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Does the technology acceptance model predict actual use? A systematic literature review

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ABSTRACT

Context: The technology acceptance model (TAM) was proposed in 1989 as a means of predicting technology usage. However, it is usually validated by using a measure of behavioural intention to use (BI) rather than actual usage.
Objective: This review examines the evidence that the TAM predicts actual usage using both subjective and objective measures of actual usage.
Method: We performed a systematic literature review based on a search of six digital libraries, along with vote-counting meta-analysis to analyse the overall results.
Results: The search identified 79 relevant empirical studies in 73 articles. The results show that BI is likely to be correlated with actual usage. However, the TAM variables perceived ease of use (PEU) and perceived usefulness (PU) are less likely to be correlated with actual usage.
Conclusion: Care should be taken using the TAM outside the context in which it has been validated.

Contents

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1. Background

The technology acceptance model (TAM) was proposed by Davis [9] and Davis et al. [10] as an instrument to predict the likelihood of a new technology being adopted within a group or an organisation. Based on the theory of reasoned action [18], the TAM is founded upon the hypothesis that technology acceptance and use can be explained in terms of a user's internal beliefs, attitudes and intentions. As a result it should be possible to predict future technology use by applying the TAM at the time that a technology is introduced. The original TAM gauged the impact of four internal variables upon the *actual usage* of the technology. The internal variables in the original TAM were: *perceived ease of use* (PEU), *perceived usefulness* (PU), *attitude toward use* (A) and *behavioural intention to use* (BI). The original TAM used BI as both a dependent variable *and* an independent variable, with BI being used as a dependent variable to test the validity of the variables PU and PEU and as an independent variable when predicting actual usage [9,10]. Fig. 1 illustrates the original TAM model.

Venkatesh and Davis [51] subsequently proposed a revised TAM, referred to as TAM2, which did not include *attitude towards use* and incorporated additional variables such as *experience* and *subjective norm*. However, the core ideology of the model remained unchanged.

The variables within the TAM are typically measured using a short, multiple-item questionnaire (see Fig. 2). When included, *actual usage* is usually measured in a similar way through self-reported variables. Since its inception, the TAM and its revisions have been applied to a variety of technologies, such as text editors [9], business intranets [23] and the Web [17]. Whenever the TAM is validated for internal consistency, it scores very highly against whatever measure is used [9,47,20]. As a consequence, the results of applying the TAM are often accepted as being accurate predictors of usage and adoption. However, the *behavioural intention to use* a particular technology is more frequently measured than the *actual usage*. For example, a study conducted by Keung et al. [30] found that the TAM predicted that a particular technology was likely to be adopted within the company in question. However, a year later the authors found that the technology was not being used. The TAM was re-applied at the later time and the results from this study were very different from the initial TAM assessment. Therefore, there is a question as to whether the TAM can act as an accurate predictor of *actual usage* rather than *behavioural intention to use*. If the TAM is *not* an accurate predictor of *actual usage*, then there is an obvious problem if organisations rely on the positive results from applying the TAM to justify the introduction of new technologies. The study by Keung et al. [30] was investigating the use of a pre-prototype of a technology where the use of that technology was optional. Therefore, it is possible that the TAM will produce different results if the users being questioned have (a) used the technology being tested previously and (b) a choice in whether to use the technology.

There have been two recent meta-analyses of the TAM. King and He [31] considered the relationships among the three main TAM variables: *perceived ease of use*, *perceived usefulness* and *behavioural intention to use*. Schepers and Wetzels [43] investigated the impact of moderating factors and subjective norm on the relationships among the TAM variables. In contrast, the aim of this study is to investigate whether the TAM is an accurate predictor of *actual use*. It is an extension to the previous review conducted by Legris et al. [36], which compared those studies that evaluated the TAM against *actual usage* with those that evaluated it against *behavioural intention to use*. The *actual usage* of a technology can be measured using both objective and subjective forms. Objective measures are usually generated from logs of usage generated by the software itself. For example, one study used tracking tools and logs within the software being evaluated to objectively measure the overall system usage and the usage of a particular feature of the software [8], while another study used similar computer-recorded measures to log the number of times the server was accessed that was running an electronic process guide [13]. One study measured the usage of electronic supermarkets objectively by using the number of log-ons to the system, the number of deliveries ordered and the number of dollars spent with the store [21]. In comparison with objective measures of actual usage, subjective measures of usage are based upon the opinion of each individual subject, usually via a completed questionnaire. Examples of subjective measures of technology use include self-reported usage measures of the frequency or intensity of using the particular technology. In Legris et al.'s study all but one of the primary studies that measured *actual usage* employed self-reported usage rather than objective measures of *actual usage*. Straub et al. [46] investigated the relationship between the two types of *actual usage* measure and reported that self-reported measures of TAM variables (such as PU and PEU) appear to be related to self-reported measures of *actual usage* but show a much weaker relationship with objective measures of *actual usage*.

This review aims to further investigate the findings of Straub et al. [46] and assess whether the TAM is an accurate predictor of *actual usage* when employing objective and subjective forms of usage measure. It also aims to investigate if other factors may influence the results of a TAM study, particularly mandatory technology usage or prior use of a technology. This will be achieved through conducting a systematic literature review (SLR) and using vote-counting meta-analysis to analyse the results.

2. Method

We followed a formal systematic literature review process for this study [41,32]. As part of the process, we developed a protocol that provided a plan for the review in terms of the method to be followed, including the research questions and the data to be extracted. The following sub-sections outline the methods used to conduct the review.

2.1. Research questions

In order to determine to what extent the TAM and its revisions have been validated for prediction of *actual usage*, this work investigates the following research questions:

Question 1: To what extent are the TAM and its revisions capable of accurately predicting the *actual usage* of a technology and, as an ancillary question, to what extent are the TAM and its revisions capable of accurately predicting the *behavioural intention* (BI) to use a technology?
Question 2: Does the type of *actual usage* measure (subjective or objective) affect the accuracy of TAM predictions?
Question 3: Do factors such as the version of the TAM, the form of technology being evaluated, prior use of the technology or whether the technology is mandatory or not affect the accuracy of the predictions?

However, when conducting the review it became apparent that very few of the studies reported any information relating to the technology being evaluated, such as if the technology had been used prior to the application of the TAM or whether the usage of the technology was mandatory. Therefore, it was not possible to perform an analysis based upon the effect that the factors had on the associations between the TAM variables and *actual usage*, and research question 3 is not considered in the remainder of this review.

The population, intervention, outcomes and empirical study designs that were of interest to the review and that were used to construct suitable search terms are summarised below.

Population: Users of information technologies.
Intervention: Technology acceptance model.
Outcomes of relevance: The relationship between TAM measures and objective and subjective measurements of actual technology usage.
Empirical study design: Correlations or regression studies relating the TAM variables to *actual usage* and to BI.

2.2. Search strategy

The following sub-sections outline the strategy used to conduct the searches for the review.

2.2.1. Strategy used to identify search terms for automated searches

The strategy used to construct the search terms used in the review was as follows:

- derive major terms from the questions by identifying the population, intervention and outcome;
- identify alternative spellings and synonyms for major terms;
- use the Boolean OR to incorporate alternative spellings and synonyms and
- use the Boolean AND to link the major terms from population, intervention and outcome.

This resulted in the preliminary search string:

(measurement OR measure OR empirical) AND "technology acceptance model" AND usage AND ((subjective OR "self-reported" or statistics OR questionnaire) OR objective OR validation) AND (year ⩾1989 AND year ⩽2006).
The search was restricted to publications published between 1989 (the year that the first TAM paper was published [9]) and 2006 (the year that the review took place).
We conducted a pilot study using the above search terms in two digital libraries: IEEE Xplore and ACM Portal. The result was that the search string shown above was found to be too restrictive as it failed to find several known studies. Therefore, the search string was amended to the following:
"technology acceptance model" AND (usage OR use OR empirical) AND (year ⩾1989 AND year ⩽2006).

2.2.2. Resources to be searched

The search of resources was conducted using six digital libraries, which search different combinations of resources. The digital libraries used were: IEEE Xplore, ACM Portal, Google Scholar, CiteSeer library, Science Direct, ISI Web of Science.

2.2.3. Search validation

Search strings were validated by their ability to detect a number of known primary studies. A prior search was conducted using a set of broad search terms and a number of relevant publications were identified. This list of publications, along with the publications identified by Legris et al. [36], was used to validate the search strings before undertaking the review.

2.2.4. Additional search criteria

The search strategy was based primarily on a search of digital libraries. However, primary sources were all checked for other relevant references.

2.2.5. Search process

The searching of the digital libraries was conducted by two primary reviewers. The digital libraries were randomly allocated to the two reviewers, resulting in each reviewer searching three digital libraries. One reviewer searched the IEEE Xplore, Science Direct and Web of Science digital libraries, while the other reviewer searched Google Scholar, CiteSeer and ACM Portal.

2.2.6. Search documentation

The search was documented in the format shown in Tables 1a and 1b, which illustrates the search process documentation for the IEEE Xplore and ACM Portal digital libraries. As each of the digital library search engines has a different interface, a preliminary search indicated that the search terms would have to be modified to adapt to the requirements of each digital library. The adapted search terms for the review are presented in Tables 1a and 1b.

2.2.7. Search result management

Details of the primary sources that were potentially relevant were stored in a *Reference Manager* database.

2.3. Study selection criteria and procedures

The full list of primary studies identified by the searches was evaluated against a set of inclusion and exclusion criteria. The following sub-sections detail the inclusion and exclusion criteria used and the process by which the criteria were applied to the lists of primary studies.

2.3.1. Inclusion criteria

Studies that evaluated the internal TAM variables against actual technology usage were of interest to the review. Therefore, the following inclusion criteria were applied:

- Publications, technical reports or 'grey' literature that describe empirical studies, of any particular study design, in which the TAM (or a TAM revision) was applied to any technology (RQ1, RQ2, RQ3).
- The TAM *actual usage* variable is measured, either objectively or subjectively (RQ1, RQ2).
- The version of the TAM being used must include measures of PEU and/or PU and the relationship to *actual usage* must be reported and the study must include a measure of *actual use* (RQ1, RQ2).
- Publications that include a measure of BI and examine the relationship between BI and *actual usage* (RQ1, RQ2).
- Where several publications have reported the same study, only the most complete publication will be included.
- Where several independent studies are reported in the same publication, each relevant study will be treated as an independent primary study. Independent means that each study was conducted with different participants. Studies using the same participants at different points in time or with the same participants assessing different technologies, were classified as non-independent.

Note that the details in brackets next to each statement identify the research question to which the particular criterion relates. The final two criteria detail how we dealt with particular issues and are not directly related to any of the research questions.

Originally, the intention was to exclude any studies from the SLR that included variables that were not part of the original TAM [9]. This was to avoid the influence on the SLR of any studies that included other variables that could have influenced the predictive capability of the original TAM variables. However, as stated in Section 1, relatively few studies included actual usage as a dependent variable, with most studies concentrating on behavioural intention to use. Therefore, in order to include as many studies as possible, it was necessary to loosen the inclusion criteria to those outlined above, for example by allowing the inclusion of studies that included other, non-TAM, variables. This enabled the review to include as many studies as possible, but did necessitate that additional sensitivity analyses were performed (Section 3.2).

2.3.2. Exclusion criteria

Studies that met the following criteria were excluded from the review:

- Studies that do not report on the TAM in relation to *actual usage*.
- TAM-based studies that are based solely on the *behavioural intention to use* a technology.
- Theoretical publications related to the TAM.
- Publications/reports for which only an abstract or a PowerPoint slideshow are available.

2.3.3. Selecting primary sources

Initial selection of primary sources was based on a review of the title, keywords and abstract. At this stage, only those primary sources that appeared to be completely irrelevant were excluded.

Full copies of all primary sources not excluded in this initial selection process were obtained, and were reviewed against the inclusion/exclusion criteria described above. Where there was uncertainty regarding the inclusion or exclusion of a particular primary study, the source was sent to one of four secondary reviewers for a second opinion. The primary studies were randomly allocated to these reviewers.

The record for each primary source in the Reference Manager database was updated to specify whether or not the primary source has been included in the review, and the reason for its inclusion/exclusion.

2.4. Included and excluded studies

Two primary reviewers conducted the initial searching of their allocated digital libraries, as detailed in Section 2.2.5. Each reviewer performed an initial screening of the search results for their particular allocated digital libraries, based on the title of each publication, the keywords associated with the publication, and the abstract. A more detailed review was then conducted on the remaining publications by applying the inclusion/exclusion criteria. Any publications where the primary reviewer was unsure regarding the inclusion or exclusion were allocated to one of four other secondary reviewers for a decision.

The total number of publications returned for each digital library is detailed in Table 3. The table also highlights the number of relevant publications found in each digital library and the percentage of the total returned publications from each library that was relevant.

The CiteSeer digital library, when searched using the standard interface, returned zero publications using the post-pilot search string. However, when the same digital library was searched using the Google search engine 45 results were returned. Therefore, CiteSeer was searched using the Google interface for the review. Also, the figures for Google Scholar are affected by the fact that the interface limits the number of results returned to 1500. Therefore, it is possible that the search would have returned a larger number of total results than quoted in Table 3. A number of relevant publications were found in several digital libraries. The greatest overlaps were between the Science Direct, Web of Science and Google Scholar digital libraries, which shared 14 of the relevant publications.

As the searching and screening processes were conducted separately by two primary reviewers, the final list of included publications was combined and checked by both primary reviewers. After this first round of searching and screening a total of 75 publications were included. However, it became apparent that in a number of cases multiple publications were reporting results based on the same dataset. If results based on the same dataset were included multiple times it could bias the results, as effectively the same results are being included several times. In order to try to discover any publications reporting the same study, the 75 publications were ordered in ascending order of sample size. Any publications reporting details of studies with the same sample size were examined to determine if the studies were based on the same dataset. A number of publications were excluded on this basis, with the publication that included the most complete results being selected for inclusion. A final check was performed by re-ordering the remaining publications in alphabetical order of author name, and any publications with the same author were checked to see if they were reporting results based on the same study. If several publications reported different relationships between the TAM variables, but based on the same dataset, then all of the publications were selected for inclusion but counted as one study during the analysis (see Section 2.6). After removing duplicates, and any publications reporting the same study, 68 publications identified from the digital libraries were included in the final review.

The papers referenced in each of the 68 publications were also checked for relevance. The screening process was similar to that used for the initial electronic searches, with each reference being screened on the basis of title and author. This process allowed any publications that appeared to be completely irrelevant to be discarded, along with any publications that had already been included in the review from the digital libraries. All other publications were obtained and reviewed against the inclusion and exclusion criteria, resulting in two extra publications being included [1,22].

The publications selected for inclusion were also compared against those selected for the review undertaken by Legris et al. [36]. Legris et al. [36] included 22 publications, of which 15 publications included a measure of *actual usage*. This comparison indicated that there were four out of the 15 publications that had not been included in our search that Legris et al. [36] had included [2,3,6,29]. One of the publications was based on the same study as Gefen and Keil [15] and so was excluded [29], while the remaining three publications were selected for inclusion. Therefore, combined with the two publications found through manual checking of the references of included papers, this resulted in an extra five publications being included. It should be noted that these five publications are included in the digital libraries that were searched, but were not identified by the search string that was used. As the search strings were validated before use, along with the fact that several search engines were used that indexed multiple databases, and the search strategy for the review included the screening of the references of all papers included (Section 2.2.4), it was felt that any papers missed by the original electronic search would be included through other means without the need to recreate the search strings.

Overall, 73 publications were included in the final review (see Appendix A for a full list).

2.5. Study quality assessment

A number of quality assessment questions were devised to assess the completeness of the information presented in the studies and, in particular, to provide data for sensitivity analyses. The criteria used to determine the quality of the included primary studies were based on the following questions:

- Is failure to observe the expected relationships between the TAM variables related to the size of the sample used?
- Are there any possible confounding factors when the intended relationship between a TAM variable and actual usage/behavioural intention to use a technology is not significant? A possible confounding factor is the presence of other variables in the model being tested, which could have an impact on the relationship.
- Is it clear how *actual usage* was measured?
- Is the information required from the study directly extractable? (i.e. does the study report the relationships between variables in terms of a correlation or a regression value with the statistical significance attached).

The study quality checklist used was as follows:

- We conducted an investigation into the sample sizes of the included primary studies, and whether sample size could explain failures to observe the expected relationships in the studies. An ANOVA was used to test whether there was a difference in sample size to determine whether the sample size of those studies that found a significant relationship was significantly larger than those that found no significant relationship.
- If a study included relationships between the variables that failed, and there were other variables present in the model, then this was recorded and used in the sensitivity analysis.
- If the study corresponded to the original inclusion criteria, but on more detailed analysis we found that it was not clear that PEU and PU were the variables used to predict *actual usage*, or if it was not clear what the researchers had done to arrive at their conclusions, the study was excluded from the analysis. Similarly, any studies for which it was impossible to discover how the *actual usage* variable was measured were excluded from the analysis relating to different types of usage measure.
- If data was not reported in an appropriate format then data extraction was preceded by a data refinement phase or the data extracted was amended appropriately. If this was not possible, we contacted the authors to request more information.

2.6. Data extraction strategy

We extracted data from the selected studies to address each of the research questions described above. It should be noted that one publication could describe several primary studies, and vice versa. For this SLR, we were interested in the primary *studies* and therefore one data extraction form was completed per study and not per publication. For example, if one publication included details about three primary studies then three data extraction forms would be completed. There were several publications included in this review where one publication included data related to several studies [1,11,9,23,45,52]. However, if one study was described in several publications only one data extraction form was completed, with the extraction form referencing each of the publications [49,50,14,13]. This was only done if each publication included different data about the particular primary study. If all of the publications provided the same details about the primary study, then as detailed in the inclusion criteria, the publication providing the most complete information about the study was included.

In this section, we summarise the types of data extracted and the process followed.

2.6.1. Primary study data

For research question 1 (see Section 2.1), we extracted the following information for each relevant primary study:

- Whether PU and PEU were significantly associated with *actual usage* ($p < 0.05$).
- Whether PU and PEU were significantly associated with BI ($p < 0.05$), in order to assess whether these studies were similar to other studies that did not report *actual usage*.
- Whether BI was significantly associated with *actual usage* ($p < 0.05$) in order to assess the value of *behavioural intention to use* as a surrogate for *actual usage*.

For research question 2, we extracted the following information from each study:

- Whether several different measures of *actual usage* were collected.
- For each measure, whether it was objective (e.g. from computing logs) or subjective.

The data extraction form used is shown in Table 2. The data extraction form also included a number of sections to address research question 3, including the version of the TAM being used, details of the technology being evaluated and if the technology had been in use prior to administration of the TAM questionnaire. As detailed in Section 2.1, very few papers actually reported this information and so, while the information was extracted when it was available, during analysis it became apparent that there was not enough data to perform any meaningful analyses.

2.6.2. Data extraction process

Each primary study included in the review was read by the two primary reviewers. For each study, one reviewer acted as the main data extractor, whilst the other reviewer acted as checker. The first reviewer was responsible for extracting the data and the second reviewer was responsible for checking that the data had been correctly extracted. First reviewers acted as main data extractors for the primary studies that were found in the digital libraries that they searched.

The checker discussed any disagreement with the data extractor. If the two reviewers could not come to an agreement about the data to be extracted, the study was reviewed by a third person (a secondary reviewer). The primary studies were randomly allocated to one of four secondary reviewers through allocation of numbers to the primary studies and generating random numbers to determine the reviewer to which the primary study should be allocated.

A consensus was then reached that was based upon the data extracted by the three reviewers. In total, there were 14 data extraction forms where there was some disagreement between the primary and secondary reviewers.

When extracting the data from the included primary studies, it become apparent that many of the studies reported the data and results relating to the TAM variables in non-standard ways or at least in ways that made it difficult to perform a formal meta-analysis. For example, in order to perform the kind of analysis necessary to determine the overall success or failure of the individual TAM variables in predicting *actual usage* (or BI), correlation matrices were needed from each study that reported the relationships between each variable. However, relatively few of the studies reported such a matrix. Therefore, a number of decisions were made as to how the data from such studies would be extracted.

- If covariance rather than correlation matrices were presented, as was the case with two included studies, it was necessary for us to calculate the correlations and significance levels ourselves [19,35]. The calculated figures, alongside the original figures, were then entered into the data extraction forms.
- Each of the TAM variables is often measured through multiple questions on a questionnaire (Fig. 2). If a study did not aggregate the usability, and ease of use questions into single factors and instead provided correlations for each individual question, then we recorded each correlation value with its significance level and treated them as *non-independent tests* within a single study [24]. The same was also done if several different ways of measuring *actual usage* were included in the study, and the study reported the correlations to all of the different *actual usage* measures rather than accumulating the measures into a single usage metric [1,5,8,21,34,40,44].
- If a study presented separate results for subsets of a dataset, then correlations from each subset were extracted along with their significance level [1,5,7,9,13,14,25–27,38,42,49,50]. These correlations were treated as non-independent tests within a single study.
- Similarly, if one study included several tests of the TAM at different points in time then the results for all of the tests were extracted but treated as non-independent tests within a single study [10,11,21,23,28,48,52,53].

The verified extracted data for each study was held in a Microsoft Word file, with a separate file being used for each study.

2.7. Data aggregation

Originally we planned to perform an effect-size based meta-analysis of the primary study, where a meta-analysis is a synthesis of the results indicating actual effect size. Therefore, in order to perform a meta-analysis as part of the SLR, an appropriate effect-size measure was required from all (or most) of the studies. King and He [31] used path coefficients but this is only valid if the path coefficients are obtained from exactly the same TAM version or the full correlation matrix is provided allowing the path coefficients for the core TAM model to be calculated. In general, beta values from regression style models cannot be used in meta-analysis [37]. If studies using different variants of the TAM publish only path coefficients, the path coefficients will not be comparable. For this reason, we intended to use correlation coefficients (if reported) and the number of subjects in each study. The data extraction form that we used included space to extract the relevant measure reported in the study for each TAM variable, such as correlation coefficients, path coefficients or levels of significance. However, due to the heterogeneity of reporting of the primary studies in terms of the type of TAM used or the statistical method, it was not possible to undertake a full effect-size meta-analysis and so a vote-counting meta-analysis was employed (Section 3.1).

3. Results

The final list of included publications is shown as Appendix A. Appendix A also includes a key that identifies if a particular publication includes data relating to multiple studies (m(n), where n is the number of studies) and/or multiple tests (t(n), where n is the number of tests). The key also indicates which publications include studies that report subjectively measured *actual usage* (S) and/or objectively measured usage (O), along with an indication of which of the TAM variables are reported in the study (PU/PEU/BI). The results of the review in relation to each research question are summarised below.

3.1. Research question 1

Question 1: To what extent are the TAM and its revisions capable of accurately predicting the *actual usage* of a technology and to what extent are the TAM and its revisions capable of accurately predicting the *behavioural intention* (BI) to use a technology?

We used a vote-counting meta-analysis of the primary studies because we could not undertake an effect-size meta-analysis since:

- many of the studies used modified versions of the TAM rather than the original model;
- many of the studies did not report correlation figures to measure the relationship between the PU, PEU and BI variables and *actual usage* and
- results were influenced by other variables that were introduced when using modified versions of the TAM model.

The vote-counting analysis was made more complex because many of the studies included multiple tests that corresponded to several administrations of the TAM to the same subjects at different times or to subsets of the same dataset. The use of multiple tests in such a way meant that in some studies all of the tests were not completely independent. This could bias the assessment of the frequency with which PU and PEU are correlated with *actual usage* or with BI. In order to address this issue, we calculated the proportion of the tests in which PU, PEU and BI predicted *actual usage* ($p < 0.05$), and the proportion of tests in which PU and PEU predicted BI ($p < 0.05$) for each study. This is referred to as the proportion of successful tests per study. The average of these proportions was then calculated across all of the studies for each particular association (e.g. PU to actual usage and PEU to actual usage).

Table 4 shows the numbers of studies that measured associations between each of the TAM variables and *actual usage*, along with the average proportion of success across all of the studies, the upper and lower 95% confidence limits for the proportion and the standard error. Table 5 shows similar figures to Table 4 but for the associations between each of the TAM variables and BI.

As shown in Table 4, 57 of the included studies reported the level of success of PU in predicting *actual usage*. The average proportion of success per study for the relationship between PU and *actual usage* is 0.75. The average proportions for PEU and BI are 0.59 and 0.9, respectively. The results show that the proportion of tests where PU predicts *actual usage* is higher than for PEU, but the difference is minor and not significant. Whilst BI has the highest average proportion of success out of the three variables, the only statistically significant difference is between the association of PEU to *actual usage* and BI to *actual usage*, which indicates that PEU is not as successful at predicting *actual usage* as BI ($p < 0.05$).

In terms of the association between the TAM variables PU and PEU and the behavioural intention to use a technology (BI), the average proportion of success per study for the association between PU and BI (of 33 studies measuring the association) is 0.85 (Table 5). The average proportion of success per study of 20 studies measuring the association between PEU and BI is 0.73. Comparing the figures in Table 5 to those of Table 4 illustrates that the TAM variables are a much stronger predictor of the *behavioural intention to use* a technology than the *actual usage* of a technology. However, there were fewer studies measuring the association between PU/PEU and BI than there were between PU/PEU/BI and *actual usage*. Only 20 studies measured the association between PEU and BI, which may be explained by the fact that the original TAM model does not include this relationship [9]. Many of the studies we found also used variations of the TAM, with many removing the BI variable altogether or only measuring its relationship to *actual usage*. Therefore, it was not possible to determine a statistically significant difference between the results for the TAM variables and *actual usage* and those of the TAM variables and BI.

3.2. Research question 2

Question 2: Does the type of *actual usage* measure (subjective or objective) affect the accuracy of TAM predictions?

The number of studies measuring the association between subjective usage measures and PU, PEU and BI are shown in Table 6, along with the average proportion of success per study and the upper and lower bounds of the confidence interval for the proportion. The standard error is also included. Table 7 shows the equivalent figures for objectively measured usage.

Comparing Tables 6 and 7 shows that the type of usage measure does have an effect on the ability of the TAM variables to predict *actual usage*. The largest difference is for the variable PU, where the average proportion of success per study for subjective usage is 0.78 whilst for objective usage the figure drops to 0.53. However, the confidence interval for PU to objective usage is very wide (0.175–0.889) because there are only nine studies that measure the association. The same is true for all of the variables, as there are fewer studies that measured objective usage against PEU (eight studies) and BI (six studies) than for the equivalent number of studies against subjective usage (43 and 32, respectively). Therefore, there is generally less confidence in the values and a wider confidence interval and it is not possible to confirm if the differences are statistically significant ($p < 0.05$). However, the results show that the average proportion of all of the three TAM variables predicting *actual usage* is lower if the *actual usage* measure is objective than if it is subjective.

3.3. Sensitivity analysis

Several studies used variations of the TAM model, which along with PU, PEU, BI and *actual usage* included other non-standard TAM variables. In such models, when a test indicates that the TAM variables fail to predict *actual usage* it is difficult to determine what effect the extra variables had on the result. During the data analysis, any tests that failed in models that included extra variables were classified as ‘failing in the presence of other variables’. In order to test the sensitivity of the results those tests that failed to predict in the presence of other variables and those that produced positive but incomplete results were removed from the calculations. Table 8 shows the number of studies and the recalculated proportions and confidence intervals for the associations between the TAM variables and subjectively measured *actual usage*, when any studies that were classified as failing in the presence of other variables were removed. Table 9 shows the same recalculated figures for objectively measured usage.

Comparing Table 8 with the recalculated proportions to the original proportions in Table 6 shows that there are only minor differences. The largest difference is between PU and *actual usage*, with an average proportion of 0.78 in the original figures and a proportion of 0.814 with the studies that failed in the presence of other variables removed, but this is not a significant difference ($p > 0.05$). A comparison of the figures for objectively measured usage in Table 7 and the recalculated values in Table 9 also shows that there are no major differences. These results suggest that our estimates of the frequency of TAM variables predicting *actual usage* are quite stable with respect to incomplete information or the negative effect of other, non-tested, variables in the models.

A further issue that could limit the validity of our results is the size of the datasets used in each of the included primary studies, particularly in the case of those studies that did not observe a significant relationship between the variables and *actual usage*. If the size of the datasets of the included primary studies that observed non-significant relationships is small, then it could be that the findings are as a result of the dataset being too small to find a correlation, even if a correlation did exist.

In order to examine the sample sizes of the included primary studies, a series of tables were created examining the sample sizes for studies measuring the association between PU and subjective usage (Table 10), PU to objective usage (Table 11), PEU to subjective usage (Table 12) and PEU to objective usage (Table 13). The tables show the number of studies where the variable failed to predict the particular type of *actual usage*, the number that were classified as ‘mixed’ (i.e. the study included multiple tests, some that failed and some that showed a positive association), and those that showed a positive association. For each classification, the tables show the mean, minimum and maximum sample size. For each dataset, we used the Kruskal–Wallis non-parametric analysis of variance to test whether the sample size of the three outcome groups were significantly different ($p < 0.05$). In no case was there evidence of significant difference in sample size between the studies that reported successful predictions, the studies that had mixed outcomes and the studies that reported no significant predictions. Furthermore, most datasets are larger than 50 and will, therefore, identify a correlation greater than 0.28 as significant, where 0.28 is the value of a correlation that would be significant with a population of 50 or above ($p < 0.05$). Therefore, the sample size can be considered to be large enough to identify a correlation of practical significance. Thus, it can be concluded that the sample sizes were sufficient to have confidence in the results.

As we are conducting an analysis based on independent validation of the TAM, one further examination is to investigate the effect on the recalculated proportions if all of the studies by the originator of the TAM are removed from the analysis [9]. In order to investigate the effect of removing the studies by the originator of the TAM, we removed all studies that included Davis as an author or co-author for studies that measured *actual usage* objectively. Objectively measured technology usage was chosen as one publication that included Davis as an author included two studies, each including six non-independent tests that included objectively measured usage and that we felt could bias the results [11]. The resulting proportions are shown in Table 14. As can be seen, removing the studies from Davis and Venkatesh [11] has an effect on the relationship of all of the TAM variables to objectively measured usage. In particular, the largest change is between PU and objective usage, which reduces to an average proportion of successful tests of 0.398 from 0.532 when the two studies are removed. The average proportion for PEU also reduces from 0.414 to 0.302.

Overall, the results illustrate that the average proportion of all three TAM variables in predicting actual usage is lower when objectives measures of *actual usage* are used compared to subjective usage. However, the difficulty in assessing significance was affected by the small number of studies that used objective measures of *actual usage*.

4. Discussion

The following section discusses our results in the context of the research questions and in comparison to other secondary studies. It also discusses the limitations and threats to validity.

4.1. Limitations of the primary studies for SLRs

We found that many studies did not publish the full correlation matrices of relationships between variables but rather published results related to the specific model they were testing. However, given the relatively small number of studies that included *actual usage* measures, we preferred to include as many studies as possible rather than restricting ourselves to studies for which actual correlations were available. Therefore, the result was that only vote-counting meta-analysis could be conducted.

Secondary studies such as SLRs were not frequently conducted within the Software Engineering (SE) or Information Systems (IS) domains within the time period considered by this study (1989–2006). Therefore, it is unlikely that researchers would consider how their work could be used within a meta-analysis. However, we believe that in the future researchers should be encouraged to think about secondary studies, such as SLRs, when publishing primary studies, particularly as SLRs are becoming more frequent within SE and IS.

A further problem that we encountered was that some studies were reported in multiple publications and, in a number of cases, it was not immediately obvious. Therefore, it was necessary to undertake further screening in order to identify any studies that we had included in the review multiple times via different publications. Firstly, it was necessary to check all of the publications that reported studies with the same sample size and secondly to check any publications with the same author(s). The author comparison was important as it enabled us to discover any studies that were based on a subset of the same dataset, as the sample size comparison would not identify such studies. This meant that it was necessary to go through several iterations of study selection in order to select relevant publications and then again to remove those reporting the same study. The duplication of the same study across multiple publications was usually because each publication presented different results, i.e. different variations on the TAM or investigated similar issues but using a subset of the data. However, even if multiple publications report different results from a single dataset, for meta-analysis all of the results must be treated as being obtained from a single study [16]. Other literature reviews or secondary studies of the TAM have suffered from similar difficulties. For example, the reviews by Legris et al. [36] and King and He [31] included two publications by Taylor and Todd [49,50], suggesting that the reviews treated the two publications as separate studies when in fact they present different results based on the same dataset.

4.2. Research questions

Overall we found that PU and PEU are worse predictors of *actual usage* than BI, with PEU being significantly worse than BI. All TAM variables are worse predictors of objective usage than subjective usage. In all cases, the upper confidence limit of the number of significant correlations between PU and PEU and subjective and objective usage was less than 95% we would expect if PU or PEU were consistent predictors of *actual usage*. This implies the results are exhibiting heterogeneity and raises the issue of under what conditions PU or PEU are (or are not) good predictors.

It is worth noting that some of the findings of this review, particularly that BI is a better predictor of *actual usage* than either PU or PEU, may be due to the inherent relationship between the TAM variables within the model. For example, the original TAM (Fig. 1) includes connections between PU and BI and between BI and *actual usage*. Our review found that the associations between PU and BI and between BI and *actual usage* were strong (average proportions of success per study of 0.85 and 0.9, respectively). However, the association between PU and *actual usage* was less strong, with an average proportion of success per study of 0.75. Therefore in this case, a possible explanation is that PU explains part of the variation in BI and BI explains part of the variation in *actual usage*, but they could each explain a *different* part of the variation, meaning that it cannot be assumed that there is an association between PU and *actual usage*. This is consistent with our findings.

Although our third research question was intended to address possible heterogeneity, studies seldom reported contextual issues about their population or the systems being evaluated in a consistent manner. Therefore, we were unable to find sufficient evidence to look for any trends related to prior use of the technology, whether the technology was mandatory or whether the technology was generic or custom-built.

4.3. Comparison with related work

Our systematic literature review is very different from King and He's meta-analysis [31] or Schepers and Wetzels' meta-analysis [43]. King and He [31] produced effect sizes for the relationships among the three major TAM variables (PU, PEU and BI). Schepers and Wetzels [43] were interested in whether subjective norm or moderating factors affected relationships among the TAM variables. In contrast, we address the issue of whether the TAM variables are related to actual usage. These are very different research questions.

The difference between our reviews is clear when the two sets of primary studies are compared. In their references and further reading lists, King and He [31] identified 88 papers that they used in their review. A comparison of the studies that we included with those included by King and He [31] indicates that 31 papers were used as primary studies by both reviews. Our study included 42 primary studies not used by King and He [31], while King and He [31] used 57 primary studies that we did not. Thus, as might be expected, the difference in our research goals has resulted in different selections of primary studies.

The lack of overlap between our study and Schepers and Wetzels' study is even more pronounced [43]. There are only 12 papers in common. Thus, Schepers and Wetzels used 39 papers that we did not, and we used 61 papers that they did not. Again, the different research goals resulted in a different selection of primary studies.

Other reviews of the TAM have been based on far fewer studies than ours or the review by King and He [31]. Ma and Liu [39] based their meta-analysis on 26 empirical studies, Deng et al. [12] based their review on 21 empirical studies and Legris et al. [36] reviewed 22 empirical studies.

The review by Legris et al. [36] is closest to the objectives of our review in that Legris et al. investigates the relationship between the TAM variables and *actual usage*. In their review of 22 studies, Legris et al. [36] found that the TAM variables PU and PEU were worse predictors of *actual usage* than BI and, of the two variables, PU was a slightly better predictor. They found that direct relationships between PEU and PU and *actual usage* were not always recorded (relationships between *actual usage* and PEU were reported in only nine cases and between *actual usage* and PU in 13 cases). PU was associated with *actual usage* in eight cases and not associated in five cases, giving a proportion of 0.62 for PU predicting *actual usage*. PEU was associated with *actual usage* in four cases and not associated in five cases, giving a proportion of 0.44 of PEU predicting *actual usage*. The primary difference between the two reviews is in the methodology used. Our review was conducted systematically, utilising six digital libraries and following a pre-defined protocol. Also, the review by Legris et al. [36] covered studies published up to the first half of 2001, whereas our review covers papers published to the end of 2006. Thus, overall our results are reasonably similar although the results presented by Legris et al. [36] are slightly less favourable to the TAM than our results.

4.4. General limitations of the TAM

The TAM is not the end point of technology introduction. As noted by Dybå et al. [13], it is important to be aware that the TAM does not measure the benefit of using a technology. Technology is usually advocated in order to improve working practices in some way (e.g. by increasing productivity, quality or timeliness of products and services). Thus, measures of technology usage (subjective or objective) are themselves surrogates for measures of technology *value*. Technology adopters need to measure the impact of technology on work performance, by using measures of effectiveness or productivity, in order to assess the business value of a new technology.

4.5. Threats to validity

The primary threats to validity of this review are concerned with the search strategy employed. Firstly, it may be possible that we have not identified all relevant publications. The completeness of the search is dependent upon the search criteria used and the scope of the search, and is also influenced by the limitations of the search engines used [4]. A known set of references were used to validate the search terms, including the references used by Legris et al. [36], before undertaking the review and the search terms were amended where necessary. However, a number of papers were identified by searching the references of included studies that were indexed by the digital libraries but were not found with the search terms used in the review. The combination of electronic searching and the searching of the references of included studies, along with the use of search engines that index multiple primary sources, such as Google Scholar, should mean that all relevant papers have been identified. The identification of 'grey literature', however, may be more problematic due to the digital libraries and search engines used and the lack of available benchmarks to use for validation.

A further search-related limitation of the review is that the search only covers publications that were published before the end of 2006. The use of 2006 as an upper bound on the search string was because this was the year in which the review was conducted. It is therefore probable that a number of other relevant studies will have been published since 2006 that we have not included in this review. Further work is scheduled to conduct a search covering the years 2007–2009 in order to update the results of the review.

Publication bias is possibly a further threat to validity, in that we were primarily searching for literature available in the major computing digital libraries. It is possible that, as a result, we included more studies reporting positive results of the TAM as those publications reporting negative results are less likely to be published. Since we have been unable to undertake a formal meta-analysis, we are equally unable to undertake a funnel analysis to investigate the possible extent of publication bias.

5. Conclusions

Our study has extended Legris et al.'s [36] study of the relationship between TAM variables and actual usage. We have included data from 73 publications compared with their 22 and in addition we have looked at the impact of different ways of measuring actual usage, i.e. subjective and objective measures. Our study is also very different to the meta-analysis undertaken by King and He [31]. Their studies and ours have limited overlap in terms of primary studies and very different research goals. The following outlines the implications of the results of the review for future TAM studies (Section 5.1), and for future SLRs (Section 5.2).

5.1. Implications for the TAM

We found that relatively few papers considered objective measures of *actual usage* and when they did, sample sizes were relatively small. The use of subjective measures of *actual usage* probably occurs because it is much more difficult to measure *actual usage* objectively than it is to measure *actual usage* subjectively, due to the need to use computer-recorded forms of usage. However, our results have indicated that it is important to measure actual use objectively as there is a difference in the relationship between the TAM variables and subjective and objective measures of actual technology use. We therefore *recommend* that where possible researchers use objective measures of *actual usage*, including computer-recorded usage and system logs of information such as the number of log-ons to a system or the number of hits on a server.

Our results suggest that PU, and particularly PEU, are not as good at predicting actual technology use as BI. Furthermore, the associations were lower for objectively measured technology usage than for subjectively measured usage. It is important, therefore, that technology adopters (or researchers) using the TAM are aware that they may be measuring *perceived* use and not *actual usage*. As Straub et al. [46] point out, perceived use can influence morale, disposition and ultimately performance but the relationship is not as straightforward as the basic TAM model implies. This may be of particular importance if technology adopters want to use the TAM to evaluate *pre-prototype* systems as suggested by Davis and Venkatesh [11] as such assessments require measures of PU and PEU prior to actual use. We *recommend* that future research

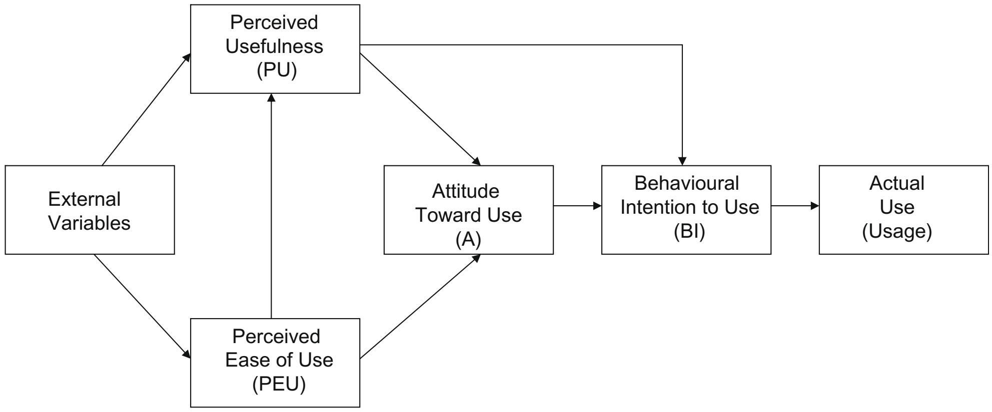

Fig. 1. The original TAM model.

The basic TAM Questionnaire

The specific name of the technology (e.g. the intranet) would replace "*the technology*" in a specific questionnaire.

Responses to statements are given on a Likert-like scale.

Perceived Usefulness Statements

Using *the technology* would improve my performance in doing my job
Using *the technology* at work would improve my productivity
Using *the technology* would enhance my effectiveness in my job
I would find *the technology* useful in my job

Perceived Ease of Use Statements

Learning to operate *the technology* would be easy for me
I would find it easy to get *the technology* to do what I want it to do
It would be easy for me to become skilful in the use of *the technology*
I would find *the technology* easy to use

Behavioural Intention to use

I intend to *use the technology* regularly at work

Fig. 2. The basic TAM questionnaire.

Table 1a
Search process documentation for ACM Portal.

Data source	Documentation
Digital library	*Name of digital library*: ACM Portal *Search strategy*: "Technology acceptance model" AND (Usage OR use OR empirical) *Search characteristic for digital library*: () allows for nested Boolean searches (X) allows only for simple Boolean searches (X) indexes full-text (X) indexes abstract (X) indexes title (X) indexes literature written in the following languages: English *Date, time and location of search*: 27/07/2005 10:00 am (preliminary search) 06/02/2006 09:00 am *Years covered by search*: 1989–2006

investigating the limits of the applicability of the TAM include usage measures and technology benefit measures.

Table 1b
Search process documentation for IEEE Xplore.

Data source	Documentation
Digital library	*Name of digital library*: IEEE Xplore *Search strategy*: ('technology acceptance model' ⟨and⟩ (usage ⟨or⟩ use ⟨or⟩ empirical) ⟨in⟩ (pdfdata, metadata)) ⟨and⟩ (pyr ⩾ 1989 ⟨and⟩ pyr ⩽ 2006) *Search characteristics for digital library*: (X) allows for nested Boolean searches () allows only for simple Boolean searches (X) indexes full-text (X) indexes abstract (X) indexes title (X) indexes literature written in the following languages: English *Date, time and location of search*: 27/07/2005 10:00 am (Preliminary search) 06/02/2006 09:00 am *Years covered by search*: 1989–2006

Our results have confirmed that PU and PEU are not as reliable indicators of usage as BI but we were unable to identify any factors that contribute to the accuracy (or otherwise) of PU and PEU as predictors of usage. We *recommend* that researchers report more contextual information about the technology being evaluated and the populations being sampled in future studies.

5.2. Implications for SLRs

When undertaking the screening of studies according to the inclusion and exclusion criteria of the review, we found that it was difficult to select studies to be included due to the fact that authors had, in some cases, published details of the same study in multiple publications. The result was that it was not possible to select the included studies with one round of screening and it was instead necessary to apply the inclusion and exclusion criteria first, and then to look more closely at the included studies to determine any duplicates. The same study was published in multiple publications largely because the authors had examined a different research goal using the same dataset, such as a variation on the TAM, or they examined similar themes but based on a particular subset of the data. However, a particular difficulty arose when different studies had used subsets of the same dataset *without* clearly referencing the publication in which the original study was reported. As detailed in Section 4.1, due to the lack of SLRs within the domain, authors are unlikely to consider how their studies could be used within a secondary study. There is evidence that this

Table 2
Data extraction form.

<table>
<tr><th>Reference number</th><th>Value</th></tr>
<tr><td>1. Reviewer name</td><td>Name of the reviewer conducting the data extraction</td></tr>
<tr><td>2. Title</td><td>Title of primary source material</td></tr>
<tr><td>3. Reference</td><td>The referencing application record identifier that contains the primary source reference data (i.e. a Reference Manager ID or reference to locate the paper within other bibliographic software)</td></tr>
<tr><td>4. Database</td><td>The name of the database where the primary study was found (i.e. Citeseer, ACM Portal, IEEExplore)</td></tr>
<tr><td>5. Type of TAM used</td><td>TAM, TAM2, modified (specify the modifications) or unknown</td></tr>
<tr><td>6. The validated technology
6a
6b
6c
6d</td><td>The technology that was validated by the TAM (or its revision) for its users' acceptance. Enter the following details:
<table>
<tr><td>The validated technology</td><td></td></tr>
<tr><td>Was the technology use mandatory? (Yes/No/Unknown)</td><td></td></tr>
<tr><td>Was the technology used for any length of time before the TAM study was conducted? (Yes/No/Unknown)</td><td></td></tr>
<tr><td>If the technology was used for any length of time prior to the TAM study, record the details (length of time etc.)</td><td></td></tr>
</table></td></tr>
<tr><td>7. Internal variables</td><td>Internal variables modelled in the study as being predictors for actual usage. As an example, for a basic TAM study the internal variables would be perceived ease of use (PEU), perceived usefulness (PU), attitude toward use (A) and behavioural intention to use (BI). PEU, PU and intention to use are the variables of particular importance to this review
<table>
<tr><td>Variable</td><td>Reported (Y/N)</td></tr>
<tr><td>PEU</td><td></td></tr>
<tr><td>PU</td><td></td></tr>
<tr><td></td><td></td></tr>
<tr><td></td><td></td></tr>
</table></td></tr>
<tr><td>8. Sample size

8a
8b
8c
8d</td><td>The size of the sample used in the empirical study
Identify the following, if available:
<table>
<tr><td>original sample size,</td><td></td></tr>
<tr><td>actual number of responses</td><td></td></tr>
<tr><td>response rate (response/sample size)</td><td></td></tr>
<tr><td>sets of sample (if any)</td><td></td></tr>
</table></td></tr>
<tr><td>9. Actual usage measure</td><td>Is the measure defined? Yes/No
If yes:
Definition of each actual usage measure, identifying whether or not it was self-assessed (subjective) or measured (objective)
Describe each measure
If several measures were taken at different times then give information concerning the times the measures were taken (disregard non-objective and non-subjective measures in the study)</td></tr>
<tr><td>10. Data transformation</td><td>Was the data transformed? Yes/no/unknown
If the data was transformed, specify what transformation was used</td></tr>
<tr><td>11. Correlations
11a
11b
11c
11d
11e</td><td>If reported in the paper, extract:
<table>
<tr><td></td><td>Value</td><td>Significance</td></tr>
<tr><td>Correlation between PEU and Actual Usage plus level of significance (Include the level of significance in brackets after the correlation value)</td><td></td><td></td></tr>
<tr><td>Correlation between PEU and Intention to Use plus level of significance</td><td></td><td></td></tr>
<tr><td>Correlation between PU and Actual Usage plus level of significance</td><td></td><td></td></tr>
<tr><td>Correlation between PU and Intention to Use plus level of significance</td><td></td><td></td></tr>
<tr><td>Correlation between Intention to use and Actual usage plus level of significance</td><td></td><td></td></tr>
</table></td></tr>
</table>

(*continued on next page*)

Table 2 (*continued*)

Reference number	Value
12a. Evaluation method other than correlation	Describe the method
	Report any statistics other than correlation that relate individual variables to actual usage
12b	Please note: – Ensure that the values relate to individual variables and their relationship to actual usage and do not include multiple variables. Linear regression values frequently correlate examine the relationship between multiple internal variables and actual usage and hence would not be useful for the review – For linear regression report the R^2 value but also report the R value (if shown in paper) as this can be used in a meta-analysis
12c	Was PU associated with actual usage (include the level of significance in brackets after the value)? Was the relationship only given in the presence of other variables? If so, report the other variables and the regression model used
12d	Was PEU associated with actual usage (level of significance)? Was the relationship only given in the presence of other variables? If so, report the other variables and the regression model used:
12e	Was PU associated with intention to use (level of significance)? Was the relationship only given in the presence of other variables? If so, report the other variables and the regression model used:
12f	Was PEU associated with intention to use (level of significance)? Was the relationship only given in the presence of other variables? If so, report the other variables and the regression model used Was intention to use associated with actual usage (level of significance)? Was the relationship only given in the presence of other variables? If so, report the other variables and the regression model used
13. Other	Any issue of importance not covered by the above A summary of the results of the study, or the results of statistical tests that are not covered by above sections of the form (i.e. correlations of multiple internal variables with usage), could be included in this section

Table 3
Digital library search figures.

Digital library	Relevant	Not relevant	Total	Percentage relevant (%)
ACM Portal	4	98	102	4.90
CiteSeer (searched through Google)	6	39	45	13.33
Google Scholar	36	1464	1500 (Google Scholar limits the number of results to 1500)	2.4
IEEE Xplore	13	217	230	5.65
Science Direct	27	229	256	10.54
ISI Web of Science (searched through Reference Manager)	43	142	185	23.24
Totals	129 (68 excluding duplicates)	2189	2318	

Table 4
Summary of numbers of studies and average proportions of success for studies associating TAM variables and *actual usage*.

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit	Standard error
PU	57	0.751	0.855	0.646	0.052
PEU	50	0.588	0.713	0.463	0.062
BI	35	0.9	0.998	0.802	0.043

Table 5
Summary of numbers of studies and average proportions of success for studies associating TAM variables and BI.

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit	Standard error
PU	33	0.848	0.97	0.727	0.06
PEU	20	0.733	0.925	0.541	0.092

Table 6
Summary of numbers of studies and average proportions of success for studies associating TAM variables and subjectively measured *actual usage*.

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit	Standard error
PU	51	0.776	0.886	0.667	0.055
PEU	43	0.631	0.77	0.493	0.069
BI	32	0.906	1	0.799	0.052

Table 7
Summary of numbers of studies and average proportions of success for studies associating TAM variables and objectively measured *actual usage*.

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit	Standard error
PU	9	0.532	0.889	0.175	0.155
PEU	8	0.414	0.746	0.081	0.141
BI	6	0.75	1	0.311	0.171

Table 8
Recalculated figures for the association between the TAM variables and subjectively measured *actual usage* (removing any studies that failed in the presence of other variables).

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit
PU	48	0.814	0.92	0.709
PEU	41	0.663	0.801	0.524
BI	31	0.935	1	0.844

Table 9
Recalculated figures for the association between the TAM variables and objectively measured *actual usage* (removing any studies that failed in the presence of other variables).

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit
PU	8	0.536	0.95	0.121
PEU	7	0.47	0.833	0.112
BI	6	0.75	1	0.311

Table 10
Sample size analysis for studies measuring the association between PU and subjectively measured technology usage.

	Number of studies	Mean sample size	Minimum sample size	Maximum sample size
Failed to predict	7	124.6	25	335
Mixed	6	105.7	61	192
Successful	36	274.4	31	1370

Table 11
Sample size analysis for studies measuring the association between PU and objectively measured technology usage.

	Number of studies	Mean sample size	Minimum sample size	Maximum sample size
Failed to predict	3	78.3	61	109
Mixed	2	51.5	43	60
Successful	3	86.7	52	116

Table 12
Sample size analysis for studies measuring the association between PEU and subjectively measured technology usage.

	Number of studies	Mean sample size	Minimum sample size	Maximum sample size
Failed to predict	13	213.3	63	458
Mixed	6	84.3	61	118
Successful	23	293.7	25	1370

Table 13
Sample size analysis for studies measuring the association between PEU and objectively measured technology usage.

	Number of studies	Mean sample size	Minimum sample size	Maximum sample size
Failed to predict	3	54.7	43	61
Mixed	3	91	65	116
Successful	1	109	n/a	n/a

Table 14
Summary of numbers of studies and average proportions of success for studies associating TAM variables and objectively measured *actual usage*, with studies by Davis et al. [11] removed.

TAM variable	Number of studies	Average proportion of successful tests per study	Upper 95% confidence limit	Lower 95% confidence limit
PU	7	0.398	0.805	0
PEU	6	0.302	0.719	0
BI	4	0.625	1	0

is changing however, and a recent review of SLRs within software engineering found that the number of SLRs had increased from six in 2004 to 15 in 2007 [33]. Therefore, we *recommend* that in the future researchers consider the bias that multiple publications based on the same dataset may have on secondary studies such as SLRs and clearly reference all preceding publications that used the same dataset.

We also found it difficult to extract quantitative information from all of the primary studies, primarily because many authors were only concerned about testing specific models of the interactions among variables than allowing for more general meta-analysis. Again, this is understandable due to the lack of awareness of secondary studies such as SLRs as a result of their relative scarcity in SE or IS publications. However, as SLRs become more frequently published, it would be useful if authors could take this into account when publishing. For example, by presenting the simple correlation matrix among all variables this would allow a variety of different meta-analyses to be performed and would not greatly increase the length of a paper. We *recommend* that in the future researchers consider that their study may be used within an SLR and publish the correlation matrix even if they are investigating a specific hypothesis in their own paper.

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Michael Rusca performed an initial literature review of the TAM as a Keele University undergraduate project and we used his work as a starting point for our study on this topic.

Appendix A. Included primary studies

In order to indicate what information was reported in each of the publications, the following key is used. The appropriate code(s) appears alongside each reference.

Key:

S = Subjectively-measured actual usage.
O = Objectively-measured actual usage.
m(n) = The publication reports data relating to multiple studies, where n is the number of studies. For example, if a publication reported data relating to three studies, the code m(3) would be used. If this code is not included, the publication only reports data relating to one study.
t(n) = The publication reports one study, but multiple non-independent tests (n). If a publication includes more than

one study, this code will appear once for each study, saying how many tests were in each study. If this code is not included, the publication only reports data relating to one test.
PU/PEU/BI = Used to indicate which of the TAM variables are reported in the publication. For example, if a publication reported only PU and PEU (but not BI) the code 'PU/PEU' would be used.

Achjari, D., and Quaddus, M. Roles of formal/informal networks and perceived compatibility in the diffusion of World Wide Web: the case of indonesian banks, in: Proceedings of the 36th Hawaii International Conference on System Sciences, IEEE Computer Society Press, 2003, pp. 188b.
Key: S, PU/PEU
Adams, D.A., Nelson, R.R, and Todd, P.A. Perceived usefulness, Ease of use, and usage of information technology: a replication, MIS Quarterly 16(2), (1992) 227–247.
Key: S, PU/PEU, m(2), t(3), t(6)
Ali, A.S.B., and Money, W.H. A study of project management system acceptance, in: Proceedings of the 38th Annual Hawaii International Conference on System Sciences (HICSS '05), IEEE Computer Society Press, 2005, pp. 234c.
Key: S, BI
Amoroso, D.L., and Guo, Y. An analysis of the acceptance of file sharing technologies by music consumers, in: Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS '06), IEEE Computer Society Press, 2006, pp. 115b.
Key: S, PU/PEU/BI (PU/PEU measured to BI only)
Agarwal, R., and Prasad, J. The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies, Decision Sciences 28(3), (1997) 557–582.
Key: S, PEU
Bajaj, A., and Nidumolu, S.R. A feedback model to understand information system usage, Information and Management, 33(4), (1998) 213–224.
Key: S, PU/PEU
Brosnan, M.J. Modeling technophobia: a case for word processing, Computers in Human Behavior 15(2), (1999) 105–121.
Key: S, PU/BI
Burton-Jones, A., and Hubona, G.S. Individual differences and usage behavior: revisiting a technology acceptance model assumption, SIGMIS Database 36(2), (2005) 58–77.
Key: S, PU/PEU, t(4)
Chau, P.Y.K. An empirical investigation on factors affecting the acceptance of CASE by systems developers, Information and Management 30(6), (1996) 269–280.
Key: S, PEU
Chen, L.D., Gillenson, M.L., and Sherrell, D.L. Enticing online consumers: an extended technology acceptance perspective, Information and Management 39(8), (2002) 705–719.
Key: S, PU/BI (PU measured to BI only)
Chen, N.-S., Huang, H.-Y., and Shih, Y.-C. Factors affecting usage of Web-based teachers' training in elementary and high school, in: Proceedings of the International Conference on Computers in Education, 2002, pp. 589–592.
Key: S, PU
Cheng, J.M.S., Sheen, G.J., and Lou, G.C. Consumer acceptance of the internet as a channel of distribution in Taiwan – a channel function perspective, Technovation 26(7), (2006) 856–864.
Key: S, PU/BI (PU measured to BI only), t(3)
Cheung, W., and Huang, W. Proposing a framework to assess Internet usage in university education: an empirical investigation from a student's perspective, British Journal of Educational Technology 36(2), (2005) 237–253.
Key: S, PU/PEU
Dasgupta, S., Granger, M., and McGarry, N. User acceptance of e-collaboration technology: an extension of the technology acceptance model, Group Decision and Negotiation, 11(2), (2002) 87–100.
Key: O, PU/PEU, t(2)
Davis, F. Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Quarterly 13(3), (1989) 319–340.
Key: S, PU/PEU, m(2), t(3), t(3)
Davis, F.D., Bagozzi, R.P., and Warshaw, P.R. User acceptance of computer technology: a comparison of two theoretical models, Management Science 35(8), (1989) 982–1003.
Key: S, PU/BI, t(2)
Davis, F.D., and Venkatesh, V. Toward pre-prototype user acceptance testing of new information systems: implications for software project management, IEEE Transactions on Engineering Management 51(1), (2004) 31–46.
Key: O, PU/PEU/BI, m(2), t(6), t(6)
De Vos, H., Ter Hofte, G.H., and De Poot, H. IM@Work. Adoption of instant messaging in a knowledge worker organisation, in: Proceedings of the 37th Annual Hawaii International Conference on System Sciences (HICSS '04), IEEE Computer Society Press, 2004, pp. 10019a.
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Dishaw, M.T., and Strong, D.M. Extending the technology acceptance model with task-technology fit constructs, Information and Management 36(1), (1999) 9–21.
Key: S, PU/BI
Dybå, T., Moe, N.B., and Arisholm, E. Measuring software methodology usage: challenges of conceptualization and operationalization, in: Proceedings of the International Symposium on Empirical Software Engineering (ISESE'05), IEEE Computer Society Press, 2005, pp. 447–458.
Key: O, PU/PEU, t(4), (Analysis conducted as one study with Dybå et al. (2004)).
Dybå, T., Moe, N.B., and Mikkelsen, E.M. An empirical investigation in factors affecting software developer acceptance and utilization of electronic process guides, in: Proceedings of the 10th International Symposium on Software Metrics (METRICS'04), IEEE Computer Society Press, 2004, pp. 220–231.
Key: S, PU/PEU/BI, t(4), (Grouped with Dybå et al. (2005) and counted as one study for analysis).
Gefen, D., and Keil, M. 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) 35–49.
Key: S, PU/PEU
Gefen, D., and Straub, D.W. Gender Differences in the perception and use of e-Mail: an extension to the technology acceptance model, MIS Quarterly 21(4), (1997) 389–400.
Key: S, PU/PEU
Ghorab, K.E. The impact of technology acceptance considerations on system usage, and adopted level of technological sophistication: an empirical investigation, International Journal of Information Management 17(4), (1997) 249–259.
Key: S, PU/PEU
Green, G.C., Hevner, A.R., and Collins, R.W. The impacts of quality and productivity perceptions on the use of software process improvement innovations, Information and Software Technology 47(8), (2005) 543–553.
Key: S, PU/PEU
Green, C.W. Normative influence on the acceptance of information technology – measurement and effects, Small Group Research 29(1), (1998) 85–123.
Key: S, PU/PEU

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Key: S, PU/PEU/BI (PU and PEU only measured to BI)

Henderson, R., and Divett, M.J. Perceived usefulness, ease of use and electronic supermarket use, International Journal of Human–Computer Studies 59(3), (2003) 383–395.
Key: O, PU/PEU, t(21)

Hendrickson, A.R., and Collins, M.R. An assessment of structure and causation of IS usage, ACM SIGMIS Database 27(2), (1996) 61–67.
Key: S, PU/PEU

Horton, R.P., Buck, T., Waterson, P.E., and Clegg, C.W. Explaining intranet use with the technology acceptance model, Journal of Information Technology 16(4), (2001) 237–249.
Key: S/O (1 study subjective, 1 study objective), PU/PEU/BI, m(2), t(1), t(4)

Huang, W., D' Ambra, J., and Bhalla, V. An empirical investigation of the adoption of eGovernment in Australian citizens: some unexpected research findings, Journal of Computer Information Systems 43(1), (2002) 15–22.
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Hung, S.Y., and Chang, C.M. User acceptance of WAP services: test of competing theories, Computer Standards and Interfaces 27(4), (2005) 359–370.
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Key: S, PU/PEU, t(3)

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Key: S, PU/PEU

Szajna, B. Empirical evaluation of the revised technology acceptance model, Management Science 42(1), (1996) 85–92.

Key: S/O, PU/PEU/BI, t(2)

Taylor, S., and Todd, P.A. Understanding Information Technology Usage – a test of competing models, Information Systems Research 6(2), (1995a) 144–176.

Key: S, PU/BI (PU only measured to BI), t(3), (Same study as Taylor & Todd, 1995b)

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Key: S, PU

Appendix B

See Figs. 1 and 2, Tables 1a, 1b, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14.

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