possible differential effect of moderators across studies, such as the nature of users, the technologies used, etc. also argued for a “random effects” approach.

Thus, the studies included in our analysis were taken to be a random sample of all studies that could be performed, which implied that the overall results could be broadly generalized. In effect, the assumptions incorporated both within-study and between-study variance into the meta-analysis, providing a more conservative significance test.

For our analysis, we select the Hedges–Olkin technique as the primary analysis method. It is one of the three popular meta-analysis methods in behavior and social sciences; the others are the Rosenthal–Rubin and Hunter–Schmidt methods. In general, results for the three methods are similar [23,81].

Cohen [10,11] and others have criticized research in behavioral and social sciences for a lack of statistical power analysis for research planning. As a response, we calculated necessary sample sizes for a 0.80 chance of detecting effects at the $\alpha = 0.05$ level.

3.1. Construct reliabilities

Table 2 shows the reliabilities of the measures of the TAM constructs across the studies. Since a reliability of 0.8 is considered to be high, all constructs were deemed highly reliable. The table also addresses “attitude” for those studies that have measured this construct. These reliabilities are consistently high with low variance, leading to the conclusion that these simple four to six items) measures have widespread potential utility in technological utilization situations.

3.2. TAM correlations

Since some of the 88 studies did not report on all relevant statistics, the “number of studies” varies from table to table in the presentation of results.

Table 2
Key constructs in TAM and their reliabilities

	Perceived ease of use (EU)	Perceived usefulness (U)	Behavioral intention (BI)	Attitude (A)
Average reliability (Cronbach α)	0.873	0.895	0.860	0.846
Minimum	0.63	0.67	0.62	0.69
Maximum	0.98	0.98	0.97	0.95
Variance	0.007	0.006	0.008	0.006
Number of studies	76	77	53 ¹	25

Note: 1. 57 studies reported reliability statistics of behavioral intention. Among them, four studies used single item measure (for single item measure, Cronbach $\alpha = 1$) and were excluded from this analysis.

Table 3
Summary of zero-order correlations between TAM constructs

	EU–BI	U–BI	EU–U
Number of samples	56	59	77
Total sample size	12205	12657	16123
Average (<i>r</i>)	0.429	0.589	0.491
Z	13.569	21.381	16.482
<i>p</i> (effect size)	0.000	0.000	0.000
Homogeneity test (<i>Q</i>)	51.835	58.755	79.618
<i>p</i> (heterogeneity)	0.596	0.448	0.366
95% Low (<i>r</i>)	0.372	0.546	0.440
95% High (<i>r</i>)	0.483	0.628	0.539
Power analysis (80% chance to conclude significance) (<i>N</i>)	40	20	30

Note: Applying Eqs. (1)–(3), the structural relationships between EU, U and BI should be close to the following magnitudes: β (EU \rightarrow BI) = 0.184; β (U \rightarrow BI) = 0.499; β (EU \rightarrow U) = 0.491.

Table 3 shows zero-order correlations effect sizes between EU, U, and BI using the Hedges–Olkin Method of random effects.

All three correlational effect sizes are significant. The correlation between U and BI is particularly strong and the correlation between EU and I is less so, together explaining about 50% of the variance in BI. The 95% confidence interval for the U–BI correlation ranges from 0.546 to 0.628, which is narrow enough to give one confidence in the extent of variance that can be explained and a good large-sample estimate of this parameter. The correlations of EU–BI and EU–U are uniformly distributed over wider ranges, while the correlation distribution for U–BI is roughly normal (all shown in Fig. 2a–c).

The homogeneity test for the random effects model is a test of the null hypothesis that the interaction error term (between the sample error and the study error) is zero. Testing results are insignificant, to some degree validating the use of a random effects analytic base. This also shows that a sample size above 40 should be adequate for purposes of identifying an underlying correlative effect.

Since these results show considerable variability in two of the three TAM relationships, the possibility that other variables were significant moderators of the basic relationships was suggested. We addressed two such moderators.

3.3. TAM path coefficients

Most researchers have been more interested in the structural relationships among TAM constructs, which help explain individuals' acceptance of new technologies, than in the zero-order correlations. Because

reports of correlation matrices are rare, we used two approaches for analyzing structural relationships:

- meta-analyzing the correlations and then converting the results to structural relationships and
- meta-analyzing path coefficients (β 's) directly.

The TAM core model (Fig. 1) suggests that EU and U are the important predictors of an individual's behavioral intention (BI); in addition, U partially mediates the effect of EU on behavioral intention. The correlation coefficients (*r*'s) and path coefficients (β 's) present the following relationship:

$$\beta(\text{EU} \rightarrow \text{BI}) = \frac{r(\text{EU, BI}) - r(\text{U, BI}) \times r(\text{EU, U})}{(1 - r_{(\text{EU, U})}^2)} \quad (1)$$

$$\beta(\text{U} \rightarrow \text{BI}) = \frac{r(\text{U, BI}) - r(\text{EU, BI}) \times r(\text{EU, U})}{(1 - r_{(\text{EU, U})}^2)} \quad (2)$$

$$\beta(\text{EU} \rightarrow \text{U}) = r_{(\text{EU, U})} \quad (3)$$

The three equations hold for linear-regression-based analyses; they may differ slightly for structural-equation-modeling-based analyses (e.g., PLS and LISREL) because of different algorithms (illustrations basing on some studies are provided in Appendix A). But the differences are trivial. Thus, we can infer the magnitude and the strength of path coefficients basing on a set of meta-analytically developed correlation coefficients. When applying the second approach (combining β 's as the effect sizes) special caution must be taken that the sampled coefficients represent the relationship between the independent and the dependent variable controlling for other factors. Fortunately, most of the proposed TAM extensions have been tested against the TAM core model, and the restricted structural relationships (β 's) among the three key constructs were reported, making the second approach workable.

Using the three equations, we calculate β 's basing on the correlations (*r*'s). We also meta-analyze β s and report the results in Table 4. The results from the two approaches are almost identical, suggesting that both are methodologically acceptable. So we focus our discussion on their path coefficients. All are significant and the coefficients fail the homogeneity test (supporting the validity of the "random effects" analysis). The paths U–BI and EU–U are the strongest, with large means and rather small standard deviations. In addition, the minimum reported path coefficient for U–BI is 0.139, indicating that almost all studies found this path to be significant and positive in the TAM nomological network. The path EU–BI is the weakest,

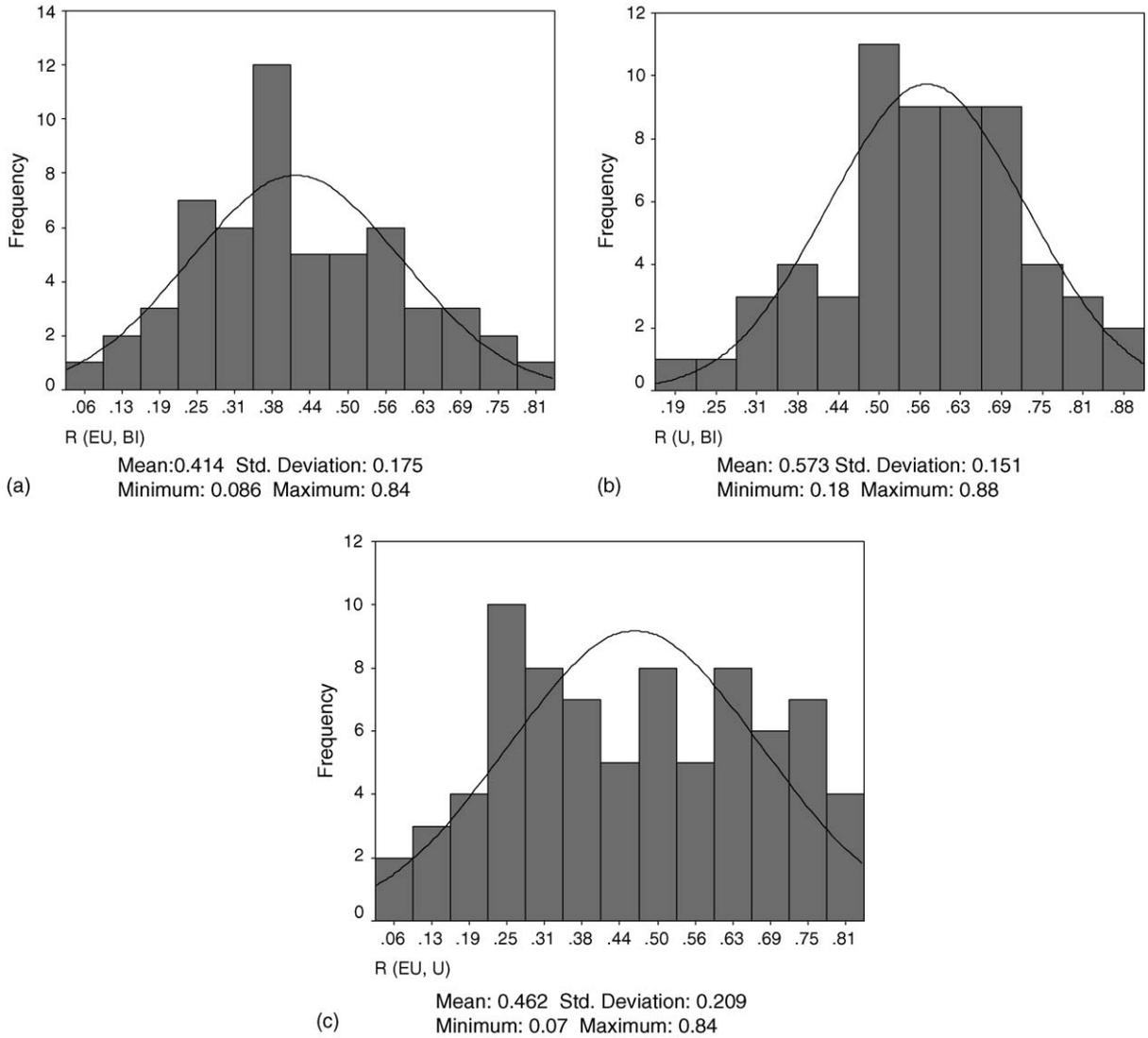


Fig. 2. (a) Histogram of correlations (EU-BI); (b) histogram of correlations (U-BI); (c) histogram of correlations (EU-U).

Table 4
Summary of the effect size of path coefficients in TAM

	EU → BI	U → BI	EU → U
Number of samples	67	67	65
Total sample size	12582	12582	12263
Average β	0.186	0.505	0.479
Z	8.731	17.749	12.821
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	70.438	66.077	65.816
p (Heterogeneity)	0.332	0.474	0.414
95% Low (β)	0.145	0.458	0.415
95% High (β)	0.226	0.549	0.538
Power analysis (80% chance to conclude significance) (N)	225	28	31

with a mean of 0.179. The median is even smaller (0.152), indicating that the distribution is negatively skewed toward smaller values. Considering the comparatively large variation (standard deviation = 0.162), this suggests that many studies have small path coefficients, and unless their sample sizes are very large, they would be insignificant for this path. The path EU-U is positive and strong, with a reported mean of 0.442. However, the large standard deviation (0.223) suggests that reported coefficients for this path are less consistent than those of U-BI. It should be noted that a sample size of 225 or more would be required to have an 80% chance of concluding significance for the EU-BI path.

3.4. Summary of effect sizes

The reported correlations for the three TAM paths were significant, with the U–BI path strongest: most studies reported positive and significant path coefficients of U–BI. With regard to EU–BI, when only the significance versus insignificance of the results are examined, the results are inconsistent. Of the 67 papers that have reported testing results of the core TAM model, 30 have reported or it can be concluded from their data that the path EU–BI was insignificant at the $\alpha = 0.05$ level. However, such inconsistency should not exclude the possibility that the “true” effect sizes are small but positive, in that significance testing is largely affected by the sample size. One such example is Barker

et al. [4] experimental study on the spoken dialogue system, in which they concluded EU was not a significant predictor for BI, with a positive but small R^2_{change} of 0.002. Their sample size was 10 endoscopists. In fact, of the 67 empirical papers, only 8 studies reported negative path coefficients of EU–BI, all of them being non-significant (all p -values larger than 0.50) and of small magnitudes (from -0.042 to -0.0004).

Thus, the major effect of EU is through U rather than directly on BI. This indicates the importance of perceived usefulness as a predictive variable. If one could measure only one independent variable, perceived usefulness would clearly be the one to choose.

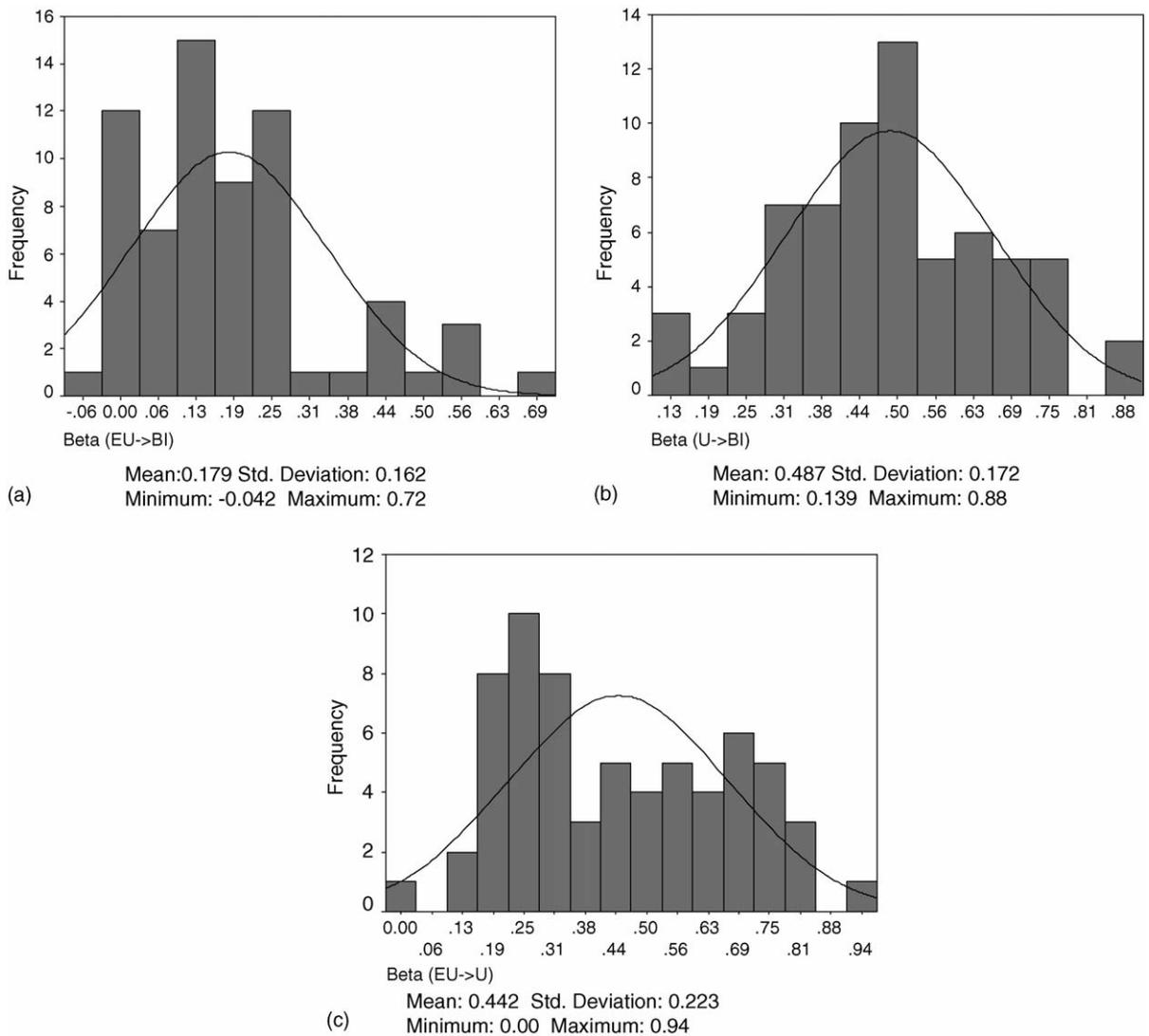


Fig. 3. (a) Histogram of path coefficients (EU–BI); (b) histogram of path coefficients (U–BI); (c) histogram of path coefficients (EU–U).

3.5. The search for moderators

Fig. 2(a–c) show histograms of the three correlation effect sizes across the studies. The two paths leading to BI have unimodal distributions that are reasonably symmetric, while the EU–U path distribution is less so. The standard deviations are somewhat high, particularly for the EU–U relationship. Generally speaking, the U–BI relationship shows relatively less variance and is more consistent and straightforward than the EU–I relationship.

Fig. 3(a–c) shows similar distributions for the effect sizes of the path coefficients.

The best-studied moderator variable in TAM is the level of experience of the users [100]. Inexperienced versus experienced users have consistently been shown to have a moderating effect. As a result, and because we could not determine experience level of subjects in most studies, we do not discuss it further.

In an attempt to better understand the distributions, the studies were broken down into subsets based on the study subject and the nature of the usage. These were the most likely moderator variables that could influence the relationships in the 88 studies.

We grouped users into three categories, based on the judgment of seven knowledgeable people who had no “investment” in the research area: “students,” “professionals” and “general users” (non-students who were not using the system for work purposes). To test for the reliability of the judgment, we selected a random sample of 20 studies, and applied Spearman–Brown’s “effective reliability” statistic where

$$R = \frac{nr}{1 + (n - 1)r}$$

R is the “effective” reliability; n the “number of judges; r the mean reliability among all n judges (i.e., mean of $n(n - 1)/2$ correlations).

Table 5
Moderator analysis by user type: students

	EU → BI	EU → U	U → BI
Number of samples	28	28	28
Total sample size	5884	5884	5884
Average (β)	0.168	0.54	0.489
Z	5.358	11.131	8.435
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	31.49	25.526	27.218
p (Heterogeneity)	0.252	0.545	0.452
95% Low (β)	0.107	0.46	0.389
95% High (β)	0.228	0.611	0.578
Power analysis (80% chance to conclude significance) (N)	275	24	30

Table 6
Moderator analysis by user type: professionals

	EU → BI	U → BI	EU → U
Number of samples	26	26	25
Total sample size	3949	3949	3911
Average (β)	0.136	0.517	0.421
Z	5.372	14.191	7.1
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	24.784	31.564	24.35
p (Heterogeneity)	0.475	0.171	0.442
95% Low (β)	0.087	0.456	0.314
95% High (β)	0.185	0.572	0.518
Power analysis (80% chance to conclude significance) (N)	421	26	41

The effective reliability for the user groupings was 0.95 across the seven judges.

3.5.1. Type of user

Table 5 shows the correlation results for the three relationships in the student category; Table 6 shows the same results for professionals, and Table 7 shows the results for general users.

These show that there are not great differences in the U–BI and EU–U relationships across the categories. However, there are differences in the EU–BI relationship. Professionals are very different from general users; students lie somewhat in between, perhaps because they are a mixture of them.

Homogeneity assumptions were violated for the three subcategories. Thus, the notion that there may be one true effect size was not validated, even for professionals who demonstrated a quite small EU–BI 95% confidence interval (0.087–0.185). This result demonstrated the power of large (combined) sample sizes as well as the complexity of technology acceptance in the real world. Indeed, many researchers have pointed out that real-world data are likely to have

Table 7
Moderator analysis by user type: general users

	EU → BI	U → BI	EU → U
Number of samples	13	13	12
Total sample size	2749	2749	2468
Average (β)	0.321	0.386	0.566
Z	5.802	7.264	7.39
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	12.172	11.947	14.019
p (Heterogeneity)	0.432	0.45	0.232
95% Low (β)	0.217	0.289	0.439
95% High (β)	0.418	0.475	0.67
Power analysis (80% chance to conclude significance) (N)	73	50	22

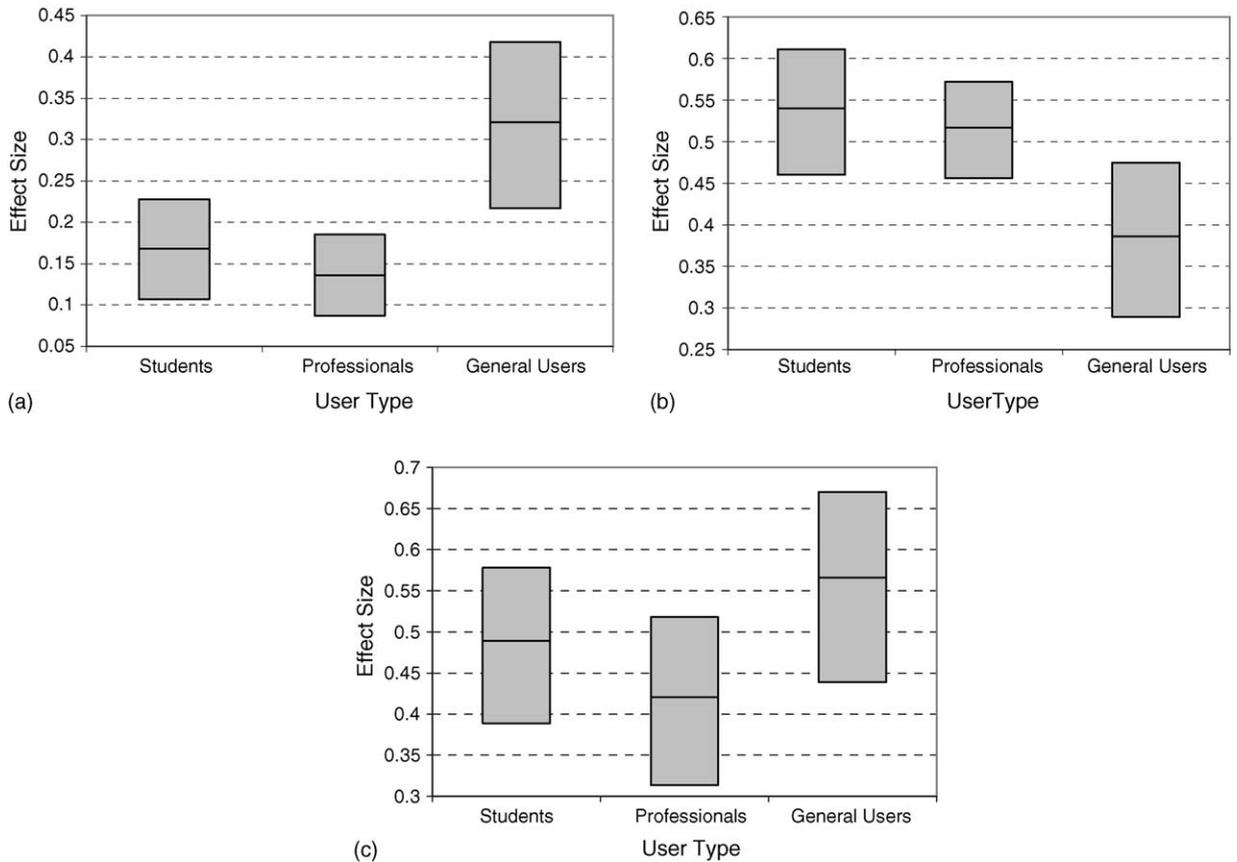


Fig. 4. (a) 95% Confidence interval for β (EU \rightarrow BI); (b) 95% confidence interval for β (U \rightarrow BI); (c) 95% confidence interval for β (EU \rightarrow U).

heterogeneous population effect sizes [71]. Therefore, the random effects model used here should generally be preferred for meta-analysis.

Fig. 4(a–c) showed 95% confidence intervals for the path coefficients of the three user groups. The most significant finding from these was the significant overlap between the student and professional groups, which may provide additional justification for the use of

students as surrogates for professionals. These depictions also clearly indicated that students are not good surrogates for general users.

3.5.2. Types of usage

The second categorization used in the search for moderators was the type of usage. Studies were categorized as:

Table 8
Moderator analysis by type of usage: job-related applications

	EU \rightarrow BI	U \rightarrow BI	EU \rightarrow U
Number of samples	14	14	13
Total sample size	2313	2313	2275
Average (β)	0.098	0.605	0.434
Z	5.424	7.511	7.202
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	15.946	12.488	13.838
p (Heterogeneity)	0.252	0.488	0.311
95% Low (β)	0.062	0.476	0.326
95% High (β)	0.133	0.709	0.531
Power analysis (80% chance to conclude significance) (N)	814	18	39

Table 9
Moderator analysis by type of usage: office applications

	EU \rightarrow BI	U \rightarrow BI	EU \rightarrow U
Number of samples	9	9	9
Total sample size	1570	1570	1570
Average (β)	0.121	0.636	0.499
Z	3.323	9.554	5.361
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	7.003	7.525	7.269
p (Heterogeneity)	0.536	0.481	0.508
95% Low (β)	0.05	0.535	0.334
95% High (β)	0.191	0.719	0.634
Power analysis (95% chance to conclude significance) (N)	533	16	28

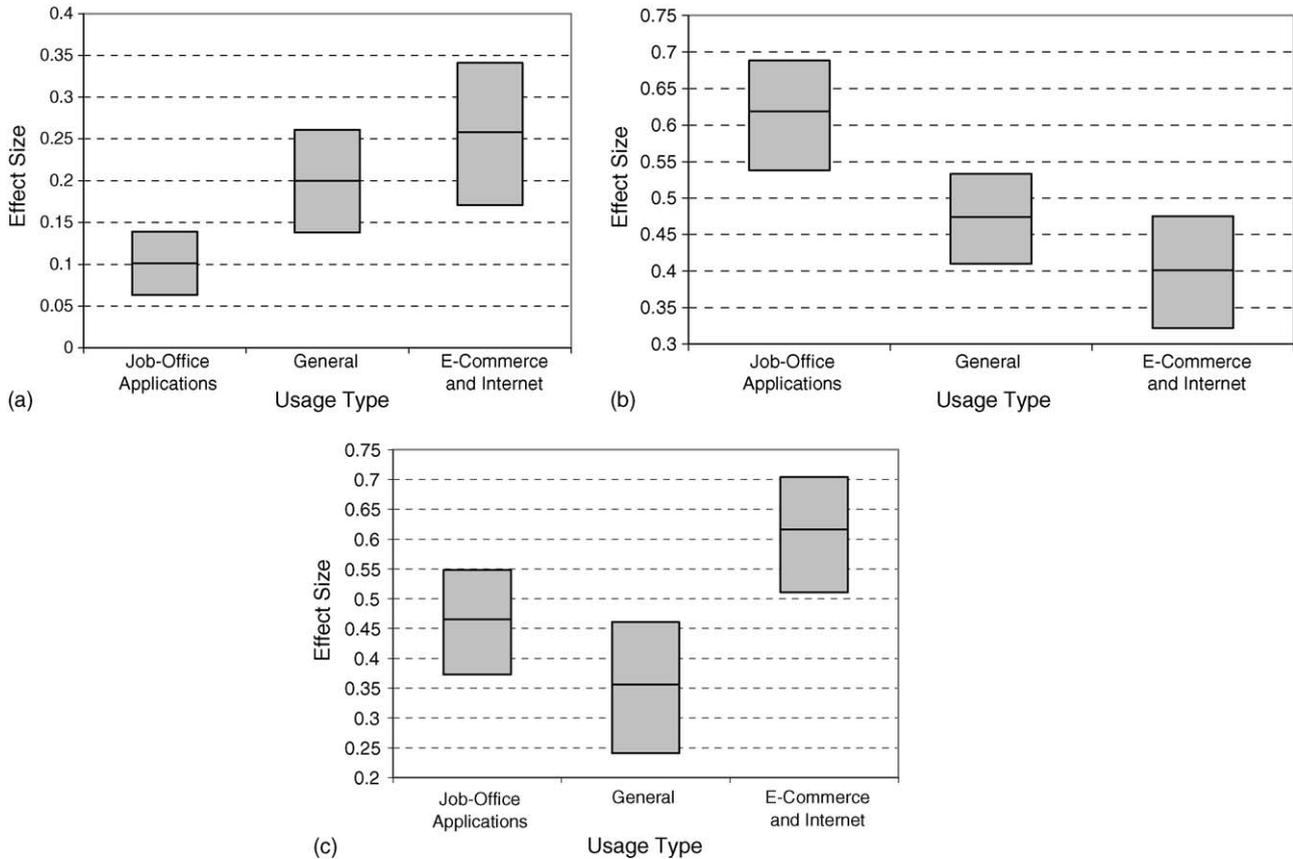


Fig. 5. (a) 95% Confidence interval for β (EU \rightarrow BI); (b) 95% confidence interval for β (U \rightarrow BI); (c) 95% confidence interval for β (EU \rightarrow U).

Table 10
Moderator analysis by type of usage: general

	EU → BI	U → BI	EU → U
Number of samples	24	24	24
Total sample size	4227	4227	4227
Average (β)	0.200	0.474	0.356
Z	6.179	12.646	5.785
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	24.549	16.683	16.853
p (Heterogeneity)	0.374	0.825	0.816
95% Low (β)	0.138	0.41	0.241
95% High (β)	0.261	0.533	0.461
Power analysis (95% chance to conclude significance) (N)	193	32	59

Table 11
Moderator analysis by type of usage: internet

	EU → BI	U → I	EU → U
Number of samples	20	20	19
Total sample size	4472	4472	4191
Average (β)	0.258	0.401	0.616
Z	5.646	9.128	9.074
p (Effect size)	0.000	0.000	0.000
Homogeneity test (Q)	22.973	18.3	21.496
p (Heterogeneity)	0.239	0.502	0.255
95% Low (β)	0.171	0.322	0.511
95% High (β)	0.341	0.475	0.704
Power analysis (95% chance to conclude significance) (N)	115	46	18

- job-related;
- office;
- general (such as email and telecom);
- internet and e-commerce.

The judgment reliability analysis, conducted in the same manner as for user-type judgments, produced a Spearman–Brown “effective reliability” of 0.99.

Table 8 shows the correlation results for job related applications. Table 9 shows the results for office applications, Table 10 shows the results for general uses, and Table 11 shows the internet results.

Fig. 5(a–c) depicts the 95% confidence intervals for the paths. There is a minor difference between them and Tables 8–11: the categories *office* and *job task* have been combined in the figures, because each involved a small

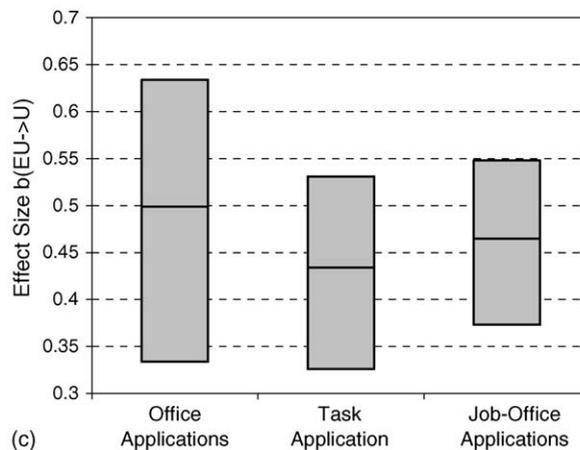
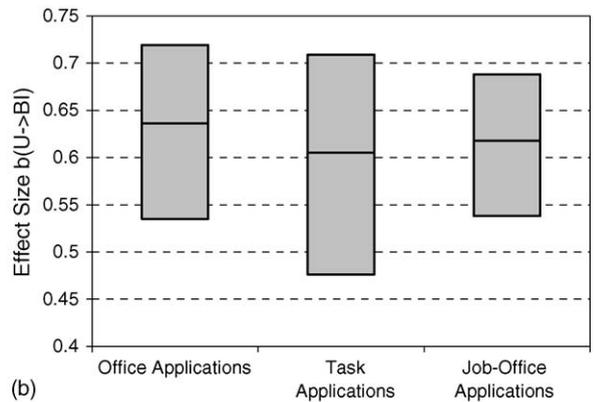
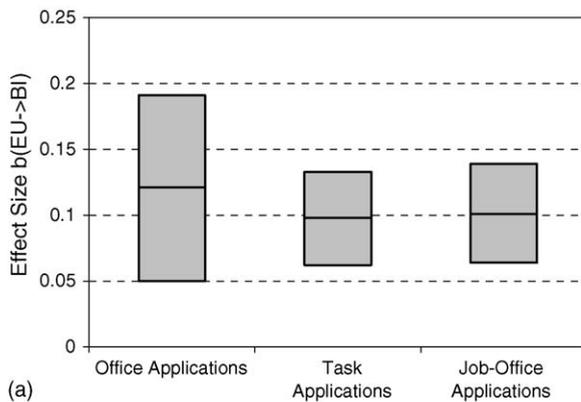


Fig. 6. (a) Usage type; (b) usage type; (c) usage type.

number of studies and the confidence intervals were heavily overlapping so we consolidated them into one (job-office applications). Fig. 6(a–c) depicts this consolidation in terms of the Betas.

The EU–BI effect is quite consistent across usage groups. The only usage group that is different is for the internet, where EU was of greater importance than for other types of usage.

4. Conclusions

This meta-analysis of 88 TAM studies involving more than 12,000 observations provided powerful large-sample evidence that:

- (a) The TAM measures (PU, U, and BI) are highly reliable and may be used in a variety of contexts.
- (b) TAM correlations, while strong, have considerable variability, suggesting that moderator variables can help explain the effects. The experience level of users was shown to be a moderator in a number of studies but was not pursued here because of the difficulty in identifying the experience level in studies that did not report it. It was possible to identify two moderators given the data from the sampled studies.
- (c) The influence of perceived usefulness on behavioral intention is profound, capturing much of the influence of perceived ease of use. The only context in which the direct effect of EU on BI is very important is in internet applications.
- (d) The moderator analysis of user groups suggests that students may be used as surrogates for professional users, but not for “general” users. This confirms the validity of a research method that is often used for convenience reasons, but which is rarely tested.
- (e) Task applications and office applications are quite similar and may be considered to be a single category.
- (f) This sample sizes required for significance in terms of most relationships is modest. However, the EU–BI direct relationship is so variable that a focus on it would require a substantially larger sample.

5. Summary

The meta-analysis rigorously substantiates the conclusion that has been widely reached through qualitative analyses: that TAM is a powerful and robust predictive model. It is also shown to be a “complete mediating” model in that the effect of ease

of use on behavioral intention is primary through usefulness.

The search for moderators in terms of type of user and type of use demonstrated that professionals and general users produce quite different results. However, students, who are often used as convenience sample respondents in TAM studies, are not exactly like either of the other two groups.

In terms of the moderating effects of different varieties of usage, only internet use was shown to be different from job task applications, general use, and office application. This suggests that internet study results should not be generalized to other contexts and *vice versa*.

Of course, as in any such analysis, there are possible sources of bias (non-significant results are seldom published and there may be a lack of objective and consistent search criteria).

We hope that this meta-analysis, coupled with the “new” economics of electronic publication, the existence of journals, which consider publishing studies that might not be accepted in “A” journals because of “negative” or insignificant results, and the ease of electronic publication or personal websites will lead to a broader basis of studies available for analysis, whether or not they involve large samples or significant results.

Appendix A. The interdependence of *r*'s and β 's

	<i>r</i> 's reported	β 's reported	β 's calculated from <i>r</i> 's
Linear regression examples			
Riemenschneider et al. [77]			
EOU → BI	0.46	Not significant	–0.003
U → BI	0.71	0.71	0.71
EOU → U	0.65	0.65	0.65
Szajna [90]			
EOU → BI	0.40	0.07	0.071
U → BI	0.72	0.72	0.686
EOU → U	0.48	0.48	0.48
Structural equation modeling (SEM) examples			
Hu et al. [41] ¹ (using LISREL)			
EOU → BI	0.24	0.12	0.118
U → BI	0.70	0.60	0.679
EOU → U	0.18	0.10	0.18
Plouffe et al. [74] (using PLS)			
EOU → BI	0.38	0.108	0.116
U → BI	0.56	0.507	0.499
EOU → U	0.53	0.531	0.53

Note: 1. β 's reported were from a replicated LISREL model testing using a covariance matrix reported in the paper.

References

(Papers marked with “*” provided effect sizes and sample sizes for the meta-analysis)

- [4] D.J. Barker, P. Van Schaik, D.S. Simpson, W.A. Corbett, Evaluating a spoken dialogue system for recording clinical observations during an endoscopic examination, *Medical Informatics and The Internet in Medicine* 28(2), 2003, pp. 85–97.*
- [10] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, second ed., Academic, New York, 1988.
- [11] J. Cohen, A power primer, *Psychological Bulletin* 112(1), 1992, pp. 155–159.
- [13] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly* 13(3), 1989, pp. 318–340.*
- [14] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, User acceptance of computer technology: a comparison of two theoretical models, *Management Science* 35(8), 1989, pp. 982–1003.*
- [15] F.D. Davis, V. Venkatesh, A critical assessment of potential measurement biases in the technology acceptance model: three experiments, *International Journal of Human-Computer Studies* 45(1), 1996, pp. 19–45.*
- [16] F.D. Davis, V. Venkatesh, Toward preprototype user acceptance testing of new information systems: implications for software project management, *IEEE Transactions on Engineering Management* 51(1), 2004, pp. 31–46.*
- [17] X. Deng, W.J. Doll, A.R. Hendrickson, J.A. Scazzero, A multi-group analysis of structural invariance: an illustration using the technology acceptance model, *Information & Management* 42(5), 2005, pp. 745–759.
- [20] M.T. Dishaw, D.M. Strong, Extending the technology acceptance model with task-technology fit constructs, *Information & Management* 36(1), 1999, pp. 9–21.*
- [21] D. Eden, T. Aviv, From the editors: replication, meta-analysis, scientific progress, and AMJ’s publication policy, *Academy of Management Journal* 45(5), 2002, pp. 841–846.
- [22] M.S. Featherman, P.A. Pavlou, Predicting E-services adoption: a perceived risk facets perspective, *International Journal of Human-Computer Studies* 59(4), 2003, pp. 451–474.*
- [23] A.P. Field, Meta-analysis of correlation coefficients: a Monte Carlo comparison of fixed- and random-effects methods, *Psychological Methods* 6(2), 2001, pp. 161–180.
- [24] A.P. Field, The problem in using fixed-effects models of meta-analysis on real-world data, *Understanding Statistics* 2(2), 2003, p. 105.
- [25] M. Fishbein, I. Ajzen, *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Addison-Wesley, California, 1975.
- [26] D. Gefen, What makes an ERP implementation relationship worthwhile: linking trust mechanisms and ERP usefulness, *Journal of Management Information Systems* 21(1), 2004, pp. 263–288.*
- [27] D. Gefen, E. Karahanna, D.W. Straub, Inexperience and experience with online stores: the importance of TAM and trust, *IEEE Transactions on Engineering Management* 50(3), 2003, pp. 307–321.*
- [31] G.V. Glass, Primary, secondary, and meta-analysis of research, *Educational Researcher* 5, 1976, pp. 3–8.
- [33] B.C. Hardgrave, F.D. Davis, C.K. Riemenschneider, Investigating determinants of software developers’ intentions to follow methodologies, *Journal of Management Information Systems* 20(1), 2003, pp. 123–151.*
- [34] L.V. Hedges, I. Olkin, *Statistical Methods for Meta-Analysis*, Academic Press, 1985.
- [38] R.P. Horton, T. Buck, P.E. Waterson, C.W. Clegg, Explaining intranet use with the technology acceptance model, *Journal of Information Technology* 16(4), 2001, pp. 237–249.*
- [39] A. Howard, Rapid application development: rough and dirty or value-for-money engineering? *Communications of the ACM* 45(10), 2002, pp. 27–30.
- [41] P.J. Hu, P.Y.K. Chau, O.R.L. Sheng, K.Y. Tam, Examining the technology acceptance model using physician acceptance of telemedicine technology, *Journal of Management Information Systems* 16(2), 1999, pp. 91–112.*
- [42] L.J. Huang, M.T. Lu, B.K. Wong, The impact of power distance on Email acceptance: evidence from the PRC, *Journal of Computer Information Systems* 44(1), 2003, pp. 93–101.*
- [43] J.E. Hunter, F.L. Schmidt, *Methods of Meta-analysis: Correcting Error and Bias in Research Findings*, Sage, Newbury Park, CA, 1990.
- [46] C.M. Jackson, S. Chow, R.A. Leitch, Toward an understanding of the behavioral intention to use an information system, *Decision Sciences* 28(2), 1997, pp. 357–389.*
- [49] W.R. King, D.I. Cleland, Manager analyst teamwork in management information systems, *Business Horizons* 14(2), 1971, p. 59.
- [50] W.R. King, J. He, Understanding the role and methods of meta-analysis in IS research, *Communications of the AIS* 16, October 2005, pp. 665–686, Article 32.
- [55] P. Legris, J. Ingham, P. Collette, Why do people use information technology? a critical review of the technology acceptance model, *Information & Management* 40(3), 2003, pp. 191–204.
- [64] Q. Ma, L. Liu, The technology acceptance model: a meta-analysis of empirical findings, *Journal of Organizational and End User Computing* 16(1), 2004, pp. 59–72.
- [67] J.W. Moon, Y.G. Kim, Extending the TAM for a World-Wide-Web context, *Information & Management* 38(4), 2001, pp. 217–230.
- [69] S. Oh, J. Ang, B. Kim, Adoption of broadband internet in Korea: the role of experience in building attitudes, *Journal of Information Technology* 18(4), 2003, pp. 267–280.*
- [71] H.G. Osburn, J. Callender, A note on the sampling variance of the mean uncorrected correlation in meta-analysis and validity generalization, *Journal of Applied Psychology* 77(2), 1992, pp. 115–122.
- [72] P.A. Pavlou, Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model, *International Journal of Electronic Commerce* 7(3), 2003, pp. 101–134.*
- [74] C.R. Plouffe, J.S. Hulland, M. Vandenbosch, Research Report: richness versus parsimony in modeling technology adoption decisions—understanding merchant adoption of a smart card-based payment system, *Information Systems Research* 12(2), 2001, pp. 208–222.*
- [77] C.K. Riemenschneider, B.C. Hardgrave, F.D. Davis, Explaining software developer acceptance of methodologies: a comparison of five theoretical models, *IEEE Transactions on Software Engineering* 28(12), 2002, pp. 1135–1145.*
- [79] R. Rosenthal, *Meta-analytic Procedures for Social Research*, Rev. ed., Sage, Beverly Hills, CA, 1991.
- [80] R. Rosenthal, M.R. DiMatteo, Meta-analysis: recent developments in quantitative methods for literature reviews, *Annual Review of Psychology* 52(1), 2001, pp. 59–82.

- [81] F.L. Schmidt, J.E. Hunter, Comparison of three meta-analysis methods revisited: an analysis of Johnson, Mullen and Salas, *Journal of Applied Psychology* 84(1), 1999, pp. 144–148.
- [82] R.L. Schultz, D.P. Slevin, The implementation profile, *Interfaces* 13(1), 1983, pp. 87–92.
- [88] D. Straub, M. Keil, W. Brenner, Testing the technology acceptance model across cultures: a three country study, *Information & Management* 33(1), 1997, pp. 1–11.*
- [90] B. Szajna, Empirical evaluation of the revised technology acceptance model, *Management Science* 42(1), 1996, pp. 85–92.*
- [96] D. Tudhope, P. Beynon-Davis, H. Mackay, Prototyping Praxis: constructing computer systems and building belief, *Human-Computer Interaction* 15(4), 2000, pp. 353–384.
- [100] V. Venkatesh, Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model, *Information Systems Research* 11(4), 2000, pp. 342–365.*
- [102] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: four longitudinal field studies, *Management Science* 46(2), 2000, pp. 186–204.*
- [103] V. Venkatesh, M.G. Morris, Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior *MIS Quarterly* 24(1), 2000, pp. 115–139.*
- [104] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, *MIS Quarterly* 27(3), 2003, pp. 425–478.*
- [108] F.M. Wolf, *Meta-analysis: Quantitative Methods for Research Synthesis*, Sage, Beverly Hills, CA, 1986.
- [9] L.D. Chen, M.L. Gillenson, D.L. Sherrell, Enticing online consumers: an extended technology acceptance perspective, *Information & Management* 39(8), 2002, pp. 705–719.*
- [12] S. Dasgupta, M. Granger, N. McGarry, User acceptance of E-collaboration technology: an extension of the technology acceptance model, *Group Decision and Negotiation* 11(2), 2002, pp. 87–100.*
- [18] S. Devaraj, M. Fan, R. Kohli, Antecedents of B2C channel satisfaction and preference: validating E-Commerce metrics, *Information Systems Research* 13(3), 2002, pp. 316–333.*
- [19] C.A. Di Benedetto, R.J. Calantone, C. Zhang, International technology transfer—model and exploratory study in the People's Republic of China, *International Marketing Review* 20(4), 2003, pp. 446–462.*
- [28] D. Gefen, M. Keil, The impact of developer responsiveness on perceptions of usefulness and ease of use: an extension of the technology acceptance model, *Data Base for Advances in Information Systems* 29(2), 1998, pp. 35–49.*
- [29] D. Gefen, D.W. Straub, Managing user trust in B2C E-services, *E-Service Journal* 22(3), 2003, pp. 7–24.*
- [30] L. Gentry, R. Calantone, A comparison of three models to explain Shop-Bot use on the web, *Psychology & Marketing* 19(11), 2002, pp. 945–956.*
- [32] E.E. Grandon, J.M. Pearson, Electronic commerce adoption: an empirical study of small and medium US businesses, *Information & Management* 42(1), 2004, pp. 197–216.*
- [35] R. Henderson, M.J. Divett, Perceived usefulness, ease of use and electronic supermarket use, *International Journal of Human-Computer Studies* 59(3), 2003, pp. 383–395.*
- [36] R. Henderson, D. Rickwood, P. Roberts, The Beta test of an electronic supermarket, *Interacting With Computers* 10(4), 1998, pp. 385–399.*
- [37] W.Y. Hong, J.Y.L. Thong, W.M. Wong, K.Y. Tam, Determinants of user acceptance of digital libraries: an empirical examination of individual differences and system characteristics, *Journal of Management Information Systems* 18(3), 2001, pp. 97–124.*
- [40] C.L. Hsu, H.P. Lu, Why do people play on-line games? An extended TAM with social influences and flow experience *Information & Management* 41(7), 2004, pp. 853–868.*
- [44] M. Igbaria, T. Guimaraes, G.B. Davis, Testing the determinants of microcomputer usage via a structural equation model, *Journal of Management Information Systems* 11(4), 1995, pp. 87–114.*
- [45] M. Igbaria, N. Zinatelli, P. Cragg, A.L.M. Cavaye, Personal computing acceptance factors in small firms: a structural equation model, *MIS Quarterly* 21(3), 1997, pp. 279–305.*
- [47] E. Karahanna, M. Limayem, E-mail and V-mail usage: generalizing across technologies, *Journal of Organizational Computing and Electronic Commerce* 10(1), 2000, pp. 49–66.*
- [48] E. Karahanna, D.W. Straub, The psychological origins of perceived usefulness and ease-of-use, *Information & Management* 35(4), 1999, pp. 237–250.*
- [51] T. Klaus, T. Gyires, H.J. Wen, The use of web-based information systems for non-work activities: an empirical study, *Human Systems Management* 22(3), 2003, pp. 105–114.*
- [52] M. Kleijnen, M. Wetzels, K. De Ruyter, Consumer acceptance of wireless finance, *Journal of Financial Services Marketing* 8(3), 2004, pp. 206–217.*
- [53] M. Koufaris, Applying the technology acceptance model and flow theory to online consumer behavior, *Information Systems Research* 13(2), 2002, pp. 205–223.*

Further reading

(Papers marked with “*” provided effect sizes and sample sizes for the meta-analysis)

- [1] I. Adamson, I. Shine, Extending the new technology acceptance model to measure the end user information systems satisfaction in a mandatory environment: a bank's treasure, *Technology Analysis & Strategic Management* 15(4), 2003, pp. 441–455.*
- [2] R. Agarwal, J. Prasad, Are individual differences germane to the acceptance of new information technologies? *Decision Sciences* 30(2), 1999, pp. 361–391.*
- [3] K. Amoako-Gyampah, A.F. Salam, An extension of the technology acceptance model in an ERP implementation environment, *Information & Management* 41(6), 2004, pp. 731–745.*
- [5] S.C. Chan, M.T. Lu, Understanding internet banking adoption and use behavior: a Hong Kong perspective, *Journal of Global Information Management* 12(3), 2003, pp. 21–43.*
- [6] P.Y.K. Chau, An empirical assessment of a modified technology acceptance model, *Journal of Management Information Systems* 13(2), 1996, pp. 185–204.*
- [7] P.Y.K. Chau, P.J.H. Hu, Investigating healthcare professionals' decisions to accept telemedicine technology: an empirical test of competing theories, *Information & Management* 39(4), 2002, pp. 297–311.*
- [8] P.Y.K. Chau, V.S.K. Lai, An empirical investigation of the determinants of user acceptance of internet banking, *Journal of Organizational Computing and Electronic Commerce* 13(2), 2003, pp. 123–145.*

- [54] A.L. Lederer, D.J. Maupin, M.P. Sena, Y.L. Zhuang, The technology acceptance model in the world wide web, *Decision Support Systems* 29(3), 2000, pp. 269–282. *
- [56] D.H. Li, J. Day, H. Lou, G. Coombs, The effect of affiliation motivation on the intention to use groupware in an MBA program, *Journal of Computer Information Systems* 44(3), 2004, pp. 1–8. *
- [57] S.S. Liaw, Understanding user perceptions of world-wide web environments, *Journal of Computer Assisted Learning* 18(2), 2002, pp. 137–148. *
- [58] J. Lim, A conceptual framework on the adoption of negotiation support systems, *Information and Software Technology* 45(8), 2003, pp. 469–477. *
- [59] F.H. Lin, J.H. Wu, An empirical study of end-user computing acceptance factors in small and medium enterprises in Taiwan: analyzed by structural equation modeling, *Journal of Computer Information Systems* 44(4), 2004, pp. 98–108. *
- [60] J.C.C. Lin, H.P. Lu, Towards an understanding of the behavioral intention to use a web site, *International Journal of Information Management* 20(3), 2000, pp. 197–208. *
- [61] H.P. Lu, H.J. Yu, S.S.K. Lu, The effects of cognitive style and model type on DSS acceptance: an empirical study, *European Journal of Operational Research* 131(3), 2001, pp. 649–663. *
- [62] H.C. Lucas, V. Spitzer, Technology use and performance: a field study of broker workstations, *Decision Sciences* 30(2), 1999, pp. 291–311. *
- [63] H.C. Lucas, V. Spitzer, Implementation in a World of workstations and networks, *Information & Management* 38(2), 2000, pp. 119–128. *
- [65] K. Mathieson, Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior, *Information Systems Research* 2(3), 1991, pp. 173–191. *
- [66] D. McCloskey, Evaluating electronic commerce acceptance with the technology acceptance model, *Journal of Computer Information Systems* 44(2), 2003, pp. 49–57. *
- [68] M.G. Morris, A. Dillon, How user perceptions influence software use, *IEEE Software* 14(4), 1997, pp. 58–65. *
- [70] C.S. Ong, J.Y. Lai, Y.S. Wang, Factors affecting Engineers' acceptance of asynchronous E-Learning systems in high-tech companies, *Information & Management* 41(6), 2004, pp. 795–804. *
- [73] L.A. Phillips, R. Calantone, International technology adoption: behavior structure, demand certainty and culture, *Journal of Business & Industrial Marketing* 9(2), 1994, pp. 16–28. *
- [75] A. Rai, S.S. Lang, R.B. Welker, Assessing the validity of Is success models: an empirical test and theoretical analysis, *Information Systems Research* 13(1), 2002, pp. 50–69. *
- [76] C.K. Riemenschneider, B.C. Hardgrave, Explaining software development tool use with the technology acceptance model, *Journal of Computer Information Systems* 41(4), 2001, pp. 1–8. *
- [78] C.K. Riemenschneider, D.A. Harrison, P.P. Mykytyn, Understanding IT adoption decisions in small business: integrating current theories, *Information & Management* 40(4), 2003, pp. 269–285. *
- [83] H.M. Selim, An empirical investigation of student acceptance of course websites, *Computers & Education* 40(4), 2003, pp. 343–360. *
- [84] A.H. Seyal, G.G.M. Pijpers, Senior Government executives' use of the internet: a Bruneian scenario, *Behavior & Information Technology* 23(3), 2004, pp. 197–210. *
- [85] H.P. Shih, Extended technology acceptance model of internet utilization behavior, *Information & Management* 41(6), 2004, pp. 719–729. *
- [86] M.R. Stafford, B. Stern, Consumer bidding behavior on internet auction sites, *International Journal of Electronic Commerce* 7(1), 2002, pp. 135–150. *
- [87] L. Stoel, K.H. Lee, Modeling the effect of experience on student acceptance of web-based courseware, *Internet Research-Electronic Networking Applications and Policy* 13(5), 2003, pp. 364–374. *
- [89] D. Straub, M. Limayem, E. Karahannaevavisto, Measuring system usage—implications for IS theory testing, *Management Science* 41(8), 1995, pp. 1328–1342. *
- [91] S. Taylor, P. Todd, Assessing IT usage: the role of prior experience, *MIS Quarterly* 19(4), 1995, pp. 561–570. *
- [92] S. Taylor, P. Todd, Understanding information technology usage—a test of competing models, *Information Systems Research* 6(2), 1995, pp. 144–176. *
- [93] H.H. Teo, H.C. Chan, K.K. Wei, Z.J. Zhang, Evaluating information accessibility and community adaptivity features for sustaining virtual learning communities, *International Journal of Human-Computer Studies* 59(5), 2003, pp. 671–697. *
- [94] J.Y.L. Thong, W.Y. Hong, K.Y. Tam, Understanding user acceptance of digital libraries: what are the roles of interface characteristics, organizational context, and individual differences? *International Journal of Human-Computer Studies* 57(3), 2002, pp. 215–242. *
- [95] A.M. Townsend, S.M. Demarie, A.R. Hendrickson, Desktop video conferencing in virtual workgroups: anticipation, system evaluation and performance, *Information Systems Journal* 11(3), 2001, pp. 213–227. *
- [97] H. van der Heijden, Factors influencing the usage of websites: the case of a generic Portal in the Netherlands, *Information & Management* 40(6), 2003, pp. 541–549. *
- [98] P. Van Schaik, J.A. Bettany-Saltikov, J.G. Warren, Clinical acceptance of a low-cost portable system for postural assessment, *Behaviour & Information Technology* 21(1), 2002, pp. 47–57. *
- [99] V. Venkatesh, Creation of favorable user perceptions: exploring the role of intrinsic motivation, *MIS Quarterly* 23(2), 1999, pp. 239–260. *
- [101] V. Venkatesh, F.D. Davis, A model of the antecedents of perceived ease of use: development and test, *Decision Sciences* 27(3), 1996, pp. 451–481. *
- [105] L.R. Vijayasarathy, Predicting consumer intentions to use online shopping: the case for an augmented technology acceptance model, *Information & Management* 41(6), 2004, pp. 747–762. *
- [106] Y.S. Wang, The adoption of electronic tax filing systems: an empirical study, *Government Information Quarterly* 20(4), 2003, pp. 333–352. *
- [107] Y.S. Wang, Y.M. Wang, H.H. Lin, T.I. Tang, Determinants of user acceptance of internet banking: an empirical study, *International Journal of Service Industry Management* 14(5), 2003, pp. 501–519. *
- [109] H.D. Yang, Y. Yoo, It's All About Attitude: Revisiting the Technology Acceptance Model, *Decision Support Systems* 38(1), 2004, pp. 19–31. *
- [110] M.Y. Yi, Y.J. Hwang, Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model, *International Journal of Human-Computer Studies* 59(4), 2003, pp. 431–449. *

William R. King holds the title university professor in the KATZ Graduate School of Business at the University of Pittsburgh. He has published more than 300 papers and 15 books in the areas of

information systems, management science, and strategic planning. He has served as founding president of the Association for Information Systems, President of TIMS (now INFORMS) and editor-in-chief of the MIS Quarterly.

Jun He is an assistant professor of MIS at the University of Michigan-Dearborn. He has an MBA from Tsinghua University and a PhD

degree from the University of Pittsburgh. His research interests include systems design and development, knowledge management, and methodological issues. He has presented a number of papers at meetings of the Association for Computing Machinery (ACM) and the Americas' Conference on Information Systems (AMCIS), published in *Communications of the Association for Information Systems*, and in a book of *Current Topics in Management*.