Technology acceptance: a meta-analysis of the TAM: Part 2

Shumaila Y. Yousafzai, Gordon R. Foxall and John G. Pallister
Cardiff Business School, Cardiff University, Cardiff, UK

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Abstract

Purpose – This paper is the second of two concerned with a meta-analysis of the technology acceptance model (TAM). This part aims to present a rigorous and quantitative meta-analytic review of 569 findings from 95 TAM studies as a basis for identifying gaps and providing guidelines for implementation management and conduct of future research. The paper also seeks to investigate the potential impact of methodological characteristics on the meta-analytic findings.

Design/methodology/approach – The approach consists of meta-analysis following Hedges and Olkin's procedures, moderator-analysis using homogeneity Q-values, analogue to ANOVA and weighted regression method.

Findings – The dominant focus in empirical investigations of the TAM has been on modelling intention for its effect on self-reported usage behaviour, while the attitudinal construct has been neglected. This raises three questions: whether the exclusion of attitude from the TAM is beneficial for understanding of technology usage behaviour in mandatory settings; whether the revised TAM holds equally for mandatory and voluntary settings; and whether the emphasis on measuring intentions and self-report use rather than actual usage is warranted. An additional question answered in the meta-analysis is about the relative importance of PU and PEOU.

Originality/value – The paper provides a rigorous meta-analysis to progress towards a unified view of the TAM.

Keywords Technology-led strategy, Research, User studies, Modelling

Paper type General review

Meta-analysis is a technique that allows quantitative accumulation and analysis of descriptive statistics across studies without acquiring access to the original data. Meta-analysis has been criticized as "mixing oranges and apples" (Hunt, 1997, p. 61). Such a criticism assumes that meta-analysis aggregates findings of different phenomena. However, Cooper (1989) notes that a convergence or "triangulation" of findings from methodologically varying studies lends credence to the validity of an effect. When a relationship remains constant, although tested under a variety of circumstances, it is clearly robust. Coined and first applied by Glass (1976), meta-analysis received its impetus from Rosenthal (1984), Hunter *et al.* (1982) and Hedges and Olkin (1985). Although the techniques used may vary, all meta-analyses aim to derive a quantitative measure, the effect size (ES), of the relationship under study. Our meta-analyses were conducted using Hedges and Olkin's (1985) procedures.

The framework guiding our discussion and empirical investigation focuses on two types of empirically tested relationship. First are the relationships proposed in Davis *et al.*'s (1989) original model; second, the relationships that have been tested by later research. Subsequent discussion centres on examining the sign of the association that

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will emerge on average. Our work attempts to determine not only the overall ES for the technology acceptance model's (TAM) relationships; but it also provides insight into methodological issues that are useful in developing guidelines for directing future research in terms of choice of subjects, research settings, measurement approaches, and the type of technology to be tested. Moreover, the research findings are corrected for sampling error to provide a more accurate picture of the relationships among the TAM's variables. Of more important foci in the meta-analysis are the estimates of the magnitude of the particular relationships and the identification of factors accounting for the variance in reported ESs.

Literature search

Following Hedges and Olkin (1985), we defined our task as combining the results from different studies to form a database to assess the existence of the relationship between the TAM's constructs. The first step in this process was to delineate a criterion for including studies in review. Candidates for inclusion were published journal articles that empirically tested at least one relationship embedded in the original Davis *et al.* (1989) model. Rosenthal (1994) suggested that an effort must be made to identify all the potential candidate articles to avoid the biased retrieval of searching only main journals, which may selectively publish only the results characterized by lower p-values and larger ESs. We therefore did not limit our search to specific journals; instead all potential published journal articles were reviewed. The exclusion of unpublished studies and dissertations may also bias the analyses (Rosenthal, 1994). We address this concern later in the paper by reporting the fail safe N, which predicts how many unpublished studies with non-significant ESs would be required to reduce the observed average ES to zero.

A computer search was made through nine databases including ABI Inform, Academic Search Premier, Business Source Premier, Computer and Information Systems Abstracts, ERIC, Lexis-Nexis' Academic Universe, PsycINFO, Social Science Abstract, and SocioAbs. Furthermore, a manual search was carried out through likely MIS, psychology, marketing and management journals. Keywords including but not limited to "TAM" "technology acceptance" "perceived ease of use" "perceived usefulness" "usage behaviour" "behavioural intentions" and "Davis *et al.* (1989)" were used to identify potentially relevant articles. Once the articles were acquired their references were reviewed to assist in locating additional articles. At this stage of the literature search, the decision rules were intentionally biased in a Type-I direction. That is, we were much more likely to include an article that was not codable than to fail to include an article that was relevant and codable. Table I provides a list of 57 journals that contributed 145 articles published on the TAM.

Meta-analytic methods

After collecting the studies on the TAM, the next step was to select a measure of association between the TAM constructs that would permit the greatest number of effects to be included in the meta-analysis. The Pearson correlation coefficient, r, was used as the primary ES estimator because most of TAM studies reported the value of r, and it is the metric to which many the TAM findings can be converted (Wolf, 1986, p. 35). Moreover, Pearson's r is more simply interpreted in terms of practical importance than are the usual d-type indices such as Hedges's g and Cohen's d

Australian Journal of Information Systems	1	*Journal of Operation Management*	1
Automation in Construction	1	*Journal of Org. Computing and E-Commerce*	1
Accounting Management & IT	1	*Journal of Travel Research*	1
Behaviour & Information Technology	5	*Journal of Retailing*	1
Computers & Education	1	*Journal of Retailing & Consumer Services*	1
Computers in Human Behaviour	2	*IEEE Software*	1
The Database for Advances in IS	4	*IEEE Transactions on Software Engineering*	1
Decision Sciences	9	*IEEE Transactions on Engg. Management*	3
Decision Support Systems	4	*Industrial Management & Data Systems*	1
Educational Technology & Society	1	*Information & Management*	15
Electronic Commerce Research & Applications	1	*Information Resources Management Journal*	1
European Journal of Information Systems	3	*Information Systems Journal*	1
European Journal of Operational Research	1	*Information Systems Research*	9
Expert Systems with Applications	1	*Information & Software Technology*	2
Group Decisions & Negotiations	1	*Information Technology & People*	1
Human System Management	1	*Interacting with Computers*	1
Journal of Academy of Marketing Science	1	*Int'l Journal of Electronic Commerce*	3
Journal of Accounting and Computers	1	*Int'l Journal of Human-Computer Studies*	8
Journal of Applied Social Psychology	1	*Int'l Journal of Information Management*	4
Journal of the Association for the IS	1	*Int'l Journal of Man-Machine Studies*	1
Journal of Business & Industrial Marketing	1	*Int'l Journal of Service Industry Management*	1
Journal of Computer Assisted Learning	1	*Internet Research*	1
Journal of Computer Information Systems	2	*Management Science*	4
Journal of End-User Computing	2	*MIS Quarterly*	13
Journal of Euromarketing	1	*OMEGA*	5
Journal of Global Information Management	1	*Psychology & Marketing*	1
Journal of Information Technology	3	*Small Group Research*	1
Journal of IT Theory & Application	1	*Telematics and Infomatics*	1
Journal of Management Information Systems	8		

Table I. Journal sources for TAM studies

(Glass *et al.*, 1981). Not all of the empirical studies, however, reported r or other measures that could be converted to r. We therefore corresponded with the authors to obtain correlation matrices for TAM constructs. Where studies have used multiple independent samples (Igbaria, 1993), were repeated over time (Davis *et al.*, 1989), or were testing multiple technologies (Subramanian, 1994), multiple correlations were considered only if each correlation represented a unique combination of sample, technology and time. Otherwise, we acted in accordance with Hunter and Schmidt's (1990) recommendations for conceptual replication; specifically, the multiple measures were used when they were highly correlated and seemed individually to exhibit construct validity (Hunter and Schmidt, 1990, p. 457). When several articles were based on one data set and measured the same variables (Chau and Hu, 2002a, b), only one publication was included. From the pool of 145 studies, eventually 95 were used in the meta-analysis, contributing a total of 569 correlations.

To ensure the quality of the correlation values and the methods and measures associated with each correlation, the studies were independently read and coded by four researchers (three authors and a research assistant) on pre-designed coding sheets. Disagreements were resolved through discussion after a review of each paper by the group with initial unanimity occurring for 97 per cent of the papers.

After coding r, the methods, and measures for each study, the third step was to average the r that tested the same hypothesis. Rosenthal (1984) notes that as the population value of r gets further and further from zero the distribution of r's sampled from that population becomes more and more skewed, thus complicating the comparison and combination of r's. To avoid this complication, we followed the procedure suggested by Hedges and Olkin (1985) according to whose procedure each r was first transformed to its corresponding Z-statistic Z_i, using Fisher's r to Z_r transformation and a weighted average of Z_r-scores then calculated. The weighted mean Z-transformed r is reported as ES in the tables. The 95 per cent confidence intervals for each correlation were generated using standard errors of the weighted mean ES. Confidence intervals reflect the "extent to which sampling error remains in the estimate of a mean effect size" (Whitener, 1990, p. 316). Once the confidence interval was established, the corresponding r-indexes for the weighted average ES were retrieved back using the inverse of Z_r-transformation (Hedges and Olkin, 1985).

Cohen (1977), in describing ES as the degree to which the null hypothesis of no relationship between the independent and dependent variable is false, suggests that an ES of $r = 0.10$ constitutes a small effect, an ES of $r = 0.30$, a medium effect, and an ES $r = 0.50$, a large effect. The formulas used for the above calculations are reported in Appendix 1.

Meta-analytic findings

The analysis of the data and the reporting of findings proceed in three phases. First, we describe the correlations between each pair-wise relationship in terms of their range, direction, statistical significance, and number of studies testing the relationship. These data highlight the diversity and nature of the findings on the TAM. Second, we present the findings from the univariate analysis of the correlations. The purpose here is to offer insight into the central tendencies of the TAM's relationships. The final stage of data-analysis centres on assessing whether the moderators identified in this study can account for the preponderance of variance in the relationships studied.

Descriptive analysis

For each pair-wise relationship, Table II reports the total number of studies, number of correlations r derived from those studies, the cumulative sample size for reported correlations, range of r, and the percentage of positive, negative and non-significant correlations.

The data in Table II make apparent the diversity in the TAM's relationships reported in the literature. The data reveal that the range of reported values can be quite broad for certain correlates in the model. As examples, the correlations for intentions-usage range from -0.197 to 0.73, for PU-usage from -0.41 to 0.91, for PEOU-usage from -0.197 to 0.98, and for PEOU-intentions the range was from -0.54 to 0.78. In addition, the correlations reported for the same correlate often contain positive and negative correlations as well as correlations that are statistically significant in the face of other correlations that are not significant. Although most of the correlations have signs that are consistent with prevailing expectations, we do find instances where the disparity in direction and statistical significance is notable. For example, for the PEOU-usage link, we find that 59 per cent of the correlations are positive and statistically significant, another 5 per cent of the correlations are negative, and the remaining 36 per cent of the correlations are not statistically significant in either direction. Table I in Part 1 of this study also suggest that PU is mostly found to

Table II. Descriptive information on TAM relationships

TAM's relationship	Results accumulated from meta-analysis: Total number of correlations	Results accumulated from meta-analysis: Cumulative (N)	Results accumulated from meta-analysis: Range of r (values)	Results accumulated from Table I (Part 1 of this study): Total no of studies	Positive correlations: Number	Positive correlations: Percentage	Negative correlations: Number	Negative correlations: Percentage	Non-significant correlations: Number	Non-significant correlations: Percentage
Intentions → usage	28	6,059	−0.19 to 0.73	25	23	92	01	04	01	04
Attitude → usage	15	4,816	−0.42 to 0.53	14	11	79	01	07	02	14
PU → usage	72	14,387	−0.41 to 0.91	72	59	82	02	03	11	15
PEOU → usage	61	11,456	−0.197 to 0.98	59	35	59	03	05	21	36
Attitude → intentions	30	8,240	0.06 to 0.87	44	40	91	–	–	04	09
PU → intentions	87	17,895	0.05 to 0.91	89	80	90	01	01	08	09
PEOU → intentions	77	16,518	−0.543 to 0.78	60	40	67	01	01	19	32
PU → attitude	40	9,962	−0.23 to 0.75	54	52	96	01	02	01	02
PEOU → attitude	36	9,048	0.08 to 0.733	51	42	82	01	02	08	16
PEOU → PU	123	24,110	−0.26 to 0.81	137	115	84	02	01	20	15

be a significant determinant of usage (82 per cent of studies), intentions (90 per cent of studies), and attitude (96 per cent of studies). On the contrary, the findings on PEOU are mixed. About 59 per cent of the studies in Table I of Part 1 found PEOU to be a significant determinant of usage, 67 per cent for intentions, and 82 per cent for attitude.

The data in Table II further indicate that far less attention in the empirical literature has been devoted to understanding the antecedents of attitude and its role in predicting intentions and usage behaviour. Only 14 studies tested the attitude-usage relationship, in contrast with 72 studies for the PU-usage, 59 for the PEOU-usage, and 25 studies for the intention-usage link. Only 13 per cent (76) of the correlations in our database pertain to attitude, as compared to 34 per cent (194) for intentions, 31 per cent (176) for usage, and 22 per cent (123) for PU. Moreover, the relationship between PEOU and PU is the most tested relationship (137 studies) in the TAM.

In all, these data bear witness to both the supremacy of the TAM and the mixed evidence on the drivers of behaviour towards technology use. Simultaneously, the data raise questions regarding the central tendency of the relationships and the statistical significance of these associations. They also raise questions as to whether the apparent variance in the magnitude and statistician significance of the reported correlations results from chance, sampling error, or differences in measures or methods. These questions are addressed below.

Analysis of direct effect

The Fisher's Z-transformed sample size weighted mean (ES) is the focus throughout the meta-analysis under the assumption that, all else being equal, correlations from larger sample (central limit theorem) produce a mean correlation closer to the population mean (Hunter and Schmidt, 1990).

The data in Table III suggests that the weighted mean ESs for the pair-wise relationships are all positive and statistically significant as suggested in the original Davis *et al.* (1989) model. Furthermore, the mean ES differs significantly from zero to the extent that hundreds to thousand of null effects would have to reside in the file drawers of the researchers to bring the respective mean ES estimate down to a level not considered statistically significant (see fail safe N in Table III). The only negative fail safe $N_{fs.05}$ (-10) is reported for the relationship between attitude-usage, concurring with the discussion in the previous section according to which very little attention has been given to the understanding of the attitude construct in the TAM. The confidence intervals reported in Table III do not include zero, thereby validating the relative precision of the estimate of mean ESs of the population of studies from which they are drawn.

Table IV presents the corresponding r-indexes for the weighted average ES that were retrieved back using the inverse of Z_r transformation (Hedges and Olkin, 1985). In Table IV, intention has the strongest correlation with usage, 0.43, followed by a PU-usage correlation of 0.38. In contrast, the mean correlations between PEOU-usage and attitude-usage are 0.28, and 0.25, respectively. Regarding the mean correlation between PU-usage, 215 null effects would have to be hidden in researchers' file drawers for the mean correlation to be non-significant in a statistical sense. However, caution is advised when interpreting the statistical significance of the mean correlation between attitude-usage and intentions-usage. Few correlations are available in the literature to

Table III. Meta-analytic results for TAM relationships

TAM's relationship	Weighted mean ES	Fail safe N^{a} $N_{fs.05}$	Standard error of the mean ES SE_{ES} (z-test)	Confidence interval (95%)	Homogeneity Q-value[b] (df)	Total variance S_r^2	Variance due to sampling error S_{er}^2 (percentage of S_r^2)	Biased population variance $S_b^2 = S_r^2 - S_{er}^2$ (percentage of S_r^2)
Intentions → usage	0.46*	19	0.013 (35.38)	$0.49 < \mu > 0.44$	315.95** (27)	0.05	0.003 (5. 8)	0.047 (94)
Attitude → usage	0.26*	−10	0.014 (18.57)	$0.29 < \mu > 0.23$	167.07** (14)	0.04	0.003 (7.5)	0.037 (92.5)
PU → usage	0.40*	215	0.008 (50.00)	$0.42 < \mu > 0.38$	608.45** (71)	0.04	0.004 (10)	0.036 (90)
PEOU → usage	0.29*	76	0.009 (30.80)	$0.31 < \mu > 0.27$	586.10** (61)	0.05	0.004 (8)	0.046 (80)
Attitude → intentions	0.56*	87	0.011 (50.91)	$0.58 < \mu > 0.54$	572.78** (29)	0.07	0.002 (2.8)	0.068 (97)
PU → intentions	0.55*	924	0.008 (72.63)	$0.56 < \mu > 0.54$	1,192.04** (86)	0.07	0.002 (2.8)	0.068 (97)
PEOU → intentions	0.34*	175	0.008 (42.50)	$0.36 < \mu > 0.32$	843.95** (76)	0.05	0.004 (8)	0.046 (92)
PU → attitude	0.53*	112	0.010 (53.00)	$0.55 < \mu > 0.51$	401.90** (39)	0.04	0.002 (5)	0.038 (95)
PEOU → attitude	0.45*	45	0.010 (45.00)	$0.47 < \mu > 0.43$	361.92** (35)	0.04	0.003 (7.5)	0.037 (92.5)
PEOU → PU	0.44*	1044	0.006 (67.80)	$0.45 < \mu > 0.43$	1,840.64** (122)	0.08	0.003 (3.8)	0.077 (96.25)

Notes: *Statistically significant at $p = 0.05$ as the value of z-test exceeds the critical value of 1.96 at $p = 0.05$; **statistically significant at $\alpha = 0.05$; [a]fail safe N represents the number of unlocated studies averaging null results ($r = 0$) that would have to exist to bring the adjusted mean down to the just significant level ($p = 0.5$); [b]the Q-value has a X^2 distribution with $k - 1$ degree of freedom (df), where k is the number of ESs

Table IV. Correlation matrix for the constructs of TAM *

	Usage	Intention	Attitude	Perceived usefulness	Perceived ease of use
Usage	1.00				
Intention	0.43	1.00			
Attitude	0.25	0.51	1.00		
Perceived usefulness	0.38	0.50	0.48	1.00	
Perceived ease of use	0.28	0.33	0.42	0.41	1.00

Note: *The corresponding r-indexes for the weighted average ES are retrieved back using the inverse of Z_r transformation (Hedges and Olkin, 1985)

report on these association and so a few studies reporting different ESs in the future could alter the conclusions.

The correlational data in Table IV support positive relationships of attitude, PU, and PEOU with intentions. In fact, the mean correlations between attitude-intention ($r = 0.51$) and PU-intentions ($r = 0.50$) are the strongest correlations reported. The data in Table IV further reveal that the perceptions of usefulness and ease of use plays a great role in developing positive attitude towards the technology. The mean correlation between PU-attitude is 0.48, and the mean correlation between PEOU-attitude is 0.42. More than 1,000 presently unknown null effects would have to exist for the mean correlation between PEOU-PU (0.41) to be statistically non-significant.

Analysis of moderator effects

Besides, documenting the distributions, central tendencies, and the magnitude of the TAM correlations, this meta-analysis explores whether the variations in the magnitude of the correlations is due to chance or the measurement and method factors discussed previously. We conducted two procedures to test the hypothesis of homogeneity. First, the homogeneity Q-values reported in Column 6 of Table III are greater than the critical value for a chi-square (χ^2) distribution with $k - 1$ degrees of freedom (k is the total number of ESs) at $\alpha = 0.05$, and thus are statistically significant. A significant Q rejects the null hypothesis of homogeneity and indicates that the variability among the ESs is greater than what is likely to have resulted from subject-level sampling error alone, and therefore, each ES does not estimate a common population mean (Lipsey and Wilson, 2001, p. 117). Second, we applied the rule of thumb provided by Hunter and Schmidt (1990) in which the total variance for the weighted mean ES S_r^2 and the associated error variance S_{er}^2 were compared. All the error variances reported in Column 8 of Table III account for less than 75 per cent of the total uncorrected variance, suggesting that there are important differences in variance among studies that have some source other than subject-level sampling error, likely due to moderating variables associated with different study characteristics (Hunter and Schmidt, 1990). Other artifacts (i.e. variations in measurement error, range restrictions, computational errors, and so on) will account for some of the remaining variance. Therefore, we conclude that the excess variability can be explained by possible moderating variables that systematically differentiate studies with larger or smaller ESs. To assess the relationship between ES and the proposed moderators we assumed a fixed effect model and two methods were used: Hedges' (1982) analogue to the analysis of variance (ANOVA) and Hedges and Olkin's (1985) modified weighted multiple regression.

The analogue to ANOVA provides a method of testing the ability of a single categorical variable, such as subject type, to explain variability in a distribution of ESs. This procedure partitions the total variability into the portion explained by the categorical variable (Q_B) and the residual pooled within groups portion (Q_W). If significant variability is explained by the categorical variable (a significant Q_B) then the mean ESs across categories differ by more than sampling error, i.e. show a statistically significant difference. If Q_W is not statistically significant, the categorical variable represented in Q_B is sufficient to account for excess variability in the ES distribution (Lipsey and Wilson, 2001).

The data in Table V indicate that all moderator variables discriminate between subclasses (except the values in italics) for the TAM's relationships, i.e. significant Q_B values. However, the fact that all Q_w values reported in Table V are statistically significant suggests the need for additional moderator variables.

We were also interested in further exploring the relationship between ESs and moderator variables and to test several moderator variables simultaneously. This was done using a modified weighted least square regression by specifying the inverse variance weight as the weight, Fisher Z-transformed values of the correlations as the dependent variable and the dummy-coded methods and measurement factors as independent variables (Hedges and Olkin, 1985). We estimated separate regression models for each pair-wise relationship having 15 or more correlations. The findings from the regression analysis reported in Table VI indicate that the regression models are relatively free of collinearity. The maximum variance inflation factor (max VIF) values are well below the threshold value of ten (except for the attitude-usage model), suggesting that collinearity is unduly influencing the estimates of the regression coefficients (Neter *et al.*, 1989).

The data in Table VI further reveal that the proposed moderators account for a significant proportion of the variance in the correlations for the following models: attitude-usage, attitude-intentions, PU-intentions, PEOU-intentions, PEOU-attitude, and PEOU-PU. However, the proposed moderators fail to account for a significant proportion of the variance in the correlations for the intentions-usage, PU-usage, PEOU-usage, and for the PU-attitude model. The respective models are not statistically significant (see Model p level in Table VI, i.e. $p > 0.05$). A focus on the coefficients in the statistically significant models reveals that subject type, method type, technology type, and type of usage measured are statistically significant ($p > 0.05$) moderators of the relationships in the TAM.

Subject type. Our findings concerning the impact of subject type on the relationships between the TAM's constructs indicate that subject type does moderate (Table V: significant Q_B) the estimates of intentions (except for PEOU-intention; $\Delta ES = 0.00$) and attitude but fail to discriminate (non-significant Q_B) for determinants of usage (except for attitude-usage) and PU.

Tables V and VI further indicate that using student samples results in higher correlation on average when attitude is correlated with intentions ($\beta = 0.03$; $\Delta ES_{s\text{-}ns} = 0.33$); PU is correlated with intentions ($\beta = 0.24$; $\Delta ES_{s\text{-}ns} = 0.10$); and PEOU is correlated with attitude ($\beta = 0.18$; $\Delta ES_{s\text{-}ns} = 0.14$). The results also suggest that student samples yield lower correlation on average when attitude is correlated with usage ($\beta = -0.06$; $\Delta ES_{s\text{-}ns} = -0.12$) and PU is correlated with attitude ($\beta = -0.03$; $\Delta ES_{s\text{-}ns} = -0.11$).

Table V. Analog to ANOVA results for moderator analysis (fixed effects model)

Moderator Variable	TAM's relationships: Usage BI → U	A → U	PU → U	PEOU → U	Behavioural intentions A → BI	PU → BI	PEOU → BI	Attitude PU → A	PEOU → A	Perceived usefulness PEOU → PU
Subject type										
Q: student (df), non-student (df)	313.05 (12), 257.58 (14)	99.96 (7), 50.31 (6)	387.27 (41), 221.02 (29)	102.70 (24), 481.92 (35)	66.64 (9), 410.193 (19)	449.94 (36), 685.57 (49)	636.83 (34), 207.09 (41)	115.47 (16), 267.48 (22)	60.13 (15), 270.15 (19)	1,076.60 (54), 755.89 (67)
Q_W (df)	313.05* (26)	150.27* (13)	608.31* (70)	584.62* (59)	476.83* (29)	1,135.51* (86)	843.92* (76)	382.95* (39)	330.28* (35)	1,832.49* (122)
Q_B (df)	*2.89 (1)*	16.8* (1)	*0.14 (1)*	*1.48 (1)*	95.95* (1)	56.54* (1)	*0.005 (1)*	18.9* (1)	31.64* (1)	*8.15 (1)*
ES: student, non-student	0.50, 0.45	0.19, .31	0.39, .40	0.31, 0.28	0.84, .51	0.62, 0.52	0.34, 0.34	0.45, 0.56	0.56, 0.42	0.42, 0.46
Method type										
Q: lab study (df), field study (df)	49.56 (10), 255.193 (16)	46.02 (3), 61.90 (10)	185.93 (19), 416.15 (51)	29.13 (18), 529.88 (41)	14.95 (5), 416.62 (23)	172.82 (23), 1,002.30 (62)	366.83 (23), 420.06 (52)	95.39 (9), 290.810 (29)	27.20 (9), 311.79 (25)	748.48 (35), 1,017.996 (86)
Q_W (df)	304.75* (26)	107.92* (13)	602.08* (70)	559.01* (60)	431.58* (29)	1,175.42* (86)	786.89* (76)	386.18* (39)	338.99* (35)	1,766.47* (122)
Q_B (df)	11.197* (1)	59.15* (1)	*6.37 (1)*	27.09* (1)	141.20* (1)	16.92* (1)	57.06 (1)	15.72* (1)	22.93* (1)	74.17* (1)
ES: lab study, field study	0.53, 0.43	0.05[NS], 0.31	0.35, 0.40	0.19, 0.31	0.99, 0.52	0.49, 0.56	0.24, 0.37	0.42, 0.54	0.58, 0.43	0.33, 0.47
Technology type										
Q: type-1 (df), type-2 (df), type-3 (df), type-4 (df)	7.68 (4), 251.15 (14) 19.82 (4), 23.44 (2)	18.73 (2), 14.86 (7) 10.11 (1), 3.22 (1)	103.88 (11), 251.60 (35) 158.84 (40), 88.88 (12)	12.41 (11), 160.78 (24) 23.82 (9), 371.18 (13)	n/a, 244.1 (12) .45 (5), 196.81 (9)	18.94 (3), 430.93 (34) 66.97 (14), 557.33 (32)	2.25 (3), 670.42 (32) 45.39 (11), 74.40 (27)	37.83 (4), 129.67 (13) 16.42 (7), 111.28 (12)	40.26 (4), 113.21 (10) 18.26 (6), 47.89 (12)	1,142.32 (45), 62 (10) 227.15 (24), 272.65 (40)
Q_W (df)	302.09* (25)	180.61* (13)	603.19* (68)	568.20* (57)	441.36* (29)	1,074.17* (83)	792.40* (73)	295.2* (36)	219.63* (32)	1,704.13* (119)
Q_B (df)	*13.86 (3)*	*− 13.54 (3)*	*5.26 (3)*	17.9* (3)	131.42* (1)	117.87* (3)	51.49* (3)	106.7* (3)	142.29* (3)	136.51* (3)

(*continued*)

Table V.

	TAM's relationships									
Moderator	Usage				Behavioural intentions			Attitude		Perceived usefulness
Variable	BI → U	A → U	PU → U	PEOU → U	A → BI	PU → BI	PEOU → BI	PU → A	PEOU → A	PEOU → PU
ES: type-1, type-2, type-3, type-4	0.32, 0.48, 0.41, 0.55	-0.02^{NS}, 0.26, 0.34, 0.47	0.37, 0.40, 0.41, 0.35	0.19, 0.30, 0.35, 0.24	n/a, 0.60, 0.23, 0.61	0.41, 0.57, 0.45, 0.64	0.45, 0.34, 0.25, 0.32	0.66, 0.53, 0.34, 0.53	0.58, 0.50, 0.26, 0.28	0.45, 0.51, 0.35, 0.35
Usage type										
Q: self-reported (df), measured (df)	124.21 (15), 155.23 (11)	68.90 (11), 14.08 (2)	404.45 (57), 203.93 (15)	538.93 (47), 25.14 (12)						
Q_W (df)	279.44* (26)	82.98* (13)	608.38* (70)	564.07* (59)						
Q_B (df)	36.51* (1)	84.09* (1)	*0.066 (1)*	21.4* (1)						
ES: self-reported, measured	0.55, 0.39	0.32, -0.014^{NS}	0.39, 0.39	0.19, 0.31						

Notes: *Statistically significant at $\alpha = 0.001$; for detail of technology type please refer to Appendix 2; n/a – not enough data available; Q_W – within groups homogeneity; Q_B – between groups homogeneity (italic values represents non-significant values); ES – effect size (all ESs reported in Table VIII are statistically significant at $p = 0.05$, except those marked by NS)

Table VI.
Weighted regression results for the moderator analysis (fixed effects model)

Moderator Variable	Usage: BI → U	Usage: A → U	Usage: PU → U	Usage: PEOU → U	Behavioural intentions: A → BI	Behavioural intentions: PU → BI	Behavioural intentions: PEOU → BI	Attitude: PU → A	Attitude: PEOU → A	Perceived usefulness: PEOU → PU
Subject type [a]										
β (standard error)	−0.08 (0.04)*	−0.06 (0.06)	0.02 (0.02)	0.11 (0.02)**	0.03 (0.05)	0.24 (0.02)**	0.07 (0.02)**	−0.03 (0.03)	0.18 (0.04)**	0.01 (0.02)
No of ESs: student, non-student	13, 15	8, 7	30, 42	25, 36	10, 20	37, 50	35, 42	17, 23	16, 20	55, 68
Method type [b]										
β (standard error)	0.21 (0.04)**	0.13 (0.12)	−0.08 (0.03)**	−0.19 (0.04)**	0.45 (0.02)**	−0.23 (0.02)**	−0.17 (0.02)**	0.11 (0.04)*	0.02 (0.05)	−0.13 (0.02)**
No of ESs: lab study, field study	11, 17	4, 11	20, 52	19, 42	6, 24	57, 30	46, 31	25, 15	21, 15	36, 87
Technology type [c]										
B (standard error)	−0.02 (.02)	0.10 (0.05)**	−0.003 (.01)	0.03 (0.01)*	−0.05 (0.02)**	−0.08 (0.08)**	−0.03 (0.01)**	−0.07 (0.01)**	−0.12 (0.01)**	−0.05 (0.01)**
No of ESs: types-1, 2, 3, 4	5, 15, 5, 3	3, 8, 2, 2	12,36,11,13	12, 25, 10, 14	1, 13, 6, 10	4, 35, 15, 33	4, 33, 12, 28	5, 14, 8, 13	5, 11, 7, 13	11, 46, 25, 41
Usage type [d]										
B (standard error)	0.22 (0.03)**	0.39 (0.14)**	−0.04 (0.03)	0.02 (0.04)						
No of ESs: self-reported, measured	16, 12	12, 3	56, 16	48, 13						
R^2 (adjusted)	0.221 (0.086)	0.583 (0.417)	0.015 (−0.044)	0.090 (0.025)	0.281 (0.198)	0.449 (0.202)	0.11 (0.073)	0.405 (0.164)	0.676 (0.407)	0.277 (0.077)
Model p level	0.199	0.049	0.905	0.253	0.033	0.000	0.036	0.088	0.000	0.023
Maximum variance inflation factor (MVIF)	2.694	15.044	1.853	2.957	2.630	1.410	1.472	1.845	2.1669	1.424
Degrees of freedom	23	10	67	56	26	83	73	36	32	119

Notes: *statistically significant at $p < 0.05$, two-tailed; **statistically significant at $p < 0.01$, two-tailed; [a]subject type is a dummy variable that assumed a value of "1" for students and "0" for non-students; [b]method type is a dummy variable that assumed a value of "1" for lab study and "0" for field study; [c]for detail of technology types please refer to Appendix 2; [d]usage type is a dummy variable that assumed a value of "1" for self-reported use and "0" for measured use

Method type. For the method type, the results in Table V clearly show that smaller ESs tend to be observed in laboratory experiments rather than in field studies. Method type moderates (Table V: significant Q_B) the estimates of usage (except for PU-usage), intentions, attitude, and PU.

Tables V and VI indicate that using lab studies yield lower correlation on average when PEOU is correlated with usage ($\beta = -0.19$; $\Delta ES_{ls\text{-}fs} = -0.12$); PU is correlated with intentions ($\beta = -0.23$; $\Delta ES_{ls\text{-}fs} = -0.07$); PEOU is correlated with intentions ($\beta = -0.17$; $\Delta ES_{ls\text{-}fs} = -0.13$); and when PEOU is correlated with PU ($\beta = -0.13$; $\Delta ES_{ls\text{-}fs} = -0.14$). The results further suggest that using lab study method results in higher correlation on average when intention is correlated with usage ($\beta = 0.21$; $\Delta ES_{ls\text{-}fs} = 0.10$); attitude is correlated with intention ($\beta = 0.45$; $\Delta ES_{ls\text{-}fs} = 0.47$); and when PEOU is correlated with attitude ($\beta = 0.02$; $\Delta ES_{ls\text{-}fs} = 0.15$). For the attitude-usage correlation, Table V reports non-significant ES for studies using lab experiments (0.05) and a medium ES for field studies (0.31).

Technology type. The moderator-analysis findings related to the impact of technology type on the TAM's correlations indicate that technology type moderates (Table V; significant Q_B) the estimates of usage (except for attitude-usage and PU-usage), intentions, attitude and PU. Perception of usefulness and ease of use of technology had higher than average correlation with attitude for communication systems, and lower than average correlations for office systems. Similarly, PEOU had higher impact on PU for communication and general purpose system in contrast with office and specialized systems. The results in Table V also indicate that the participants' positive or negative attitude towards specialized systems had higher effect on their intentions to use as compared with office systems. Finally, PU is highly correlated to intentions for specialized system in contrast with a low correlation for communication systems. Table VII summarizes the results for the moderator analysis of technology type.

Usage type. Finally, we discuss the findings related to studies that have used either subjective (self-reported use) or objective measure (actual use or frequency recorded by computerized systems) of technology usage as dependent variable. The proposed moderator has a significant Q_B (Table V) when intentions, attitude, and PEOU are correlated with usage. However, it failed to discriminate for the PU-usage correlation. The data in Tables V and VI further indicate that the correlation between attitude-usage was higher than average ($\beta = 0.39$; $ES_{sr} = 0.32$) when the measure of technology usage was subjective. Similarly intention were highly correlated with self-reported use ($ES_{sr} = 0.55$), in contrast with measured use ($ES_{sr} = 0.39$).

Table VIII and Figure 1 shows the results from the moderator analysis. These results are discussed in the following section.

Discussion of the meta-analytic findings

The meta-analysis was designed to synthesize and analyze the empirical findings on the TAM as one approach for taking stock of current knowledge, offering insight into technology usage behaviour, and identifying areas where research is deficient. Several of these insights are discussed next.

The meta-analysis makes it apparent that the dominant focus in empirical investigations of the TAM has been on modelling intention for its effect on self-reported usage behaviour, while the attitudinal construct has been neglected

Table VII.
Moderator analysis results for technology type

TAM's relationship	~ Rank 1	~ Rank 2	~ Rank 3	~ Rank 4
Intentions → usage	*Regression model $p = 0.199$; β = non-significant; Q_B = non-significant			
Attitude → usage	Q_B = non-significant			
PU → usage	Regression model $p = 0.905$; β = non-significant; Q_B = non-significant			
PEOU → usage	Regression model $p = 0.253$			
Attitude → intentions	General purpose sys.	Specialized sys.		Office sys.
PU → intentions	Specialized sys.	General purpose sys.	Office sys.[a]	Communications sys.
PEOU → intentions	Communications sys.	General purpose	Specialized sys.	Office sys.
PU → attitude	Communications sys.	General purpose	Specialized sys.	Office sys.
PEOU → attitude	Communications sys.	General purpose	Specialized sys.	Office sys.
PEOU → PU	General purpose	Communications sys.	Specialized sys.	Office sys.

Notes: *when not reported, regression model $p \leq 0.05$; [a]the ES of underlined technologies is lower than the mean ES reported in Table VI; ~ the ranking is based on the value of ES reported in Table VIII; for technology type details, please refer to Appendix 2

Table VIII. Summary of moderator-analysis

Impact of subject type on TAM's correlations	Impact of method type on TAM's correlations	Impact of technology type on TAM's correlations	Impact of usage measurement type on TAM's correlations
1. Attitude – usage correlation is higher for non-student sample	1. Intention – usage correlation is higher for lab study	1. PU – intentions correlation is higher for specialized system and lower for communication systems	1. Intention – usage correlation is higher for self-reported use
2. Attitude – intentions correlation is higher for student sample	2. Attitude – usage correlation is higher for field study	2. PEOU – intentions correlation is higher for communication and general purpose systems and lower for specialized and office systems	
3. PU – intentions correlation is higher for student sample	3. Attitude – intention correlation is higher for lab study	3. PU – attitude and PEOU – attitude correlations are higher for communication system and lower for office systems	
4. PU – attitude correlation is higher for non-student sample	4. PU – intentions correlation is higher for field study	4. PEOU – PU correlation is higher for communication and general purpose systems and lower for specialized and office systems	
5. PEOU – attitude correlation is higher for student sample	5. PEOU – intentions correlation is higher for field study	5. Attitude – intentions correlation is higher for specialized systems and lower for office systems	
	6. PU – attitude correlation is higher for field study		
	7. PEOU – attitude correlation is higher for lab study		
	8. PEOU – PU correlation is higher for field study		

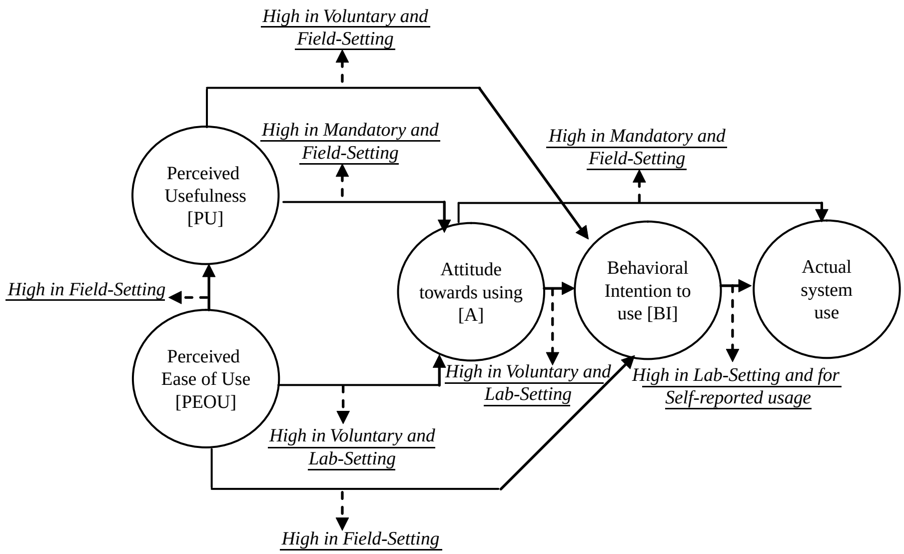

Figure 1.
TAM: meta-analysis results

(see Table I in Part 1). This raises three questions: whether the exclusion of attitude from the TAM is beneficial for our understanding of technology usage behaviour in mandatory settings, whether the revised TAM (Davis *et al.*, 1989) holds equally for mandatory and voluntary settings, and finally whether the emphasis on intentions rather than measuring actual usage is warranted. An additional question raised through the literature review of TAM is about the relative importance of PU and PEOU.

Our findings concerning the impact of subject type and study setting on the attitude-usage relationship indicate larger ESs for non-student samples and for field settings (Table V). However, the field settings and non-student sample exhibited smaller ESs for the attitude-intention relationships. There are several explanations for these results. In voluntary settings attitudes have been shown to correlate highly with behavioural intentions, e.g. Davis *et al.* (1989). However, where attitude is a key determinant of usage in organizational settings, the association between attitude and intentions is smaller in contrast to voluntary environments, as employees will intend to use a system regardless of their positive or negative attitude towards it. Additionally, Davis (1989) found a direct link between PU and intentions, reconfirming the possibility of a direct belief-intention linkage. This linkage has been empirically supported in other research where normative beliefs and control beliefs have been linked directly to intentions (Fishbein and Ajzen, 1975; Mathieson, 1991). Seemingly, individuals may develop intentions to use a technology because they perceive it as useful for their job performance, socially important, or convenient even though they do not enjoy using the technology (and, hence, possess a negative attitude towards the technology). One explanation for the attitude-usage link in terms of external validity suggest that students and laboratory tasks have little in common with real organizational settings; hence, field estimates of the effect between attitude and mandatory usage would be more meaningful. These results have important implications for research and practice. With the mandatory use of IS in organizational settings becoming a common practice, the organizations are concerned that the employees may reject the technology, underutilize it, or become more inefficient through decrease in productivity or increase in absenteeism and turnover. As discussed earlier, we contend that attitude will be a critical factor in understanding the mandated use environment because it represents the degree to which users are satisfied with the system (Melone, 1990). Underscoring attitude's importance in the development process, Robey (1979) urged designers to create a favourable user attitude by involving users in system-development process. This suggests that in organizational settings (mandatory use) excluding the attitude construct from the TAM will not provide an accurate representation of the phenomenon. Future research is needed for theoretical development and empirical validation of attitudinal construct in the specific area of predicting technology usage in mandatory adoption environment.

The relatively large ESs (Table III) for the relationships of PU and PEOU with attitude follows the indication by Bagozzi (1982) that, through learning and affective-cognitive consistency techniques, positively valued outcomes often increase one's feelings towards the behaviour that leads to the achievement of the outcome. However, this finding is contrary to Davis *et al.* (1989), who suggests a weak direct link between PU and attitude. Results from the moderator analysis facilitate to understand this contradiction in findings. The relationship PU-attitude has a higher mean ES for non-student sample and for field studies, whereas, the link PEOU-attitude has higher mean ES for student sample and for laboratory studies (Table V). These findings may be explained in terms of the realism of the field settings. Subjects in the field, unlike those in a laboratory setting, are usually accountable for future consequences of their behaviour and performances. The same holds for the heterogeneity in evaluation and motivation towards performance between knowledge workers and students. Thus, the non-student sample in field settings will develop their positive or negative attitudes on the basis of how useful the technology is in improving their job performance. Furthermore, in the laboratory experiments, the tasks need to be completed in a specific time period. This suggests that, the users will give more importance to the ease of use, thus undermining the importance of usefulness in the attitude development process.

The literature review of TAM (Table I in Part 1) indicate that 43 per cent of the studies have focused solely on the determinants of intentions to use an IS, and thus have not validated their models in respect to the prediction of actual behaviour and are consequently unable to show that the explanation is valid for the behaviour of interest. Additionally in 47 per cent of the TAM studies, the predictor (intention) and dependent (usage) variable were usually measured at the same time, longitudinal studies are rare, and few are conducted in predominantly mandatory environment. As noted earlier, under conditions of incomplete volitional control, intention is not a sufficient predictor of behaviour (Ajzen, 1991). Additionally, two major problems related with measuring intention and behaviour at the same time (Fishbein and Ajzen, 1975). First, the psychological influences that leads to a strong correlation between measures of intentions and self-reported usage. Second, it is not a true test of the TAM's power to predict future behaviour, rather it is a test of predicting current behaviour and there is no guarantee that this will continue. In fact, Karahanna *et al.* (1999) present evidence showing that pre- and post-adoption user beliefs are different. They also distinguish between adoption and usage. This short-term bias can be avoided by alternate conceptualizations based on long-term sustained usage, e.g. the idea of using the system as part of the daily work routine, i.e. routinization (Hage and Aiken, 1970) or continued-sustained implementation (Zaltman *et al.*, 1973). In a similar vein, Fichman and Kemerer (1999) underscored the importance of studying assimilation, i.e. continued usage over longer time horizon, as acceptance. These research directions also tie in with previous calls for longitudinal research to better understand the changes that occur in the process of technology adoption, calls that generally have gone unheeded. Linked to this is the issue of causality. Causality is a fundamental characteristic of a good theory. Despite the fact that certain external factors have been proven to affect two TAM variables (PEOU and PU), the issue of whether causality impacts user acceptance of a specific technology remains unresolved. As an important dimension of causal relationships (including both connectedness and directionality), causal links in TAM should receive more attention. Most of the intention-based models follow the causal relationships suggested by reference theories. For instance, TAM follows the Theory of Reasoned Action (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), which proposes the basic "beliefs attitude intention behavior" causal path. It works well for factors that belong to different categories in the above causal path, e.g. beliefs and intention. However, for factors in the same category, e.g. two beliefs, we have to assume causal directions based on theoretical reasoning. As a result, the causal directions between some factors in technology acceptance research are still unclear. Majority of research on TAM mentions the methodological limitation of the currently used covariance-based statistical approaches, such as structural equation modeling (SEM) techniques, in detecting causal directions. These techniques are of a confirmatory nature and insensitive to causal directions. To infer causality from cross-sectional, non-experimental data that are frequently found in empirical TAM research, new data-analysis techniques has recently been proposed by some studies. For example, Zheng and Pavlou (2007) have proposed data-analysis technique based on Bayesian Networks that aims to discover causal relationships among latent variables and Sun and Zhang (2004) have proposed process theories – mix level of analysis approach.

Another major issue is the compatibility of dependent variable with action, context, target and time (Ajzen and Madden, 1986). TAM studies have tended to include frequency and/or duration of use as dependent variable without maintaining consistency across the measures. Related problems occur with these dependent variables that would be more readily solved if consistency of measures were adhered to (Rawstorne *et al.*, 2000): does greater use and frequency indicate more acceptance, or inefficient usage, or something else? The new measures of usage would be especially valuable for technologies where the amount or frequency of usage is not important for establishing acceptance of technology (Szajna, 1996). Until valid measures are developed and consistently used in this area of research, it will remain difficult for researchers to determine whether TAM is to be blamed for poor prediction or whether results are based on incompatible dependent variables, faulty methodology, or faulty measurement.

In accordance with Szajna (1996), the intention-usage link appears to be dependent on the measurement method for usage. The moderator analysis results indicate a high-mean ES for the effect of intention on self-reported use, whereas a medium ES for measured use. Ideally, future research will take measures of actual usage; however, such an approach is often impractical because obtaining access to system-monitored usage data is often difficult. Follow-on studies that employ actual measures of the system use would be an important step in further defining the relationship between TAM constructs and objective usage. In addition, studies that look at the relationship between actual and perceived levels of system usage would be of value (Straub *et al.*, 1995). For example, Sproull and Kiesler (1986) provide some evidence that users tend to overstate their actual level of usage.

On the relative importance of PU and PEOU in TAM, the meta-analysis results are consistent with relationships observed in Davis *et al.* (1989). The results indicate that PU and PEOU are indeed related to attitude, intentions and usage but the strength of the PEOU relationships is much weaker then the relationship documented for PU (Table IV), and PEOU effects may not always be statistically significant (Table II). Thus, while the direct effect of PEOU on usage and intentions has been found in the selected studies to account for the most variance (Lu and Gustafson, 1994) and other emphasize the importance of capturing PEOU in TAM (Igbaria *et al.*, 1997), the cumulative findings indicate that PEOU is not a dominant predictor of usage and intentions in TAM. The implication of this finding might be that a heavy emphasis on PEOU, particularly at the cost of functionality, is not advisable, as was also suggested by Davis *et al.* (1989). However, this claim should be qualified. While PEOU might not be important in determining the level of use of a system, it may influence the initial decision to adopt a system in voluntary settings. In fact, an interesting finding from the meta-analysis was that the PEOU was found to be more important than PU in determining the attitude of student samples and in laboratory experiments. The significance of the PEOU-attitude relationship is consistent with Lepper's (1985) contention that the easier a system is to interact with, the greater should be the user's attitude regarding his or her ability to operate the system. In the context of process literature, this implies that when there is little conflict over needs, or the user has the influence to resolve the conflict and change the system to fit their needs, the system will be easier to use and will increase one's intentions to use it.

Conclusion

Our meta-analytic study yields a summary of 15 years of work on the TAM. The findings from the meta-analysis contribute to future technology acceptance research in several important ways. First, they allow researchers to put into perspective the incremental contribution of additional substantive and empirical studies in this area. For example, research that introduces new concepts and variables and/or any research of the constructive replication variety can be evaluated in terms of relative importance and contribution by calculating ESs of the new findings presented in the research study and comparing them to those found in this meta-analytic review. Second, our work suggests domains that might profit most from additional research. Third, our findings regarding the impact of methodological characteristics – subject type, method type, technology tested, and usage-measurement approaches – are useful for the design of future TAM studies.

The parsimony of the TAM combined with its predictive power make it easy to apply it to different situations. However, as Venkatesh (2000) suggests, while parsimony is TAM's strength, it is also the model's key limitation. The original TAM is predictive but its generality does not provide sufficient understanding from the standpoint of providing system designers with the information necessary to create user acceptance for new systems in different settings (Mathieson, 1991). Moreover, the application of the TAM beyond the workplace raises problems, as the TAM's fundamental constructs do not fully reflect the variety of the user's task environment and how well the technology meets the requirements of that task. This lack of task focus in evaluating technology and its acceptance has contributed to the mixed and equivocal results. While PU implicitly includes task, that is to say usefulness means useful for something, more explicit inclusion of task characteristics may provide a better model of technology acceptance. In their extensive discussion of parsimony, Mulaik *et al.* (1989) suggest that a model that provides good prediction while using the fewest predictors is preferable. However, other researchers have argued that parsimony, in and of itself, is not desirable, but rather is desirable only to the extent that it facilitates understanding (Browne and Cudeck, 1993; McDonald and Marsh, 1990). Based on this reasoning, we would assert that, assuming reasonable fit and explanatory power, models should be evaluated in terms of both parsimony and their contribution to the understanding. Finally, Bob Zmud suggests that, "simple, voluntary and *shallow usage* diffusion models of past should be expanded into complex, mandatory and *deep usage* diffusion models for the future" (Chin and Marcolin, 2001, p. 9). To conclude, user acceptance of information technology remains a complex, elusive, yet extremely important phenomenon. Research on the TAM, starting with that of Davis *et al.* (1989) has made significant contributions towards unravelling some of its mysteries. The meta-analysis of the TAM reported here advances theory and research on this important issue.

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Further reading

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Appendix 1

Statistics	Description	Formula
Z_i	Fisher's r to Z transformation	$Z_i = (1/2)\log\ e[1 + r_i \div 1 - r_i]$
ES	Average of Fisher's z-scores (Rosenthal, 1984)	$\mathrm{ES} = \sum_{i=1}^{N} w_i Z_i \div \sum_{i=1}^{N} w_i$, where $w = N - 3$
$N_{\mathrm{fs}0.05}$	Fail safe N (Wolf, 1986, p. 38)	$N_{\mathrm{fs}\,0.05} = [\sum \mathrm{ES} \div 1.65]^2 - N$
$\mathrm{SE}_{\mathrm{ES}}$	Standard error of the mean ES (Lipsey and Wilson, 2001, p. 132)	$\mathrm{SE}_{\mathrm{ES}} = \sqrt{1/\sum_{i=1}^{N}[w_i]}$, where $w = N - 3$
Z	z-test (Lipsey and Wilson, 2001, p. 132)	$z = \mathrm{ES} \div \mathrm{SE}_{\mathrm{ES}}$
$\mathrm{CI}_{\mathrm{ES}0.05}$	Confidence interval (Lipsey and Wilson, 2001, p. 132)	$\mathrm{CI}_{\mathrm{ES}0.05} = \mathrm{ES} \pm 1.96\ (\mathrm{SE}_{\mathrm{ES}})$
Q	Homogeneity analysis (Lipsey and Wilson, 2001, p. 116)	$Q = [\Sigma w_i \mathrm{ES}_i^2] - ([\Sigma w_i \mathrm{ES}_i]^2/\Sigma w_j)$, where $w = N - 3$; Q has a χ^2 distribution with $k - 1$ degree of freedom (k = total number of ESs)
Q_{B}	Between groups homogeneity[a] (Lipsey and Wilson, 2001, p. 121)	$Q_{\mathrm{B}}[\Sigma w_j \mathrm{ES}_j^2] - ([\Sigma w_j \mathrm{ES}_j]^2/\Sigma w_j)$, Q_{B} is the Q between groups, ES_j is the weighted mean ES for each group, w_j is the sum of weights within each group, and j equal 1, 2, 3, etc. up to the number of groups
Q_{w}	Pooled within groups homogeneity (Lipsey and Wilson, 2001, p. 121)	$Q_{\mathrm{w}} = \Sigma w_j [Z_i - \mathrm{ES}_j]^2$ Z_i is the individual ES, ES_j is the weigted mean ES for each group, w_i is the weight for each ES, I equals 1,2,3, etc. up to the number of ESs, and j equals 1,2,3, etc. up to the number of groups
R	Inverse of the Z transformed correlation	$r = (e^{2\mathrm{ES}} - 1)/(e^{2\mathrm{ES}} + 1)$, where $e \approx 2.718$

Notes: [a]A simpler strategy is to compute a separate Q for each group of effect sizes and then sum those Qs. The result is Q_{W}; Q_{B} is then found through subtracting the total Q from Q_{w} (Lipsey and Wilson, 2001, p. 121)

Table AI. Formulas for meta-analytic calculations

Appendix 2

Table AII. Technology type categorization

System main category	System sub-category	Code
Communications systems	Bulletin board systems	1
	E-mail	
	Fax	
	Desktop video conferencing	
	Dial-up systems	
	Interactive TV	
	Mobile phone	
	Moderated group chat	
	Voice mail	
General purpose systems	Computer resource center	2
	Digital library	
	Electronic billing service	
	GroupWare	
	Intranet	
	Operating systems	
	PC (micro computers)	
	WWW (e-commerce/internet)	
	Workstations	
Office systems	Database programs	3
	File editor	
	Graphics software	
	Presentation software	
	Spread sheet	
	Word processor	
Specialized systems	Computerized model	4
	CASE tools	
	DSS, GSS, GDSS	
	Expert support systems	
	Hospital IS (tele-medicine)	
	Interactive support systems	
	MRP	
	Online trading system	
	Other specialized software	
	Programming languages	
	Technological equipments	

Source: Lee *et al.* (2003)

Corresponding author
Shumaila Y. Yousafzai can be contacted at: YousafzaiS@cardiff.ac.uk