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Research

Extending the technology acceptance model with task–technology fit constructs

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Abstract

During the past decade, two significant models of information technology (IT) utilization behavior have emerged in the MIS literature. These two models, the technology acceptance model (TAM) and the task–technology fit model (TTF), provide a much needed theoretical basis for exploring the factors that explain software utilization and its link with user performance. These models offer different, though overlapping perspectives on utilization behavior. TAM focuses on attitudes toward using a particular IT which users develop based on perceived usefulness and ease of use of the IT. TTF focuses on the match between user task needs and the available functionality of the IT. While each of these models offers significant explanatory power, a model that integrates constructs from both may offer a significant improvement over either model alone. We discuss the theoretical foundation of both these models and present a theoretical rationale for an integrated model. The result is an extension of TAM to include TTF constructs. We test our integrated IT utilization model using path analysis. Our integrated model provides more explanatory power than either model alone. Research using the integrated model should lead to a better understanding of choices about using IT. © 1999 Elsevier Science B.V. All rights reserved.

Keywords: Technology acceptance model; Task–technology fit; TAM; TTF; Software utilization

1. Introduction

While information technology (IT) utilization studies are common in the MIS literature [13, 38], early studies lacked a strong theoretical foundation. Two significant models have emerged which provide a strong theoretical base for studies of IT utilization behavior. The first model, the technology acceptance model (TAM) [10], is well known and widely accepted in the MIS literature. The second model, the task–technology fit model (TTF) [22, 23], addresses utilization from a different, although not entirely orthogonal, perspective.

We believe that TAM and TTF overlap in a significant way and, if integrated, could provide an even stronger model than either standing alone. Both these models were developed to understand users' choices and evaluations of IT. The outcome variable for both, TAM and TTF, is the actual use of IT or a related variable. Applications of TAM usually focus early in the outcome chain on intention to use or actual use, whereas TTF applications focus later in the outcome

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chain on actual use or individual performance attributable to actual use.

The objective of this research is to develop and evaluate an integrated TAM/TTF model. To accomplish this objective, we examine the theory underlying TAM and TTF and assess their similarities and differences, which provides the theoretical foundation for our integrated TAM/TTF model. We empirically compare the three models, TAM, TTF, and TAM/TTF, using the same set of data collected in several organizations. Our results indicated that adding TTF constructs to TAM explains significantly more of the variance in utilization than either TAM or TTF alone.

An integration of TAM and TTF will be useful in understanding software utilization in a broader variety of circumstances, which is extremely important for software authors and managers of the software users. They need to understand how the customers and end-users of software actually choose to use or not use certain functions. The key to understanding software use decisions lies in understanding how the functions provided by the software fit the perceived needs of the user.

2. Modeling information technology utilization

2.1. The technology acceptance model (TAM)

The technology acceptance model [10, 12], in Fig. 1, is a specific adaptation of the theory of reasoned action (TRA) model [4, 20] to the study of IT usage. The TRA and its successor, the theory of planned behavior (TPB) [2], are well known, and have been widely employed in the study of specific behaviors [4]. In general, these theories (TRA, TAM) state

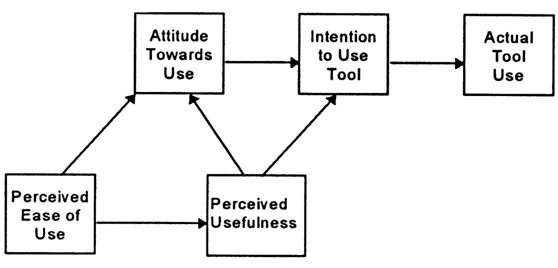

Fig. 1. Technology acceptance model (TAM).

that a behavior is determined by intention to perform the behavior. Actual behavior and intention have been found to be highly correlated [10, 20]. Intention, itself, is determined by attitude toward the behavior.

Davis' research, in essence, examines the external variables which determine or influence attitude toward IT use. The TAM identifies perceived ease of use, and perceived usefulness as key independent variables. Perceived usefulness is also influenced by perceived ease of use. The TAM includes the very important assumption that the behavior is volitional, which is to say voluntary or at the discretion of the user. The TAM has been tested in several studies of IT use [1, 12, 29, 32].

TAM differs from TRA in two key ways. First, it specifies usefulness and ease of use as the two external variables or beliefs that determine attitude toward an IT, intention to use, and actual use. Thus, TAM does not need to be tailored to each behavior, as long as that behavior is use of IT. Second, TAM does not include the subjective norms construct in TRA. Subjective norms, along with attitude, account for intention to perform a behavior in TRA. For TAM, the subjective norms construct has not been significant [12, 29]. One possible explanation is the use of students in many of the tests of TAM; subjective norms may be more important in an organizational setting [36]. Since we have data from an organizational setting in which users may feel some social pressure to use the IT, we test the significance of subjective norms.

The theory of planned behavior (TPB) [2, 3, 5], an extension of TRA, includes behavioral control as a construct to measure and account explicitly for the extent to which users have complete control over their behaviors, that is, the extent to which the behavior is truly at the discretion of the user. TAM does not include the behavioral control construct. In TPB, behavioral control directly affects intention to perform a behavior, and may directly affect behavior in situations where the user intends to perform the behavior, but is prevented from doing so [2]. Whether behavioral control is significant depends on the particular behavior. For example, behavioral control was important in accounting for whether students intended and actually received an 'A' in a course, but not for whether students attended classes [5].

For IT usage behavior, behavioral control has had limited importance. Comparisons between TAM and

TPB have largely concluded that TAM's ability to account for variance in intention to use or in actual use is about the same as TPB's [29, 36]. Like subjective norms, the reason for this lack of effect could be the use of students in comparing the models. Since we collected data from firms, we test whether the addition of behavioral control improves TAM. We expect behavioral control to have some, but minor, significance as compared to the other variables in TAM. In the organizations we studied, use is voluntary. The information technologies we studied are tools that software maintainers may use, but do not need to use, to complete their maintenance tasks. While management in these organizations invested heavily in advanced support tools for maintainers, maintainers generally complete their maintenance tasks in the way they deem most effective. Such voluntary use at the individual level is common with CASE tools [9].

In summary, TAM represents the tailoring of a well-developed social psychology theory, the TRA [19], to the specific behavior of using IT, by defining and developing measures for two variables, usefulness and ease of use [10, 11, 12]. The choice of these two variables is consistent with previous empirical research in several MIS-related disciplines [11]. TAM has also been tested and compared to revisions of TRA by several authors independent of the original developers of TAM.

A weakness of TAM for understanding IT utilization is its lack of task focus. IT is a tool by which users accomplish organizational tasks. The lack of task focus in evaluating IT and its acceptance, use, and performance contributes to the mixed results in IT evaluations [23]. While TAM's usefulness concept implicitly includes task, that is to say usefulness means useful for something, more explicit inclusion of task characteristics may provide a better model of IT utilization. The task–technology fit perspective addresses this problem.

2.2. *Task–technology fit model*

The ability of IT to support a task is expressed by the formal construct known as task–technology fit (TTF), which implies matching of the capabilities of the technology to the demands of the task [23]. TTF posits that IT will be used if, and only if, the functions available to the user support (fit) the activities of the user (see Fig. 2). Rational, experienced users will choose those tools and methods that enable them to complete the task with the greatest net benefit. Information technology that does not offer sufficient advantage will not be used.

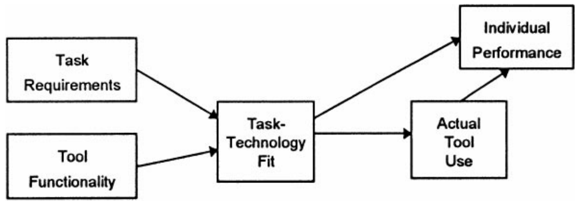

Fig. 2. A basic task–technology fit (TTF) model.

In contrast to TAM, TTF, as a theoretical and measurable MIS construct and as part of a model of IT utilization and performance, is still evolving. The basic ideas of TTF and models built around it are shown in Fig. 2, which is one TTF model that has been tested [23]. Since other versions of TTF-based models exist[2], the model shown in Fig. 2 should not be interpreted as the 'TTF model'. For example, utilization is a recent addition to the technology to performance chain [23]. Earlier TTF models employed individual performance as the only outcome variable because these models were developed from work adjustment theory which does not include a construct for behaviors, such as utilization.

A common addition to a TTF model is individual abilities [21, 23]. The inclusion of individual abilities is supported by both, work adjustment theory from which TTF was originally derived and recent MIS studies in which experience with particular IT is generally associated with higher utilization of that IT [24, 37]. In tests of TTF models, individual abilities, operationalized as computer literacy, negatively affected perceived fit between task and technology [22] and, operationalized as experience with the particular IT, positively affected utilization [17].

Although TTF is relatively new in the MIS literature, the concept of fit, also called correspondence or matching, is common in organizational theories. For example, the theory of work adjustment, from which TTF was originally developed, considers the correspondence between the abilities of an individual and the ability requirements of a job in determining an

[2]See Refs. [22, 23] for a review of TTF and related models.

individual's satisfactoriness for the job [21, 23]. Research on strategic fit, which is the correspondence between an organization and its environment, has influenced the methods for computing TTF [18, 22, 40].

The general concept of fit has appeared in the MIS literature. For example, research on data representation, such as tables and graphs, has concluded that the best representation depends on task requirements [35]. Systems implementation research notes the need for fit between tasks, technologies, and users [30]. Data quality research emphasizes the need for data to fit the needs of user tasks [16, 33, 34]. Research on problem solving and problem representation has developed the concept of cognitive fit, which means that problem solving works best when the problem representation and any tools or aids all support the processes required to perform that task [42, 43].

We test the TTF model shown in Fig. 3. Since we are focusing on models of IT utilization, utilization is our only outcome variable. Like the basic TTF model shown in Fig. 2, task and technology characteristics are the antecedents of TTF. We also test for direct effects of task and technology characteristics on utilization (the dotted lines in Fig. 3). Tool experience, representing individual abilities, is expected to directly affect utilization.

While TTF models explicitly include task characteristics, which is a weakness of TAM, they do not explicitly include attitudes toward IT, which is the core of TAM. Rather than arguing for TTF as an alternative to TAM, we propose adding the strengths of TTF models to TAM to produce an integrated model incorporating both attitudes toward IT and the fit between IT functionality and the characteristics of the tasks that IT users are accomplishing with IT.

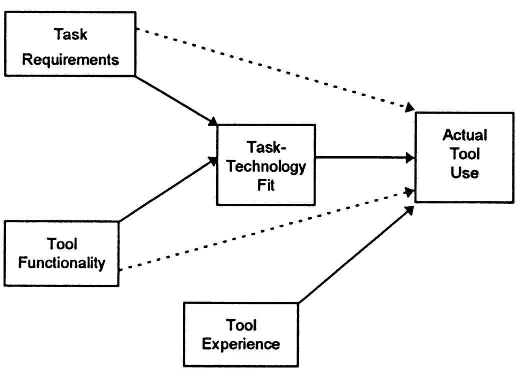

Fig. 3. TTF model.

2.3. Integration of the TAM and the task–technology fit model

A justification for elaborating the TAM to include explicit references to task and technology is provided by the arguments of Goodhue [21, 22]. Goodhue linked his TTF model with the technology usage model of Bagozzi [7], which, like TAM, was developed from attitude/behavior models to explain technology utilization. The general argument for combining the models is that they capture two different aspects of users' choices to utilize IT. TAM, and the attitude/behavior models on which it is based, assume that users' beliefs and attitudes toward a particular IT largely determine whether users exhibit the behavior of utilizing the IT. Critics note that users regularly utilize IT that they do not like because it improves their job performance. TTF models take a decidedly rational approach by assuming that users choose to use IT that provides benefits, such as improved job performance, regardless of their attitude toward the IT [22]. Both aspects, attitude toward the IT and rationally determined expected consequences from using the IT, are likely to affect users' choices to utilize IT. That is, combining the two models is likely to provide a better explanation of IT utilization than either an attitude or a fit model could provide separately.

We posit that constructs in the TTF model determine, in part, three variables in the TAM. TTF constructs are expected to directly affect utilization, as they do in TTF models. TTF constructs may also determine, in part, TAM's two determinants of attitude toward IT, namely *perceived usefulness* and *perceived ease of use*. User beliefs about usefulness and ease of use are likely to be developed, in part, from rational assessments of the characteristics of the IT and the tasks for which it could be used. In addition, these two TAM variables indirectly include aspects of the technology and the task for which the technology could be used. For example, the whole notion of usefulness implies that the software is useful for something. The proposed integrated TAM/TTF model is shown in Fig. 4.

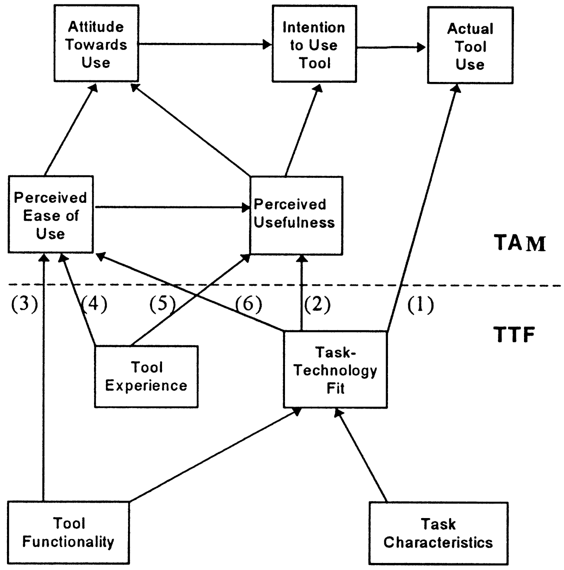

Fig. 4. Integrated TAM/TTF model.

The integrated model has six paths, labeled (1)–(6) in Fig. 4, connecting the TTF model to the TAM. As in TTF models, the TTF construct is expected to directly affect utilization (Fig. 4, Path (1)). While direct paths from task characteristics and tool functionality to utilization are not shown in the integrated model, these will be tested if they hold in the TTF model when tested by itself.

If only Path (1) was included in the integrated model, we would be assuming that the two models are independent. Attitude/behavior models, however, assume that attitudes are developed from beliefs, which in the case of TAM are perceived usefulness and ease of use [4, 11]. These beliefs, in turn, are developed from knowledge. Specifically, we learn which behaviors are associated with favorable consequences [3]. Our integrated model posits that this knowledge comes from rational assessments of task characteristics and tool functionality, their resulting fit, and from experiences with the technology.

Paths (2)–(4) represent our primary hypotheses about how rationally developed task and technology assessments affect user beliefs about the usefulness and ease of use of the IT. These links are reasonable because the underlying assumption in the TRA family of models, including TAM, is that a person engages in a behavior because he or she has evaluated the benefits of engaging in that behavior and expects a certain result. Specifically, we believe that TTF determines, in part, *perceived usefulness* (Path (2)). This path follows directly from the definitions of TTF and *perceived usefulness* [22, 23]. That is, if the technology provides a good fit with the task, users should perceive that the technology is useful for that task.

Perceived ease of use of an IT should be determined, in part, by the functionality available in the tool (Path (3)) and by the user's experience with the tool (Path (4)). Specifically, tools with more functionality are likely to be harder to use. As users acquire more experience with the tool, however, the tool becomes easier for them to use. While the TTF model includes tool experience as a direct effect on IT utilization, the integrated model assumes that this effect actually works through perceived ease of use. Although there is no direct effect of tool experience in the proposed integrated model, we will check empirically for the direct effect to test this assumption.

In TAM, there is a relationship between *ease of use* and *usefulness* [11]. *Usefulness* is influenced somewhat by *Ease of Use*. Since TTF includes aspects of both task and technology, TTF may also determine, in part, *perceived ease of use*. Similarly, increased experience with the IT may lead to increased perceived usefulness as the user develops an understanding of how the functionality of the IT can be used to accomplish tasks. While paths (5)–(6) are not the key paths linking TTF with TAM, they are expected to provide some explanatory power.

3. Method

3.1. Subjects

The subjects for the study were working programmer analysts completing maintenance projects in three Fortune 50 firms. These were established firms that were leaders in their respective industries: financial services; aerospace manufacturing; and insurance. All had large MIS applications groups who expended a large proportion of their annual budgets on software maintenance. The organizations were located in different geographic regions of the United States. Their information systems environments were all based on IBM 3090 mainframes running MVS COBOL/CICS applications. The software application groups' budget in each firm was dominated by software maintenance costs. The installed program base consisted of hundreds of COBOL programs with over 100 million lines in each organization. Each organization in the study provided similar, although not entirely identical, maintenance support tools to their programmers. The maintenance projects included in the study were from the existing maintenance backlog.

3.2. Data collection procedures

The TAM and TTF variables were collected using questionnaires administered to maintenance programmers. The questionnaires were pre-tested with working programmers, which resulted in removing some unclear questions and re-wording others. Using the revised questionnaires, a pilot study was conducted with one maintenance group who reported on ten projects. The data collection procedures used in this research were previously used in a study of software development teams in which software developers in several organizations completed multiple questionnaires about characteristics of their software development projects [24, 25]. No problems were encountered during the pilot study. The pilot projects are not included in the analyses reported in this paper.

At the start of the full study, all participating programmers answered questions about their background and experience, as well as questions about the capabilities of the maintenance support software tools. Before the start of a project, the programmer also answered questions about his or her intention to use software maintenance support tools during the project, attitude toward use of these tools, perceived usefulness of the tools, and perceived ease of use for the tools. After a project was completed, the programmer completed questions about actual tool use and the actual task characteristics.

3.3. Operationalization and measurement of variables

As much as possible, the questionnaire items for each variable were taken or modified from previous studies. The sources of items for each variable are described below. The actual items used to measure each variable, with its Cronbach α, are listed in Appendix A.

3.3.1. Technology acceptance model (TAM) variables

TAM is a well-established model with published questionnaire items for each variable. The published items for intention to use, attitude toward use, perceived ease of use, and perceived usefulness [11] were used directly with only minor changes to reflect the tools being used.

3.3.2. Task–technology fit (TTF) model variables

For the TTF model, task–technology fit is computed by matching characteristics of a maintenance task to supporting functionality in a software maintenance tool, using an interaction approach [18, 40]. Such an approach is common in the strategy literature (see, e.g. Refs. [26, 28, 31]). An example of this type of fit model in the task literature is found in Ref. [39].

A model of maintenance task activity [41] and a model of CASE tool functionality [27] provide the dimensions on which to compute fit. Maintenance task activities include planning, knowledge building, diagnosis, and modification. Respondents reported the relative frequency of each type of activity on a 1–7 Likert scale. From the model of CASE technology [27], we focused on the production dimension, which includes functionality for representation, analysis, and transformation. The tool-functionality questions were designed to elicit, a priori, the functionality anticipated by the programmer to be available in the tool to complete the maintenance project. The programmer assessed the functions available in the software tools on a 1–7 Likert scale.

From the task characteristics reported for the maintenance project and the functionality reported to exist in the maintenance tools, we computed TTF. Further details of this computed TTF approach are described in Refs. [14, 18]. While TTF has been operationalized in the form of user perceptions [21, 22], the computed approach more directly corresponds to the definition of task–technology fit as the matching of the capabilities of the technology to the demands of the task.

Tool experience was operationalized using three questions that measured experience level, prior level of use, and prior hours of use, for each of the tools used. These variables were combined into a tool experience factor. Each of these variables is a composite; computed as the mean of the values reported for several tools. Finally, these composite variables are combined in the factor tool experience by taking the sum of the normalized scores for each variable.

3.3.3. *Tool utilization*

The tool-utilization construct is operationalized with questions that assess the amount of time spent using the tool using a seven-point, Likert scale [24, 25]. These questions were asked for each tool used by programmers. We excluded a small number of tools, such as the language compiler, that are required for the completion of a maintenance task under all circumstances. The dependent variable, *tool use*, is computed as the mean of the use levels of each maintenance tool reportedly used by the programmer for a particular project.

3.4. *Data analysis*

The data for the analyses are from 60 maintenance projects collected from the three organizations. Each variable was formed by averaging the responses to the relevant items in the questionnaires (see Appendix A for means and standard deviations of the variables). All variables have sufficient reliability (see Appendix A for reliability statistics).

We examined our integrated model using path analytic techniques [8], specifically the AMOS package in SPSS for Windows [6]. Input was the covariance matrix. Before testing our integrated model, we first tested that the TAM and the TTF model hold for our data. For each model, we added direct links between independent and dependent variables so that we were not forcing only the indirect links from the underlying theory. Any direct links that held in the individual TAM and TTF models are also included in the integrated model.

4. Results

4.1. *Technology acceptance model*

A path analysis of the TAM (see Fig. 5) shows acceptable fit to the data ($X^2 = 4.6$, df $= 4$, $p = 0.33$, AGFI $= 0.89$). The direct path from ease of use to attitude is not shown because the path weight is near zero. Previous studies have also found the direct effect of ease of use to be weak [1, 11]. A direct effect from *perceived usefulness* to *utilization*, in addition to the indirect effects in TAM, also provides some explanatory power.

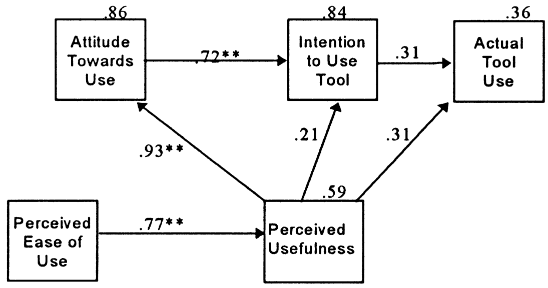

Fig. 5. TAM path analysis ($^{**} = 0.01$, $^{*} = 0.05$).

The amount of variance in the dependent variable, utilization, explained by this model was 36%. The total effects on utilization were 0.52 for usefulness, 0.44 for ease of use, 0.27 for intention, and 0.20 for attitude. These results are similar to other recent tests of the TAM (e.g. accounting for 34% of the variance in utilization, 52% variance in intention, and 73% variance in attitude with an AGFI $=$ 0.84 [36]).

We also tested TAM with subjective norms (used in TRA and TPB) and behavioral control (used in TPB). The link from subjective norms to intentions was near zero (-0.06). The links from behavioral control to intention (0.20) and to utilization (0.13) were higher, but the model fit was much worse (AGFI $= 0.40$), the variance accounted for in usage was lower (0.34 instead of 0.36), and the total effect of behavioral control on usage was low (0.16). Thus, adding subjective norms or behavioral control to TAM was not an improvement over the basic TAM. These results are supported by previous research that compared TAM and TPB [29, 36]. Since our data is from professionals rather than students, these results do not support the conjecture that the lack of significance of subjective norms is attributable to an artificial student environment. Our results provide further evidence that subjective norms are not important in understanding individual choices to use IT.

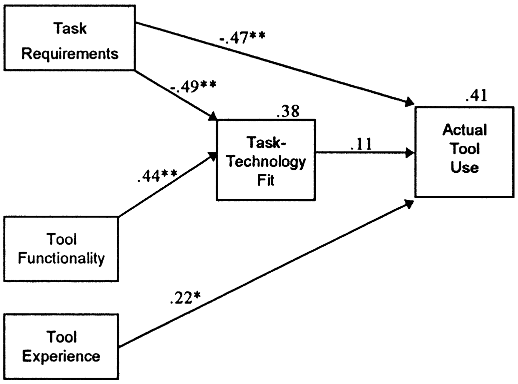

Fig. 6. TTF path analysis ($^{**}=0.01$, $^{*}=0.05$).

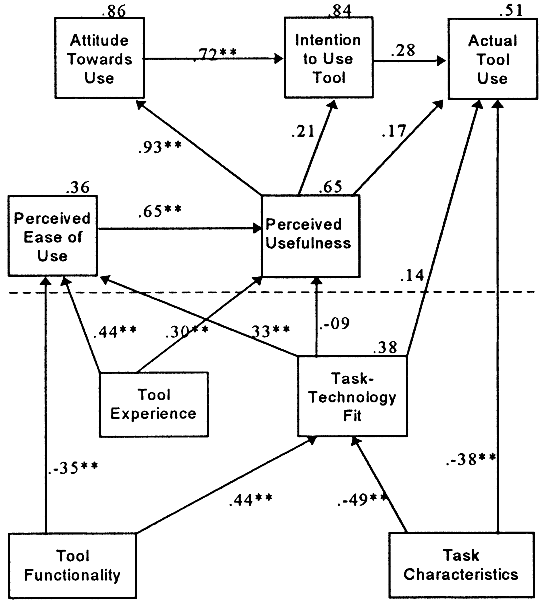

Fig. 7. Integrated path model ($^{**}=0.01$, $^{*}=0.05$).

4.2. Task–technology fit model

A path analysis of the TTF model (see Fig. 6) shows acceptable fit to the data ($X^2 = 0.12$, df $= 1$, $p = 0.73$, AGFI $= 0.99$). The amount of variance in the dependent variable, utilization, explained by this model was 41%, which is somewhat higher than the variance accounted for by TAM. The total effects on utilization were -0.69 for task requirements, 0.17 for task-technology fit, and 0.13 for tool experience.

The negative relationship between task and TTF is supported by previous research [22, 23]. Fit decreases as task requirements increase; that is, tasks can become too large and complex for IT to provide adequate support. The positive relationship between technology and TTF is also supported by previous research [22, 23]. As IT functionality increases, fit increases.

The strong direct effect of task characteristics on utilization contrasts with the lack of effect of tool functionality. The path from tool functionality to utilization is not shown because the path weight is near zero. A stronger effect for task, as compared to tool, characteristics is consistent with previous research [22, 23]. These results can be interpreted to mean that task requirements together with the fit between the task requirements and the technology functionality drive IT utilization. As expected, experience with the IT is positively, and directly, associated with utilization.

4.3. Integration of TAM and the task–technology fit model

The integrated path model (see Fig. 7) shows acceptable fit to the data ($X^2 = 19.8$, df $= 18$, $p = 0.34$, GFI $= 0.94$, AGFI $= 0.84$). The amount of variance in the dependent variable, utilization, explained by this model was 51%, which is higher than the variance accounted for by either TAM or TTF alone. The total effects on utilization were -0.61 for task requirements, 0.37 for usefulness, 0.29 for task–technology fit, 0.26 for ease of use, 0.25 for intention to use, 0.18 for attitude toward the tool, and 0.15 for tool experience.

There are seven paths between the TTF constructs and TAM, the six hypothesized and a seventh direct link between task characteristics and utilization that held in the TTF model. Six of these seven links have path weights as expected. The exception is the weak link between TTF and perceived usefulness.

As in the TTF model, there are direct effects of TTF and task characteristics on utilization of approximately the same strengths as in the TTF model. As expected, perceived ease of use of an IT tool is affected by the functionality of the tool and the individual's experience with the tool. More experience is associated with higher ease of use, while more tool functionality is associated with lower ease of use.

In addition to the strong effect of tool experience on perceived ease of use, tool experience is also associated with perceived usefulness. As expected, more experienced users are better able to see the usefulness of the tool. When a direct path from tool experience to utilization was added, as in the TTF model tested, the link was near zero.

Perceived ease of use is also affected by TTF, that is, when fit between the task and the tool is higher, users perceive the tool to be easier to use for that task.

An unexpected result is the lack of a direct path between TTF and perceived usefulness. The correlation between these two variables is low (0.21) and not significant, which supports the path analysis results. From a theoretical view, this was expected to be a strong association; good fit between the functionality of the tool and the characteristics of the task should be interpreted by a user as high perceived usefulness of the tool for that task. We did note a significant indirect path between TTF and perceived usefulness, mediated by perceived ease of use. In other words, the tool may be perceived to be useful only if it is also perceived to be easy to use.

Table 1
Comparison of the three models

	TAM	TTF	Integrated
Utilization variance explained	36%	41%	51%
X^2/df (closer to 1 is better)	1.15	0.12	1.10
p (not significant is better)	0.33	0.73	0.34
GFI (above 0.9 is good fit)	0.97	0.99	0.94
AGFI (above 0.8 is good fit)	0.89	0.99	0.84
RMSEA (0.05 or less is better)	0.05	0.00	0.04
Total effects on utilization from:			
perceived usefulness	0.52		0.37
perceived ease of use	0.44		0.26
task–technology fit		0.17	0.29
task characteristics		−0.69	−0.61
tool experience		0.13	0.15
intention to use	0.27		0.25
attitude	0.20		0.18

5. Discussion

Given the above results, does extending TAM with TTF constructs provide better and more useful results than TAM alone? Table 1 summarizes the results from the evaluations of the three models. Overall, the answer to this question is yes. The integrated model explains much more of the variance in the dependent variable, utilization, than did either TAM or TTF alone. The improvement in variance explained is significant at 0.05 for both the cases. That is, adding TTF constructs to TAM is a significant improvement (a change from 36% to 51%, which is significant at 0.025), as is adding TAM to TTF (a change from 41% to 51%, which is significant at 0.04). Furthermore, six of the seven paths between the TTF model and the TAM produced path weights as expected. Only one, the lack of a direct path between TTF and perceived usefulness, was not expected.

TAM, by itself, is an excellent model. It is internally sound and based directly on well-tested attitude/behavior models. Tests of TAM have consistently produced similar results. TAM, however, does have some weaknesses. While TAM provides excellent explanation of intention to use, it is much weaker for actual use. The TPB hypothesizes that a behavioral-control construct may explain cases in which attitude does not adequately account for intention or actual behavior. For IT utilization, however, this explanation does not hold. Tests of TPB vs. TAM have consistently shown approximately equal explanatory power.

In the integrated model, TAM's two independent variables, namely perceived usefulness and perceived ease of use, are still important contributors to explaining utilization (total effects of 0.37 and 0.26 rather than 0.52 and 0.44 in TAM). Task characteristics, however, provide the strongest total effect (−0.61). TTF has a stronger effect (0.29) than does perceived ease of use (0.26). The result of the integrated model is more variance explained (51% rather than 36% in TAM) and this variance is explained by perceived usefulness, perceived ease of use, task–technology fit, task characteristics, and tool experience rather than only perceived usefulness and perceived ease of use in TAM. The total effects from intention to use and from attitude are approximately the same in the integrated model as in TAM.

TAM's weaknesses for understanding IT utilization may be primarily attributable to its lack of explicit inclusion of task characteristics and how well the IT meets the requirements of that task. This weakness may be especially apparent in our data because software maintenance is a difficult task. Software maintenance is much more difficult than the word processing and E-mail tasks used in previous tests of TAM. The integrated model addresses these weaknesses and, as a result, explains more of the variance in utilization.

These results have implications for research and practice. For research, the differences and overlap between the TAM and TTF should be explored further. Our results suggest that some aspects of utilization are determined by users' perceptions of the usefulness and ease of use of the tools and general attitude toward using the tools, while other aspects are affected by the matching of a specific tool functionality to the specific needs of a task. In practice, software authors need to be aware that actual utilization depends not only on perceived usefulness and ease of use, but also on how well the tool functionality matches the needs of the task at hand. Managers of software users, especially managers of software maintenance tool users, should be aware that low utilization of support tools may be caused by lack of fit between tool functions and task demands, rather than on the general usefulness and usability of the tools.

Like all research, our study has its limitations. A significant advantage of this study is that the data were collected from maintenance programmers working on their normal maintenance projects using the tools they normally use. The downside of this advantage is a relatively low sample size. While we have realistic data and good model fit statistics, our sample size necessitates that our proposed integrated model be further tested in other situations.

Beyond replicating and further testing our proposed integrated model, our results suggest several avenues for future research. The lack of a direct path between TTF and perceived usefulness, and the apparent mediating role of perceived ease of use, deserves further study. Apparently, the relationships among these three variables are more complex than originally thought.

Tool experience also deserves further attention. Our results show an indirect effect of tool experience through perceived ease of use and usefulness. Previous studies (e.g. Ref. [37]) have shown weaker indirect, as compared to moderating and direct, effects of experience. Our sample size was not large enough to split the sample and test for differences between high experience and low experience, which is the standard method of testing for moderating effects using path analysis.

6. Conclusion

Our results indicate that extending TAM with TTF constructs provides a better explanation for the variance in IT utilization than either TAM or TTF models alone. Our integrated TAM/TTF model combines an attribute/behavior model (TAM) with models of task–technology fit. In our integrated model, TTF constructs direct affect IT utilization and indirectly affect IT utilization through TAM's primary explanatory variables, perceived usefulness and perceived ease of use.

Our integrated TAM/TTF model holds much promise for helping researchers and practitioners better understanding why individuals choose to use IT for particular tasks. Such understanding is especially important to IT managers who are investing in tools for information users and IT professionals. It should also help tool developers understand how tool characteristics and their fit with task characteristics lead to user choices in respect of using the tool.

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Appendix A

The variables measuring the constructs in the task–technology fit (TTF) model and the technology acceptance model (TAM) were formed from several items. All statistics were computed using SPSS for Windows. Unless otherwise noted, all items are on a scale of 1 to 7, where 1 is very small extent and 7 – very large extent. The number of cases is 60. Each variable is formed by taking the mean of its items. Cronbach α's for the variables are all within an acceptable range, from 0.98 to 0.72.

A.1. TAM items

To what extent do you agree with the following?

A.1.1. Attitude toward tool use ($\alpha = 0.96$, mean $= 5.23$, SD $= 1.71$)

I think it would be very good to use the software maintenance tools rather than manual methods for this task.

In my opinion it would be very desirable to use the software maintenance tools rather than manual methods for the project.

It would be much better for me to use the maintenance tools rather than manual methods.

A.1.2. Intention to use tool ($\alpha = 0.92$, mean $= 5.02$, SD $= 1.74$)

I will use the software maintenance tools rather than manual methods to complete this project.

My intention is to use the software maintenance tools rather than manual methods in completing this project.

In completing this project, I would rather use the software maintenance tools than use manual methods alone.

A.1.3. Perceived ease of use ($\alpha = 0.97$, mean $= 4.77$, SD $= 1.60$)

I will find it easy to get the software maintenance tools to do what I want them to do.

My interaction with the software maintenance tools will be clear and understandable.

I will find the software maintenance tools to be flexible to interact with.

I will find the software maintenance tools easy to use.

A.1.4. Perceived usefulness ($\alpha = 0.98$, mean $= 5.12$, SD $= 1.63$)

Using the software maintenance tools will enable me to accomplish my tasks more quickly.

Using the software maintenance tools will enable me to improve my performance on this project.

Using the software maintenance tools will enable me to increase my productivity on this project.

Using the software maintenance tools will enable me to enhance my effectiveness on this project.

Using the software maintenance tools will make it easier to do this project.

I will find the software maintenance tools useful in this project.

A.2. TTF items

A.2.1. Maintenance tool function items ($\alpha = 0.72$, mean $= 1.31$, SD $= 1.34$)

To what extent do the maintenance software tools available to you supply the following functions?

Construct representations of entities, relationships, or processes in a diagram or model.

Represent the objects, relationships, or processes of the system or part of the system in terms of models (data flow diagrams, entity-relationship diagrams, flowcharts, etc.)

Model a system in terms of process, flow, or data models.

Produce a high level specification (e.g., diagram) from a lower level, or more detailed representation.

A.2.2. Maintenance task activity items ($\alpha = 0.82$, mean $= 3.62$, SD $= 1.37$)

To what extent did you perform the following?

I had to weigh and evaluate a large volume of information about the system I was maintaining.

I made extensive use of my knowledge of the programming language(s) and database system in which the software is written.

I learned a great deal about the system by mentally processing parts of the system code.

I examined samples of the input data.

I obtained information about the system through examining the source code.

I frequently consulted system documentation.

I obtained information about the system from comments in the body of the programs.

I learned a great deal about the system by mentally processing parts of the system code.

I added new functions to this system.

I consulted manuals to obtain information about the programming language(s) and/or database system.

I asked a colleague for technical information during this project.

A.2.3. Tool experience ($\alpha = 0.72$, mean $= 3.92$, SD $= 2.34$)

How many total hours have you used this tool?

How frequently do you use this tool?
How much experience do you have with this tool?
Note: Since the tool experience items are on differing scales, the items were normalized before the mean was taken.

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