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The Role of Individual Characteristics in Software Utilization Models

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Abstract

MIS researchers have developed a number of models for studying the software utilization choices of end users. In this paper, we focus on one of these, the Task-Technology fit model. We explore the addition of various personal characteristic constructs, especially Computer Self-Efficacy and Experience.

Keywords: Task-technology fit, computer self-efficacy, experience, individual characteristics

Introduction

Human-computer interaction (HCI) research has traditionally focused on understanding the fit between humans and computers. The ultimate goal of this research is to design better computer systems that are more easily used by people. Much of this research focuses on the user interface because it is the immediate means by which people interact with computers.

In the MIS field, there are streams of research with a similar goal, that is to design better computer systems that are more useful to people. In MIS, the focus is more on improving the fit between the computer system and the tasks people need to perform (Mathieson & Keil, 1998). That is, the focus is more on usefulness rather than usability. Usability is not ignored; for example, usefulness and ease of use are the key independent variables in the Technology Acceptance Model (TAM), in which ease of use is both an independent variable and influences usefulness (Davis, 1989). The TAM measures usefulness and ease of use, but does not explicitly focus on what makes a computer system useful or easy to use.

Our broad research goal is to understand software utilization choices of end users. That is, how do we explain which software systems people choice to use? MIS researchers have developed models to study the software utilization choices of end users. The most frequently used models are the Technology Acceptance Model (Davis, 1989) and the Task-Technology Fit Model (Goodhue, 1995). We start from the task-technology fit model, which focuses on how well the functionality of a computer system fits the task needs of users.

The specific purpose of this paper is to investigate the addition of individual characteristics to the task-technology fit model. This is important for several reasons. First, there is increasing evidence in the literature that individual differences do affect users' choices about technology (Agarwal & Prasad, 1999; Hong et al., 2002). Second, while a number of individual characteristics have been added to various models, especially TAM, there is a need for research that examines relationships among various individual characteristics and their effect on choices about technology. Finally, the addition of individual characteristics serves to bring some of the concerns of traditional HCI research into MIS research.

Task-Technology Fit Model (TTF)

The core of a Task-Technology Fit Model is a formal construct known as Task-Technology Fit (TTF), which is the matching of the capabilities of the technology to the demands of the task, that is, the ability of IT to support a task (Goodhue and Thompson, 1995). TTF models have four key constructs, task characteristics, technology functionality, which together affect the third construct task-technology fit, which in turn affects the outcome variable, either performance or utilization. TTF models posit that IT will be used if, and only if, the functions available to the user support (fit) the activities of the user. 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. The general form of a TTF model is shown in Figure 1.

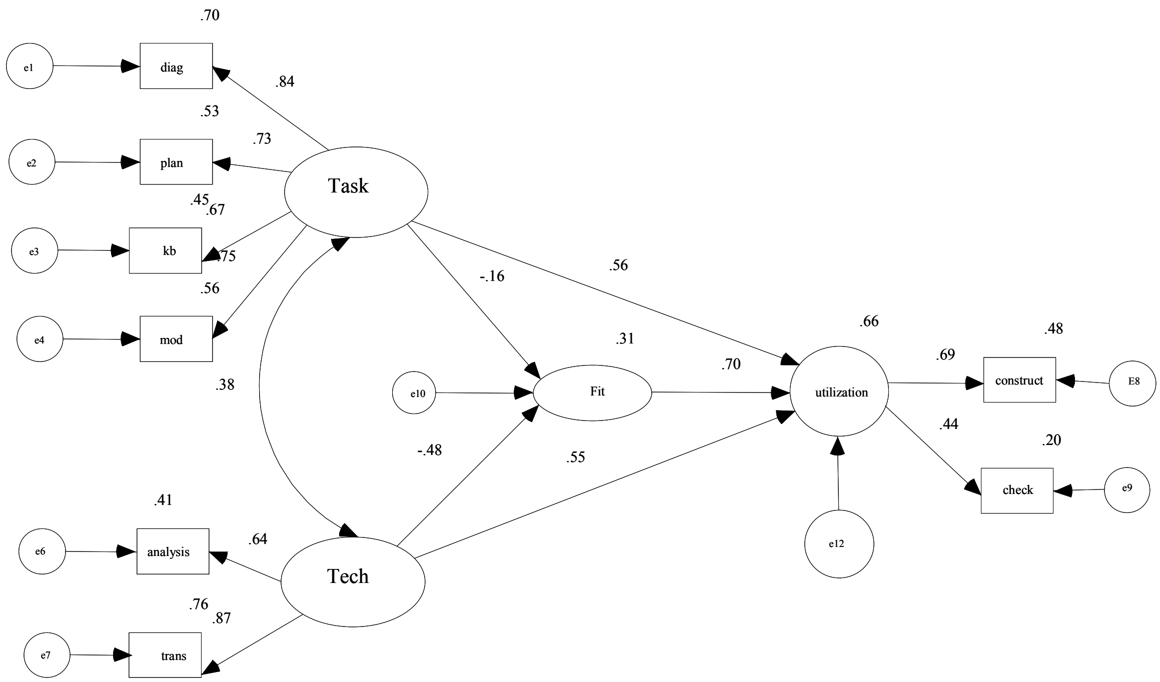

Figure 1. TTF Models

Individual Characteristics Constructs

The inclusion of individual characteristics is supported by work adjustment theory from which TTF was originally derived, and is a common addition to a TTF model (Goodhue, 1988; Goodhue and Thompson, 1995). While the TTF model as theoretically stated includes individual characteristics, empirical work has generally not estimated them (Marcolin et al., 2000). Most tests of individual characteristics, if they are estimated as part of an overall model, use the TAM.

Individual characteristics covers a wide range of possible constructs. For example, experience with particular IT is generally associated with higher utilization of that IT (Guinan et al., 1997; Thompson et al, 1994). Other studies have examined computer literacy (Goodhue, 1995), personal innovativeness (Agarwal and Prasad, 1998) and computer playfulness (Agarwal and Prasad, 1998; Webster and Martochhio, 1992), among others.

Marcolin et al. (2000) have classified many of these individual characteristics as dimensions of user competence. One axis of their framework is the Conceptualizations of Competence, which include Cognitive Outcomes (the declarative knowledge users have about a technology and how to use it), Skill-based outcomes (the procedural, compiled knowledge users hold that contribute to higher performance), and Affective Outcomes (attitudes and motivation toward technology). Cognitive outcome constructs are common in the literature. While some studies measure knowledge directly with tests of computer skills, many studies use some form of experience measure to capture knowledge or expertise. The MIS literature notes that computer users need knowledge or experience with both the technology and the task (Mackay and Elam, 1992). Skill-based outcomes are rarely measured, while the most common affective outcome measure in the recent literature is Computer Self-Efficacy (Marcolin et al., 2000). In this study, we are testing the basic TTF model with the addition of Computer Self-Efficacy (an affective outcome measure) and with Experience (a cognitive outcome measure).

Computer Self-Efficacy

Research on IT utilization behavior has a number of research streams other than TAM and TTF, e.g., a model tailored for personal computing (Thompson, et al., 1991). Notable in this area is the study of Perceived Computer Self-Efficacy (Compeau & Higgins, 1995), which examines users' beliefs regarding their ability to perform specific tasks using a software package.

Computer Self-Efficacy (CSE) may be defined as a judgment of one's ability to use a computer. This construct is derived from the Social Cognition literature and is a specialized definition of Self-efficacy, i.e., a person's belief in their ability to accomplish a specific task (Compeau & Higgins, 1995). The work of Compeau and Higgins (1995), based in part on Bandura's work on self-efficacy, produced a 10-item, single factor measure of CSE. Studies of Computer Self-Efficacy have shown it to be associated with IT usage or intention to use (Venkatesh, 2000; Hong et al., 2002).

The Compeau and Higgins (1995) conceptualization of CSE is primarily concerned with general computer self-efficacy. In other studies of CSE, the construct has been more narrowly defined as the ability to use or employ specific software (c.f Venkatesh & Davis, 1996). Agarwal, et al. (2000) describe a more formal model incorporating the notion of specific CSE. Since the users we survey are using different software applications, we continue to use the general CSE measure as do others, e.g., (Hong et al., 2002).

Experience

Experience in various forms has been used in several studies. Examples include role with respect to technology (user or IS), tenure in the workforce, level of education, prior similar experiences (with technology), and participation in training (Agarwal & Prasad, 1999), experience with the task and experience with the technology (Dishaw & Strong, 2003), knowledge of the search domain (Hong et al., 2002). Of these, tenure in the workforce and task experience did not have significant effects. Some of these measure task knowledge, e.g., experience with the task and knowledge of the search domain; others measure technology knowledge, e.g., prior similar experiences (with technology) and experience with the technology; while others potentially capture both, e.g., tenure in the workforce.

As individual characteristics, Computer Self-Efficacy and Experience have unique effects (Marcolin et al., 2000). They are also related and in fact may affect each other over time. Self-Efficacy is considered an important construct in the educational literature because higher self-efficacy, that is, higher perceptions of one's ability to perform, contributes to learning and performance. Thus, self-efficacy has the effect of increasing experience over time (Bandura, 1986). Increased experience in turn contributes to higher Self-Efficacy (Marcolin et al., 2000). Another way to view this reciprocal relationship is suggested by Bandura, who indicates that Self-Efficacy is a better measure of potential performance when experience is low, which is why Self-Efficacy is a critical construct in educational studies. When experience is high, experience overwhelms Self-Efficacy and is a better indicator of performance. In this study, we will investigate these arguments. Since our subjects are students, we expect Self-Efficacy to be the better indicator in most cases, but there are some students with higher levels of experience.

Research Method

The subjects for the study are undergraduate students enrolled in courses that involve problem solving and modeling. The students complete assignments in the areas of statistics, simulation, or programming. Depending on the problem, the students will use software products such as Minitab, SPSS, ProModel, or a CASE tool in completing the assignments. The students are asked to complete a questionnaire within a few days of completing their assignments. The questionnaire uses the previously published items for CSE (Compeau and Higgins, 1995) and for the TTF (Dishaw and Strong, 1998a, 1998b). Minor editing of the items was done in order to generalize for the tasks and software technologies used in this study.

The 136 data points from our first round of data collection are used to test the basic TTF model and to test the addition of the CSE construct. Path analysis is applied to these data using Amos 4.0 as supplied by SPSS. This technique allows us to estimate goodness of fit of the research model while also determining the strength, sign, and statistical significance of the relationships between the model variables. Note that fit is estimated as a latent variable in the path model. A more detailed description of these methods may be found in Dishaw & Strong (1999).

Currently, a second round of data collection is underway. In this round, we are not only collecting data on the TTF and CSE constructs, but we are also collecting Experience and the TAM constructs. At this point, we have preliminary results from the first set of data. We will have the second set of data and the full analysis ready to report at AMCIS.

Models and Preliminary Results

We test a series of models, starting with the basic TTF model. While the TTF model is well-established in the literature (Goodhue, 1995, Goodhue and Thompson, 1995, Dishaw and Strong 1998c), we need to estimate it with our data to provide a baseline for testing the addition of constructs representing various individual characteristics. We then test a model with the CSE construct added.

Model 1: General TTF Model

The TTF model with the four key variables, task characteristics, technology functionality, fit, and utilization of the technology, as estimated with the first data set is included in Figure 2. The fit statistics are good (Chi Sq.=26.77, df=17, p=0.06, AGFI=0.89, and GFI=0.95). This provides the baseline for the next model.

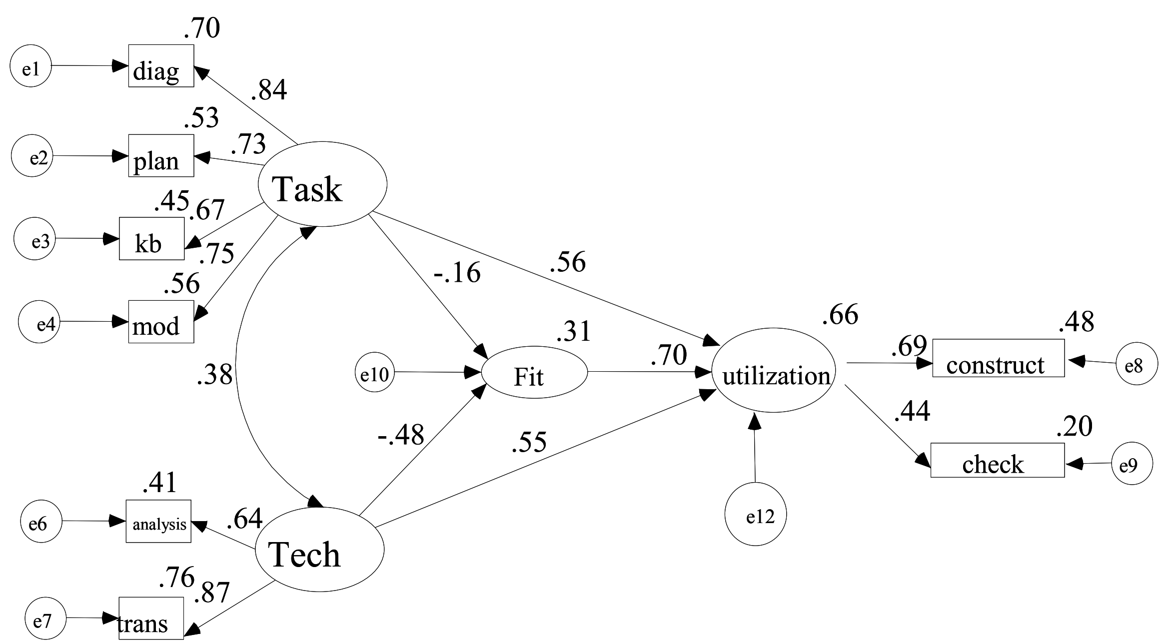

Figure 2. General TTF Model

Model 2: General TTF Model with Computer Self-Efficacy

The TTF model with CSE added is shown in Figure 3. The fit statistics are better than the previous model (Chi Sq.=27.24, df=22, p=0.20, AGFI=0.91, and GFI=0.96).

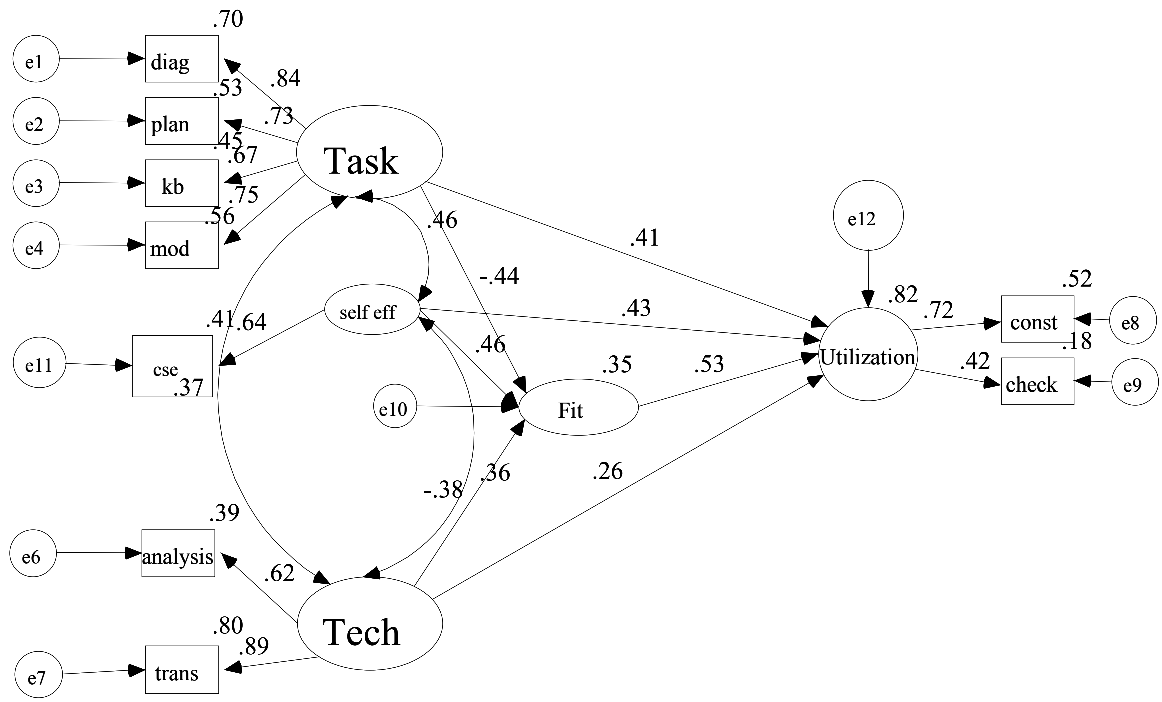

Figure 3. TTF Model with CSE

Model 3: General TTF Model with Computer Self-Efficacy and Experience

When we have our second round of data, we will test two TTF models with experience. The first will include Experience instead of CSE. The second will include both Experience and CSE.

Integrated Models

The two major models used to study IT utilization, the Technology Acceptance Model (Davis, 1989) and the Task-Technology Fit Model (Goodhue, 1995), have been combined into a comprehensive model (Dishaw & Strong, 1999). 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 using the IT. Critics note that users regularly use 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 (Goodhue, 1995). Both aspects, attitude toward the IT and rationally determined expected consequences from using the IT, are likely to affect users' choices to use IT. The combined model provides a better model of IT utilization than either an attitude or a fit model separately.

We intend to estimate the TAM with our second data set, as well as the combined TAM/TTF model. Then we will test the added individual characteristic constructs, CSE and Experience, with the TAM as well as the combined model.

With the new data set, we can test the combined model with a different set of data. In addition, we will be able to compare TTF, TAM, and the combined model with this new set of data. We will also be able to test and compare the addition of the individual characteristic constructs in all three models.

Conclusion

Preliminary results are presented above. Adding CSE to the TTF model provides a better fit than the TTF model alone. Results for Model 3 and the integrated model will be available for presentation at AMCIS.

Limitations

The primary limitation of the study stems from the use of undergraduate students as subjects. Students at this level can be considered to be to be novices in the problem space and may have motivations and social contexts that differ from professionals and/or experienced users of the software. Therefore, caution is warranted in generalizing these results to experts or to professionals in this area without further information or tests of the model with a different subject population. However, we have no *a priori* expectations that the findings would not generalize as the items and method employed are well known or have been previously used with non-student populations.

Contributions

Our research goal is to understand better users' choices about the software they use. Our approach is to explore the similarities and differences among the models and constructs already in the literature, rather than to add to the list of newly developed constructs and models. We are doing this by collecting a new data set with many of the key constructs in the literature. This serves both to re-test existing models with new data in different domains, and to provide a basis for comparing models and individual characteristic constructs with comparable data. This approach is one piece of building cumulative research results (Berthon, et al., 2002). In addition to testing existing MIS models, we are exploring the connection of these models to traditional HCI research, since the MIS models we examine have similar goals to the goals of HCI research.

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