Understanding Information Technology Usage: A Test of Competing Models

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The Technology Acceptance Model and two variations of the Theory of Planned Behavior were compared to assess which model best helps to understand usage of information technology. The models were compared using student data collected from 786 potential users of a computer resource center. Behavior data was based on monitoring 3,780 visits to the resource center over a 12-week period. Weighted least squares estimation revealed that all three models performed well in terms of fit and were roughly equivalent in terms of their ability to explain behavior. Decomposing the belief structures in the Theory of Planned Behavior provided a moderate increase in the explanation of behavioral intention. Overall, the results indicate that the decomposed Theory of Planned Behavior provides a fuller understanding of behavioral intention by focusing on the factors that are likely to influence systems use through the application of both design and implementation strategies.

Information technology usage—Technology acceptance model—Theory of planned behavior—Innovation characteristics

1. Introduction

A key objective of much IT research is to assess the value of information technology to an organization and to understand the determinants of that value. The objective of such research is to help firms better deploy and manage their IT resources and enhance overall effectiveness. There are many levels from which to approach this problem. Some researchers have suggested macroeconomic approaches (Panko 1991 provides a review and critique of this approach). Other researchers have examined this issue at the firm level by assessing the relationship between IT expenditure and firm performance (see Banker et al. 1993 for a review and critique of this research from a variety of perspectives). A third approach has been to examine the determinants of IT adoption and usage by individual users (e.g., Davis 1989, Davis et al. 1989). Early work in this area focused on the examination of usage as a surrogate measure for information systems success (DeLone and McLean 1992).

Recently, usage has been studied as a phenomenon of interest in its own right (Davis 1989, 1993; Davis et al. 1989, 1992; Adams et al. 1992; Mathieson 1991; Moore and Benbasat 1993; Thompson et al. 1991; Hartwick and Barki 1994). As a

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key dependent variable in the IT research literature, understanding usage is of increasing theoretical interest. It is also of increasing practical importance as the usage of IT becomes more pervasive. From a pragmatic point of view, understanding the determinants of information technology usage should help to ensure effective deployment of IT resources in an organization. Such usage is a necessary condition for ensuring productivity payoffs from IT investments (Davis 1989, Mathieson 1991).

In recent years, a variety of theoretical perspectives have been advanced to provide an understanding of the determinants of usage. One important line of research has employed intention-based models which use behavioral intention to predict usage and, in turn, focus on the identification of the determinants of intention, such as attitudes, social influences, and facilitating conditions (Davis et al. 1989, 1992; Hartwick and Barki 1994; Mathieson 1991). This work is grounded in models from social psychology, such as the Theory of Reasoned Action (TRA) (Ajzen and Fishbein 1980), and the Theory of Planned Behavior (TPB) (Ajzen 1985, 1991).

From this stream of research, the Technology Acceptance Model (TAM) has emerged as a powerful and parsimonious way to represent the antecedents of system usage through beliefs about two factors: the perceived ease of use and the perceived usefulness of an information system (Davis 1989, 1993; Davis et al. 1989, 1992). TAM is an adaptation of the TRA. In TAM, intention is determined by attitude towards usage as well as by the direct and indirect effects of perceived ease of use and perceived usefulness (see Figure 1a). The practical utility of the model stems from the fact that ease of use and usefulness are factors over which a system designer has some degree of control. To the extent that they are key determinants of usage, they provide direction to designers as to where efforts should be focused.

Empirical tests of TAM have shown that it explains much of the variance in usage intention and self-reported usage (Davis 1989, 1993; Davis et al. 1989; Mathieson 1991). However, TAM has not been tested with actual measures of usage behavior. Rather, tests of the model have relied on measures of usage intention or self-reported measures of usage which are often collected coincidentally with the measurement of beliefs, attitudes and intention. In addition, the complete model has not been tested simultaneously; rather, various parts of the model have been examined separately using regression-based approaches. A complete assessment of the model, incorporating actual measures of usage, is important to fully examine the extent to which the model can help to understand usage behavior (Davis 1989, Davis et al. 1992). This study includes such a test using actual behavior data collected over time.

A second line of research has examined the adoption and usage of information technology from a Diffusion of Innovations perspective (Rogers 1983; Tornatzky and Klein 1982). This research examines a variety of factors which are thought to be determinants of IT adoption and usage, such as: individual user characteristics (Brancheau and Wetherbe 1990), information sources and communication channels (Nilikanta and Scammell 1990), and innovation characteristics (Hoffer and Alexander 1992, Moore 1987, Moore and Benbasat 1993). Moore and Benbasat (1993) have integrated the intentions and innovations literatures in an examination of the determinants of end-user computing, combining concepts from the Theory of Reasoned Action and the perceived characteristics of innovations (Rogers 1983).

This paper further extends, integrates and compares models resulting from these two lines of research by contrasting three models of IT usage derived from the intentions and innovations literatures. We extend Mathieson's (1991) comparison

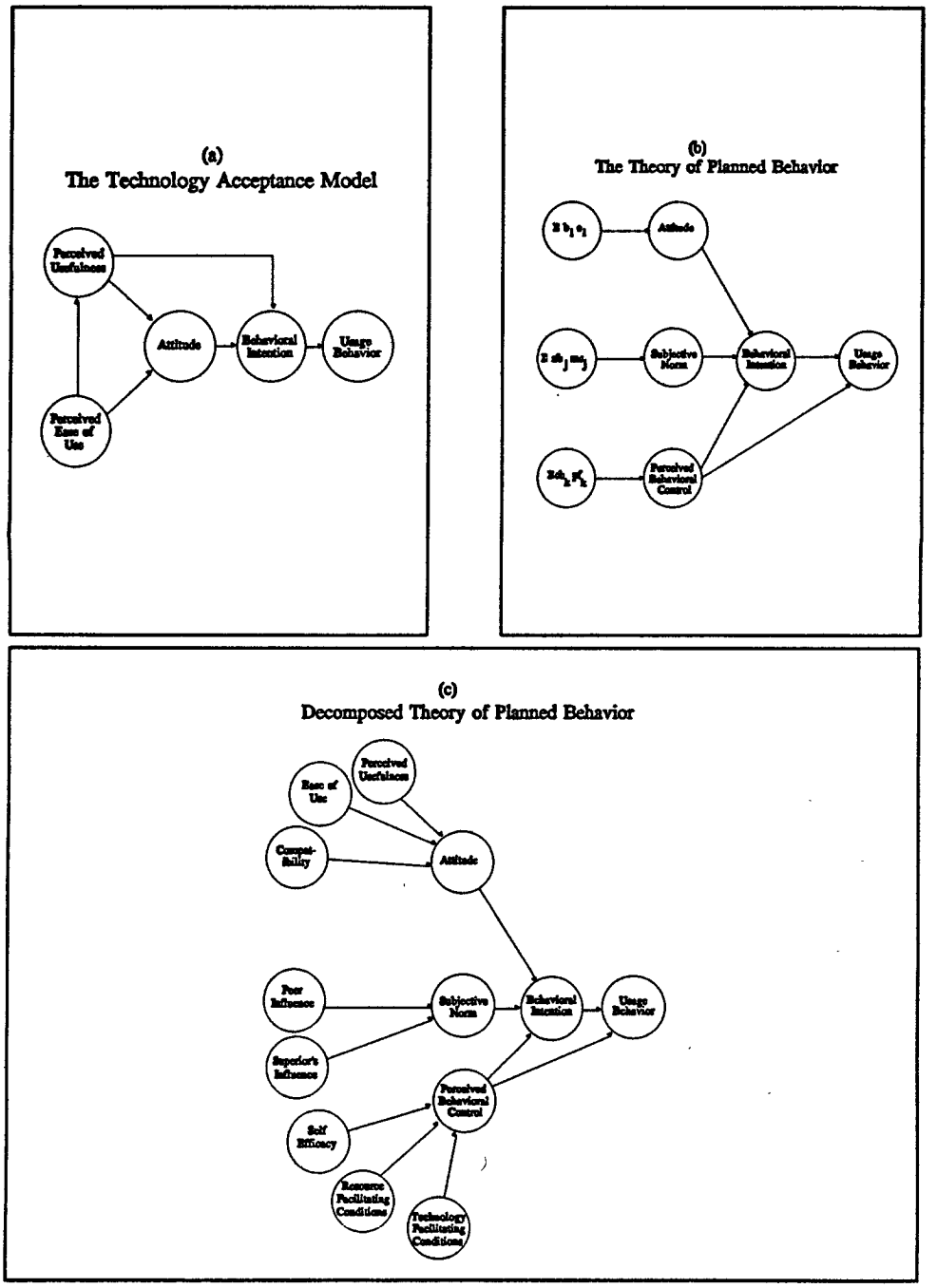


FIGURE 1. Theoretical Models.

of the Technology Acceptance Model and the Theory of Planned Behavior, which focused only on predicting intentions, by incorporating measures of usage behavior, and testing the full versions of both TAM and TPB. The TPB model (see Figure 1b) asserts that attitude, subjective norm and perceived behavioral control are direct determinants of behavioral intention, which in turn affects behavior. In a study of intention to use spreadsheet software, Mathieson (1991) found that while TPB was predictive of user intention, it did not provide as complete an explanation of intention as TAM.

A third model, the decomposed TPB (see Figure 1c), is also introduced. This model draws upon constructs from the innovations characteristics literature, and more completely explores the dimensions of subjective norm (i.e., social influence) and perceived behavioral control by decomposing them into specific belief dimensions. This decomposed TPB model has advantages similar to TAM in that it identifies specific salient beliefs that may influence IT usage. Because it incorporates additional factors, such as the influence of significant others, perceived ability and control that are not present in TAM, but have been shown to be important determinants of behavior (Ajzen 1991), it should provide a more complete understanding of usage.

The three models are compared in terms of the extent to which each can be used to understand intention to use and subsequent usage of information technology. This assessment of contribution to understanding is made using structural equation modelling, comparing the models on the basis of overall model fit, explanatory power and significance of paths. To test the models, data were collected from 786 potential users of a student computer resource center. This facility is designed for the exclusive use of business school students and is used on a voluntary basis for the preparation of final reports and presentations on a fee for use basis.

The paper proceeds as follows. In the next section, we review the theoretical models (TAM, TPB and Decomposed TPB) which underlie this research. In §3, we provide an overview of the empirical study designed to test the models. Section 4 presents the findings. Section 5 provides a discussion of results and a comparison of the models. Section 6 provides concluding comments, discusses the limitations of the study and suggests some directions for further research.

2. Theoretical Models of IT Usage

2.1. *Model 1—The Technology Acceptance Model*

The Technology Acceptance Model (TAM) (Davis 1989, 1993; Davis et al. 1989) (see Figure 1a) is an adaptation of the Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975) which specifies two beliefs, perceived usefulness and perceived ease of use, as determinants of attitude towards usage intentions and IT usage (Davis et al. 1989). Usage intentions are, in turn, the sole direct determinant of usage. Introducing intentions as a mediating variable in the model is important for both substantive and pragmatic reasons. Substantively, the formation of an intention to carry out a behavior is thought to be a necessary precursor to behavior (Fishbein and Ajzen 1975). Pragmatically, the inclusion of intention is found to increase the predictive power of models such as TAM and TRA, relative to models which do not include intention (Fishbein and Ajzen 1975).

In the Technology Acceptance Model, usage behavior (B) is modelled as a direct function of behavioral intention (BI). BI is, in turn, a weighted function of: attitude

towards usage (A), which reflects feelings of favourableness or unfavourableness towards using the technology, and perceived usefulness (U), which reflects the belief that using the technology will enhance performance (see Figure 1a). Attitude is determined jointly by perceived usefulness and perceived ease of use (E). Finally, ease of use is modelled as a direct determinant of perceived usefulness.

Stated more formally,

$$B \equiv BI = w_1 A + w_2 U,$$

$$A = w_3 U + w_4 E,$$

$$U = w_5 E.$$

TAM can be considered a special case of the Theory of Reasoned Action, with only two beliefs comprising attitude and no role for subjective norm (i.e., social influences). TAM departs from TRA in one significant way. The direct path from perceived usefulness to intention violates the TRA model which claims that attitude completely mediates the relationship between these types of beliefs and intention. According to Davis et al. (1989), the reason for this deviation is that in work settings, intentions to use IT may be based on anticipated job performance consequences of using the system regardless of overall attitude. In other words, an employee may dislike a system, (i.e., have a negative attitude towards it), but still use the system because it is perceived to be advantageous in terms of job performance (Davis et al. 1989).

According to Davis et al. (1989), all other factors not explicitly included in the model are expected to impact intentions and usage (B) through ease of use and perceived usefulness. These external variables might include: system design characteristics, training, documentation and other types of support, as well as decision maker characteristics that might influence usage (Davis et al. 1989). Thus, according to TAM, the easier a technology is to use, and the more useful it is perceived to be, the more positive one's attitude and intention towards using the technology. Correspondingly, the usage of the technology increases.

The appeal of this model, then, is that it is both specific and simple. It suggests a small number of factors which jointly account for usage. These factors are specific, easy to understand, and can be manipulated through system design and implementation. In addition, they should also be generalizable across settings.

TAM has received empirical support in information technology research. For example, Davis et al. (1989) found that TAM predicted software usage intention better than the Theory of Reasoned Action ($R^2_{BI} = 0.47$ at time 1, immediately after the introduction of new software, and 0.51 at time 2, 14 weeks after the introduction of the software, compared with 0.32 and 0.26 for TRA at time 1 and time 2 respectively). However, the ability of the models to predict self-reported behavior was limited ($R^2_B = 0.12$). Davis (1993) reports an $R^2_B = 0.3$ for a modified version of TAM which omits BI, and where behavior measures were collected co-incidentally with other model measures. Mathieson (1991) found that TAM predicted intention to use a spreadsheet package better than the Theory of Planned Behavior ($R^2_{BI} = 0.69$ for TAM and 0.60 for TPB). Mathieson did not include any measures of behavior.

While these tests show that the model has reasonable explanatory power, tests of the relationships in the model have not produced consistent results in all cases. The strongest results have been in support of the importance of perceived usefulness as a direct determinant of intention. In addition, the relationship of perceived usefulness

to attitude has been consistent. The role of ease of use has been equivocal and to a large extent mediated by perceived usefulness.

Although it is a special case of the TRA, TAM excludes the influence of social and personal control factors on behavior. The Theory of Planned Behavior, described next, takes these factors into account and thus might be expected to increase our understanding of user behavior.

2.2. *Model 2—The Theory of Planned Behavior*

The Theory of Planned Behavior (TPB) (Ajzen 1985, 1991) extends the Theory of Reasoned Action (Fishbein and Ajzen 1975), to account for conditions where individuals do not have complete control over their behavior. The TPB asserts that behavior (B) is a direct function of behavioral intention (BI) and perceived behavioral control (PBC) and that behavioral intention is formed by one's attitude (A), which reflects feelings of favourableness or unfavourableness towards performing a behavior; subjective norm (SN), which reflects perceptions that significant referents desire the individual to perform or not perform a behavior; and perceived behavioral control (PBC), which reflects perceptions of internal and external constraints on behavior (Ajzen 1985, 1991). More formally, behavior is a weighted function of intention and perceived behavioral control; and intention is the weighted sum of the attitude, subjective norm and perceived behavioral control components (See Figure 1b). Thus, according to the TPB model:

$$B = w_1 BI + w_2 \text{PBC}$$

$$BI = w_3 A + w_4 SN + w_5 \text{PBC}.$$

Each of the determinants of intention, i.e., attitude, subjective norm and perceived behavioral control, is, in turn, determined by underlying belief structures. These are referred to as attitudinal beliefs[1] (b_i), normative beliefs (nb_j), and control beliefs (cb_k) which are related to attitude, subjective norm and perceived behavioral control respectively. These relationships are typically formulated using an expectancy-value model which attaches a weight to each belief in a fashion similar to Vroom's (1969) expectancy theory.

Stated more formally, attitude (A) is equated with the attitudinal belief (b_i) that performing a behavior will lead to a particular outcome, weighted by an evaluation of the desirability of that outcome (e_i), that is,

$$A = \Sigma b_i e_i.$$

For example, an individual may believe that using information technology will result in better job performance (b_i), and may consider this a highly desirable outcome (e_i).

Subjective norm is formed as the individual's normative belief (nb_j) concerning a particular referent weighted by the motivation to comply with that referent (mc_j), that is,

$$SN = \Sigma nb_j mc_j.$$

For example, an individual may believe that his/her peers think that one should use

[1] Fishbein and Ajzen (1975) refer to these beliefs as "behavioral beliefs". For clarity, they will be referred to in this paper as "attitudinal beliefs", to maintain a clear distinction with "behavioral control beliefs" associated with PBC.

information technology (nb_j) but that complying with the wishes of peers is relatively unimportant (mc_j).

The role of subjective norm as a determinant of IT usage is somewhat unclear. Neither Davis et al. (1989) nor Mathieson (1991) found a significant relationship between *SN* and *BI*. However, these results may have been due to the fact that there were no real consequences associated with the behavior under study and little external pressure to perform the behavior (Davis 1993, Davis et al. 1992, Hartwick and Barki 1994). Indeed, studies in organizational settings have found subjective norm to be an important determinant of *BI* or self reported usage of IT (Hartwick and Barki 1994, Moore and Benbasat 1993). Thus, in a setting where actual behavior with real consequences is studied, subjective norm would be expected to be an important determinant of intention and usage. Furthermore, its relative importance may be a function of the phase of implementation of the technology; subjective norms have been found to be more important prior to, or in the early stages of, implementation when users have only limited direct experience from which to develop attitudes (Hartwick and Barki 1994).

According to Ajzen (1985, 1991; Ajzen and Driver 1992; Ajzen and Madden 1986; Madden et al. 1992), perceived behavioral control reflects beliefs regarding access to the resources and opportunities needed to perform a behavior, or alternatively, to the internal and external factors that may impede performance of the behavior. This notion encompasses two components. The first component is "facilitating conditions" (Triandis 1979), which reflects the availability of resources needed to engage in a behavior, such as time, money or other specialized resources. The second component is self-efficacy; that is, an individual's self-confidence in his/her ability to perform a behavior (Bandura 1977, 1982). Perceived behavioral control is formed as the sum of the control beliefs (cb_k) weighted by the perceived facilitation (pf_k) of the control belief in either inhibiting or facilitating the behavior, that is,

$$\text{PBC} = \Sigma cb_k pf_k$$

For example, an individual may feel that he/she does not have the skill to use information technology (cb_k) and that skill level is important in determining usage (pf_k).

The IT literature to date demonstrates that PBC may be an important determinant of usage. In a direct test, Mathieson (1991) found that PBC did have a significant relationship with behavioral intention, though it did not provide substantial explanatory power. Other indirect evidence with respect to PBC can also be found in the literature. For example, Moore and Benbasat (1993) found that perceived voluntariness, which they liken to perceived behavioral control, was a significant determinant of usage. Similarly, Hartwick and Barki (1994) noted that mandated and voluntary use result in different relative impacts for Attitude and Subjective Norm in TRA. Furthermore, Compeau and Higgins (1991b) have shown that self-efficacy has a significant impact on usage. Overall, this literature suggests that PBC should influence IT usage.

The relationship between the belief structures and the determinants of intention (*A*, *SN*, and PBC) are not particularly well understood (Ajzen 1991). This is due to two factors. In the TPB, the belief structures are combined into unidimensional constructs (i.e., $\Sigma b_i e_i$, $\Sigma nb_j mc_j$, $\Sigma cb_k pf_k$). Such monolithic belief sets may not be consistently related to attitude, subjective norm or perceived behavioral control (Bagozzi 1981, 1982; Miniard and Cohen 1979, 1981, 1983; Shimp and Kavas

1984). Secondly, the belief sets, especially those relating to attitude, are idiosyncratic to the empirical setting, making it difficult to operationalize the TPB. This is in contrast to TAM which proposes a belief set, consisting of ease of use and usefulness, that is consistent and generalizable across different settings (Davis et al. 1989). In our third model, we address these two limitations of the TPB by recommending a set of stable, decomposed belief structures for the TPB model.

2.3. *Model 3—The Decomposed Theory of Planned Behavior*

An alternative version of the TPB model with decomposed belief structures is presented in Figure 1c. In this model, attitudinal, normative and control beliefs are decomposed into multi-dimensional belief constructs. This decomposition approach provides several advantages. First, it has been noted that it is unlikely that monolithic belief structures, representing a variety of dimensions will be consistently related to the antecedents of intention (Bagozzi 1981, Shimp and Kavas 1984). By decomposing beliefs, those relationships should become clearer and more readily understood. In addition, the decomposition can provide a stable set of beliefs which can be applied across a variety of settings. This overcomes some of the disadvantages in operationalization that have been noted with respect to the traditional intention models (Berger 1993, Mathieson 1991). Finally, by focusing on specific beliefs, the model becomes more managerially relevant, pointing to specific factors that may influence adoption and usage. These factors may be manipulated through systems design and implementation strategies. In this way, the decomposed TPB shares many of the same advantages associated with TAM. It differs in that it is more complex because it introduces a larger number of factors that may influence usage. Because of this, the decomposed TPB should provide a more complete understanding of IT usage relative to the more parsimonious TAM.[2]

2.3.1. *Decomposing Attitudinal Belief Structures.* For the TRA and TPB models, the identification of a stable set of relevant belief dimensions for attitudinal beliefs has traditionally been problematic (Berger 1993). Indeed, the difficulties associated with establishing a set of salient beliefs may be one reason why Davis et al. (1989) and Mathieson (1991) found that TRA and TPB did not explain usage intentions as well as TAM. The measures of ease of use and usefulness in TAM were based on well developed, refined and validated measures (Davis 1989). In contrast, the belief measures used for TRA and TPB were based on a salient belief elicitation measure which develops a scale idiosyncratic to a specific setting. Under such conditions, measures of beliefs may be less than ideal. The belief structure may reflect a variety of underlying dimensions which obscure its relationship to attitude. For example, the attitudinal belief measure used by Davis et al. (1989, p. 990) to test the TRA appears to include several dimensions such as advantages and disadvantages (or perceived usefulness), ease of use and facilitating conditions.

We suggest that a set of attitudinal belief dimensions can be derived from the literature describing the *perceived characteristics of an innovation* (Rogers 1983), an approach that has been used explicitly and implicitly in previous studies of computer

[2] For simplicity, our discussion of decomposition presents the decomposed belief structures as independent constructs. We recognize that there may be relationships and crossover effects between these constructs and our modelling takes these possible correlations into account.

technology adoption (Hoffer and Alexander 1992, Moore and Benbasat 1991). Indeed, the ease of use and usefulness measures proposed in Davis (1989) are, in part, attributed to this literature. According to the innovations literature, there are five perceived characteristics of an innovation that influence adoption (Rogers 1983), three of which—relative advantage, complexity, and compatibility—have been found to be consistently related to adoption decisions in general (Tornatzky and Klein 1982) and to IT usage specifically (Moore and Benbasat 1993).

Relative advantage refers to the degree to which an innovation provides benefits which supersede those of its precursor and may incorporate factors such as economic benefits, image enhancement, convenience and satisfaction (Rogers 1983). It is analogous to the "perceived usefulness" construct in TAM which Davis (1989, p. 320) defines as "the degree to which a person believes that using a particular system would enhance his or her job performance". Both constructs have been defined in similar ways (i.e., as relative improvement in performance), and their measures have been operationalized in terms of their relative impact on performance (Davis 1989, Moore and Benbasat 1991).[3] *Complexity* represents the degree to which an innovation is perceived to be difficult to understand, learn or operate (Rogers 1983). It is analogous (although in an opposite direction) to the "ease of use" construct in TAM (Davis 1989).[4] *Compatibility* is the degree to which the innovation fits with the potential adopter's existing values, previous experiences and current needs (Rogers 1983).

In general, as the perceived relative advantages and compatibility of information technology usage increase, and as complexity decreases, attitude towards information systems usage should become more positive. Such an outcome would be consistent with the general diffusion of innovations literature and with specific results observed for information technology usage (Hoffer and Alexander 1992, Davis 1989, Davis et al. 1989, Mathieson 1991, Moore and Benbasat 1993).

2.3.2. *Decomposing Normative Belief Structure.* Several studies have suggested approaches to the decomposition of normative belief structures (nb_jmc_j) into relevant referent groups (Burnkrant and Page 1988, Shimp and Kavas 1984, Oliver and Bearden 1985). We hypothesize that the importance of decomposition for nb_jmc_j will be related to the possible divergence of opinion among the referent groups. For example, three important referent groups in an organizational setting are peers, superiors and subordinates. Each may have differing views on the use of IT. For example, one's peers may be opposed to the use of a particular system, thinking it requires too much change in their work processes. At the same time, one's superiors may be encouraging the use of the system, anticipating certain productivity payoffs. In such a situation, a monolithic normative structure may show no influence on subjective norm or intention because the effects of the referent groups may cancel each other out. Because the expectations of peers, superiors, and subordinates may be expected to differ, we suggest a decomposition into these referent groups. For this study, involving student participants, we use two groups, peers (other students) and superiors (professors).

2.3.3. *Decomposing Control Belief Structure.* The decomposition of control beliefs follows directly from Ajzen's (1985, 1991) discussion of the construct. He refers to both the internal notion of individual "self-efficacy" (Bandura 1977) and to external resource constraints, similar to Triandis's notion of "facilitating conditions". The

[3] For the sake of consistency with the preponderance of MIS research in this area, we will refer to relative advantage as perceived usefulness, or simply usefulness.

[4] Again for the sake of consistency within the MIS literature, we will refer to this as perceived ease of use.

first dimension, self-efficacy, is related to perceived ability. With respect to IT usage, we would anticipate that higher levels of self-efficacy will lead to higher levels of behavioral intention and IT usage (Compeau and Higgins 1991b). With respect to IT usage, the facilitating conditions construct provides two dimensions for control beliefs: one relating to resource factors such as time and money and the other relating to technology compatibility issues that may constrain usage. All other things equal, behavioral intention and IT usage would be expected to be less likely as less time and money are available, and as technical compatibility decreases. In essence, the absence of facilitating resources represents barriers to usage and may inhibit the formation of intention and usage; however the presence of facilitating resources may not, per se, encourage usage.

3. The Study

3.1. *The Computing Resource Center*

Tests of the three models outlined above were conducted based on usage of a computing resource center (CRC) by business school students. The CRC is a facility, much like an information centre in an organization, which provides specialized computing and printing services, as well as technical support for students. A variety of word processing, spreadsheet, graphics, statistical and other specialized software packages are available for use. The facility supports both IBM and MacIntosh computers, and provides specialized services such as CD-ROM, scanners, laser and color printing as well as projection equipment.

The CRC is staffed, with an attendant on duty at a help desk. The attendant also controls access to the facility and the assignment of users to one of the 18 workstations. The CRC is open approximately 80 hours a week. The primary use of the CRC is for document and presentation production. It is intended to support the production of finished products and is not used as a general purpose computing facility. Basic input, such as typing or data entry, is not permitted in the CRC. Rather, the center provides access to high-end equipment that supplements what is available to students in general purpose computer labs and through their own resources. Access to the CRC is free; however, students are charged a fee for all hardcopy output generated.

Use of the CRC is voluntary in the sense that there are alternative facilities on campus that provide similar services to the students, and most of the work done in the CRC is not specifically required for courses (i.e., instructors do not typically require that reports, presentations, and assignments be computer generated and laser printed). Use of the CRC by undergraduate and graduate business students is the target behavior of interest for this study.

3.2. *Instrument Development*

Development of the scales to measure each of the constructs in the models proceeded through a series of steps. As a first step, items to measure behavioral intention, attitude, subjective norm and perceived behavioral control were generated based on the procedures suggested by Ajzen and Fishbein (1980) and Ajzen (1985, 1991). Items to measure perceived usefulness, ease of use and compatibility were based on innovation characteristic scales developed by Moore and Benbasat (1991) and Davis (1989). Facilitating conditions and self-efficacy items were generated based on the work of Compeau and Higgins (1991a) and Ajzen (1985, 1991). Consistent with the recommendations of Fishbein and Ajzen, and operationalizations by other IS

researchers (e.g., Davis 1989, Mathieson 1991), all questionnaire items relate specifically to the use of the CRC rather than to general computer usage.

Construct measurement was common across models. That is, the same measures were used for perceived usefulness and perceived ease of use in tests of both TAM and TPB. Davis (1989; Davis et al. 1989) notes that "ease of use" and "perceived usefulness" correspond to the "complexity" and "relative advantage" constructs in the diffusion characteristics literature; thus they were operationalized in the same way for the analysis reported here. The operational measures were based on the scales developed by Davis (1989) and Moore and Benbasat (1991). They were adjusted to reflect the specific target behavior, use of the CRC. The scales were also shortened to facilitate the inclusion of the 12 constructs of interest into the questionnaire.

Initial items to measure each construct were identified based on the existing scales as described above. Discussions with CRC staff and users were then employed to ensure that the beliefs were consistent with the CRC context. Card sorts were then performed to assess construct validity. Six raters sorted the questionnaire items into categories representing each of the underlying constructs (e.g., perceived usefulness, compatibility, etc.). This sort resulted in a correct classification of items to constructs in 90 to 100 percent of the cases for the constructs of interest. On the basis of these results, some items were modified, and some deleted; a questionnaire was then developed and subjected to pilot testing.

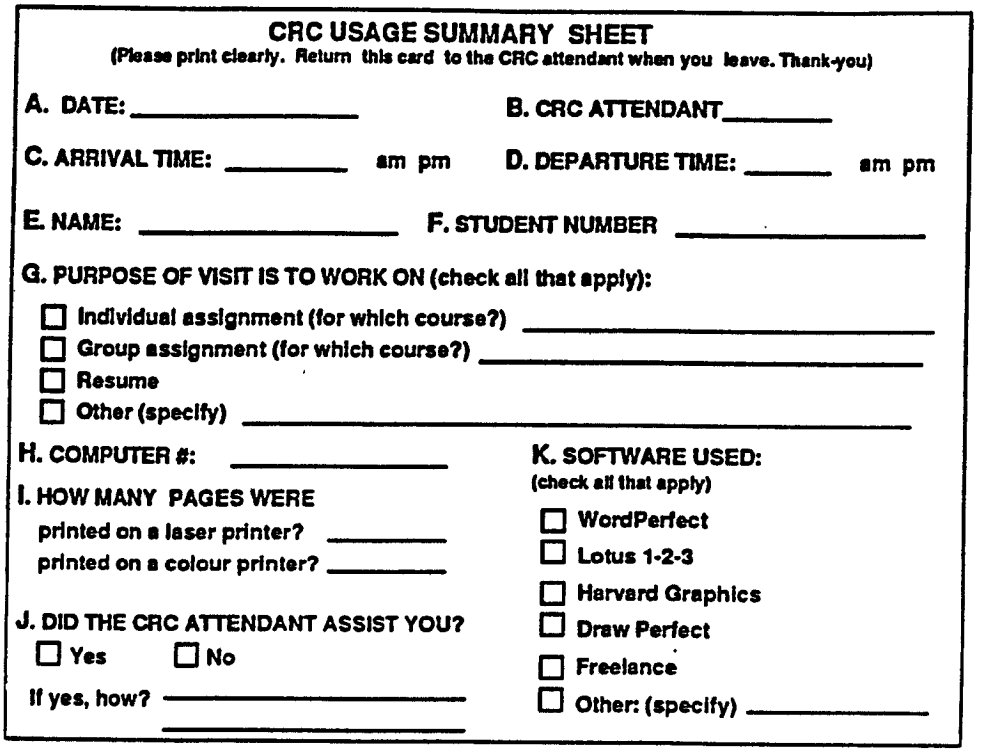
The pilot test was conducted to further improve the scales, to determine problems in completion of the instrument and to estimate the time required to complete the questionnaire.[5] Fifty seven participants completed the pilot test. Reliabilities for the scales ranged from 0.69 for facilitating conditions to 0.95 for subjective norm. Nine of the scales had reliabilities of 0.80 or more. Based on the results of this pilot test, the questionnaire was further modified and shortened. The final questionnaire contained 35 questions to measure the constructs of interest, as well as some demographic and other related questions. In total, the questionnaire contained approximately 60 items. The scales for each construct included in this study are reproduced in the Appendix. Note that there are no unique items for the monolithic belief structures (i.e., $\Sigma b_i e_i$, $\Sigma n b_j m c_j$, $\Sigma c b_k p f_k$), rather, each was created as a composite of the decomposed beliefs. For example, $\Sigma b_i e_i$ includes all the items from the perceived usefulness, perceived ease of use and compatibility scales.

The usage measures are based on forms completed each time a student used the CRC over a 12-week period. The form recorded the user's name and student number, the purpose of the visit to the CRC, the software used and the number of pages printed, as well as other information about the use of the facility. The usage record was designed so that it would take no more than 30 seconds to complete. The key usage measures derived from the form are total number of visits per user during the period (based on a count of the number of usage forms for each user), the total time spent in the CRC during the period (based on the time recorded for each visit) and the number of different assignments, projects and other activities completed while using the CRC. A sample usage form is reproduced in Figure 2.

3.3. *Participants*

Participants in the study were all business school students in a midsize university. The total number of students enrolled in the business school was approximately

[5] Behavior was not measured in the pilot test.



CRC USAGE SUMMARY SHEET

(Please print clearly. Return this card to the CRC attendant when you leave. Thank-you)

A. DATE: _____ B. CRC ATTENDANT _____

C. ARRIVAL TIME: _____ am pm D. DEPARTURE TIME: _____ am pm

E. NAME: _____ F. STUDENT NUMBER _____

G. PURPOSE OF VISIT IS TO WORK ON (check all that apply):

- ☐ Individual assignment (for which course?) _____
- ☐ Group assignment (for which course?) _____
- ☐ Resume
- ☐ Other (specify) _____

H. COMPUTER #: _____

I. HOW MANY PAGES WERE

printed on a laser printer? _____

printed on a colour printer? _____

J. DID THE CRC ATTENDANT ASSIST YOU?

☐ Yes ☐ No

If yes, how? _____

K. SOFTWARE USED:

(check all that apply)

- ☐ WordPerfect
- ☐ Lotus 1-2-3
- ☐ Harvard Graphics
- ☐ Draw Perfect
- ☐ Freelance
- ☐ Other: (specify) _____

FIGURE 2. CRC Usage Card.

1,000. In total, 786 participants completed the survey (which measured intention to use the CRC and its determinants), of whom 582 were undergraduate students; 204 were MBA students. Over half of the participants (486 of 786) had used the CRC prior to completing the survey. Most participants reported that they were relatively familiar with the CRC's services, averaging four on a seven point familiarity scale, where seven is highly familiar.

Of the 786 respondents to the survey, 451 used the CRC in the subsequent 12-week period during which usage was recorded. Thus, our sample is made up of 58% CRC users and 42% non-users, reflecting the fact that usage of the facility is truly voluntary.

3.4. *Setting and Data Collection Procedures*

Data were collected in two stages. Approximately one month after the fall semester began, research assistants administered the surveys to students during class time. The surveys assessed the respondents' beliefs, determinants of intention and their intentions to use the CRC over the remainder of the term. Prior to completing the questionnaire, all participants were provided with an information sheet describing the CRC and its services. This way, even respondents who had never used the CRC had access to information about the services typically available to users of the CRC. Respondents were informed that the data were being collected as part of a university research study, and would also be used to assess the services provided by the CRC.

Behavior data were collected separately. For a three month period, all visitors to the CRC were asked to complete a short survey card (see Figure 2). These survey

TABLE 1
Summary of Measurement Scales

Measure	# Items	Mean	Standard Deviation	Reliability[a]
CRC Usage				
# of visits	1	4.81	7.44	–
# of assignments	1	3.05	4.82	–
time (in hours)	1	3.22	5.86	–
Behavioral Intention (BI)	3	5.15[b]	1.63	0.91
Attitude (A)	4	5.43	0.92	0.85
Subjective Norm (SN)	2	4.24	1.44	0.88
Perceived Behavioral Control (PBC)	3	5.38	1.10	0.70
$\Sigma b_i e_i$	10	4.32	0.94	0.89
$\Sigma nb_j mc_j$	4	2.75	1.19	0.92
$\Sigma cb_k pf_k$	9	3.86	0.93	0.78
Perceived Usefulness	4	4.68	0.92	0.68
Ease of Use	3	6.17	0.51	0.71
Compatibility	3	3.93	1.32	0.82
Peer Influences	2	2.01	1.23	0.92
Superior Influences	2	3.49	1.53	0.80
Self Efficacy	3	3.98	1.63	0.85
Resource Facilitating Conditions	3	2.92	1.01	0.50
Technology Facilitating Conditions	3	4.68	1.47	0.78

[a] Guttman's Lower Bound.
[b] All scales have been standardized to a 0–7 scale.

cards were distributed to users by the CRC attendant who controlled the use of the facility and assigned users to specific computers. The card was premarked by the attendant with the date, the attendant's name, the computer number the user was assigned to, and the user's arrival time. The user returned the completed usage survey to the CRC attendant prior to leaving the facility. The attendant checked the card and filed it away for later coding. These procedures ensured the quality and completeness of the usage data.

3.5. *Measurement*

For the purposes of analysis, all belief items were combined with the evaluative component using the expectancy-value approach suggested in the TPB (i.e., $b_i e_i$, $nb_j mc_j$, $pf_k cb_k$) (Ajzen 1985, 1991). This approach was taken for all three models in order to focus on substantive differences between models, rather than confounding these substantive differences with measurement issues. Scales for each of the constructs were developed by averaging responses to the individual items. As will be discussed later, these composite scales were created to accommodate the estimation technique employed in the analysis. A summary of the scale characteristics is shown in Table 1. All scales except for perceived usefulness and resource facilitating conditions had reliabilities above 0.70.

The scales were subjected to a confirmatory factor analysis (CFA) involving all of the measures (including behavior) in order to assess construct validity. The CFA was conducted with LISREL8 (Joreskog and Sorbom 1993). To assess the model, multiple fit indices are presented. The traditional χ^2 fit test is reported. However, since the χ^2 test has been recognized as an inappropriate test for large sample sizes

(Browne and Cudeck 1993, Marsh 1994), three other indices are also included: the AGFI (Adjusted Goodness of Fit Index) (Joreskog and Sorbom 1993), the RNI (Relative Non-Centrality Index) (McDonald and Marsh 1990), a relative fit measure which compares the tested model with a null model; and the RMSEA (Root Mean Square Error of Approximation) (Steiger 1990), an absolute measure of lack of fit (assessing the discrepancy between the population covariance matrix and the fitted matrix). RMSEA takes into account parsimony as well as fit by examining discrepancy per degree of freedom. Acceptable model fits are indicated by values of: AGFI exceeding 0.80,[6] though clearly higher values are preferable, RNI values exceeding 0.90 (Marsh 1994), and RMSEA values below 0.10 with values lower than 0.08 suggestive of reasonable fit (Browne and Cudeck 1993).

The data were generally consistent with our hypothesized structure although the χ^2 value was significant ($\chi^2_{587} = 1961.90, p < 0.0001$). The other three fit statistics, AGFI, RNI, and RMSEA are all indicative of good fit (AGFI = 0.85; RNI = 0.92; RMSEA = 0.055).

In order to further assess the validity of measures, Bollen (1989) suggests examining the λ values (factor loadings) and the squared multiple correlations between the items and the constructs. In addition, as suggested by Fornell and Larker (1981) internal consistency values for each construct were calculated based on the λ values from the confirmatory factor analysis. These measures are analogous to Cronbach's alpha (Barclay et al. 1994).

Our analysis indicated significant loadings for each item on its hypothesized construct ($p < 0.01$ in all cases). In addition, there was little variance in the λ values within each construct, indicating that the items tended to contribute equally to the formation of the construct. Squared multiple correlations between the individual items and the constructs were generally high; only 7 of the 38 multiple correlations were below 0.40, indicating that, in general, the items shared substantial variance with their hypothesized constructs. Three of the seven lower multiple correlations were between items measuring facilitating conditions and the two facilitating condition constructs. Finally, the values for internal consistency suggest that the measures are reliable. Ten of the 13 scales were above 0.7. The three scales with lower than desired internal consistency values were PBC, with a value of 0.68, Resource Facilitating Conditions, with a value of 0.52, and Ease of Use, with a value of 0.60.

The measures of behavior were taken from the usage cards. Three measures were used: the number of visits made to the CRC, the total time spent in the CRC over the 12-week period, and the number of projects and assignments worked on in the CRC. These measures were derived by summing the individual visit data for each respondent.

Over the 12-week period during which usage was monitored, a total of 3,780 visits to the CRC were made by survey respondents. Those using the CRC made an average of 8.38 visits[7] over this time period, using the facility about once every 10 days. They spent an average of 5.6 hours using the CRC while working on approximately five

[6] We are not aware of any definitive statement on appropriate values for AGFI, however the literature seems to indicate that 0.80 is conventionally applied as the cutoff for good model fit.

[7] The numbers are the averages for the 451 individuals in our sample who used the CRC one or more times during the data collection period. They do not include the 351 respondents to the intention survey that did not use the CRC over this time. Including these nonusers, the average number of visits per respondent is 4.8.

different assignments and projects. For those who used the facility, usage ranged from 1 visit to 54 visits per user over the 12-week period. Thus, there was a considerable amount of variance in usage. In addition, recall that 335 respondents to the questionnaire made no use of the CRC at all during the 12 weeks of monitoring.

4. Findings

The hypothesized paths in each of the three models described above (see Figure 1) were tested using LISREL8 (Joreskog and Sorbom 1993) with weighted least squares (WLS) estimation.[8] LISREL is suggested as an appropriate technique for *comparing* alternative theoretical models (Joreskog 1993); furthermore, LISREL is especially appropriate when testing well-developed theories (Barclay et al. 1995). In conducting the analysis, each of the constructs, with the exception of behavior, was modelled as a single indicator using the mean of the summated scale adjusted to form a 7-point measure.[9] As suggested by Bollen (1989, p. 168), θ_δ and θ_ϵ were set to equal [(1 − reliability)*variance] for each summated scale. This permits us to take measurement error into account even though we are using aggregate measures for all of the constructs, except behavior. In modelling behavior, the three measures—the number of assignments worked on in the CRC, the number of visits to the CRC, and the total time spent in the CRC—were each included separately as censored variables (see Joreskog and Sorbom 1993, p. 45).[10] In conducting the analysis, the ψ matrix was set as diagonal and free, implying that the errors of the prediction equations are not correlated; the ϕ matrix was set as symmetric and free, allowing the independent constructs to correlate with one another. While allowing these independent constructs to covary results in a somewhat inflated model fit, it is important to recognize that relationships exist among these variables. As required for WLS, an asymptotic covariance matrix was used in the analysis (see Table 2 for the original covariance matrix). Seven hundred and eighty six usable responses were analyzed.

For each model, overall fit, predictive power and the significance of paths were considered. R^2 for each dependent construct was examined to assess explanatory power, and the significance of individual paths was assessed. The fit statistics and R^2 values for each of the four models are shown in Table 3. Path coefficients for each model and their significance are shown in Figures 3, 4, and 5. The total effects for each construct on behavioral intention and usage are shown in Table 4.[11]

[8] Weighted least squares estimation, rather than maximum likelihood, was used since the data were not multivariate normal (Mardia's test of multivariate normality: $\chi^2 = 70680.97$). WLS does not require the data to be multivariate normal.

[9] The use of WLS places restrictions on the number of variables allowed in the model as a function of sample size. The sample size is required to be a minimum of $1.5*K*(K+1)$ where K is the number of variables in the model. In our case, if all questionnaire items were entered individually in the model, we would have 38 variables and thus require a sample size of 2023. Therefore, in spite of our relatively large sample it was not possible to introduce each of the questionnaire items into the model individually; rather, the summated scales were employed.

[10] A censored variable is used in LISREL when a large number of observations take on a single value. This is done because excessive skewness and kurtosis in the data, which can result when many observations take on a single value, may affect tests of model fit and path significance (Bollen 1989). In our case this skewness is due to the values of 0 for the behavior measures of the 335 respondents who did not use the CRC during the 12 weeks that usage was monitored.

[11] Bollen (1989) stresses that it is important to look not only at direct effects (indicated by paths in the model) but also at indirect and total effects in interpreting results in a structural equation model. Total

4.1. Model 1—The Technology Acceptance Model

Overall, the fit statistics indicate that TAM provides a good fit to the data ($\chi^2_{12} = 98.14$, $p < 0.0001$; AGFI = 0.85; RNI = 0.998; RMSEA = 0.096[12]). Although the χ^2 value is significant, all other fit statistics are within the range suggestive of a good model fit. The model accounts for 34% of the variance in behavior, 52% of the variance in intention and 73% of the variance in attitude (see Table 3).

As indicated in Figure 3, most path coefficients were as hypothesized. The paths from ease of use to perceived usefulness and attitude were significant, as were the paths from perceived usefulness to attitude and intention. The path from intention to behavior was also significant. However, the path from attitude to intention was not significant.

Table 4 also indicates that perceived usefulness and ease of use both had significant total effects on usage, but that attitude did not.

4.2. Model 2—The Theory of Planned Behavior

Overall, the fit statistics indicate that the TPB model also provides a good fit to the data, though again the χ^2 is significant ($\chi^2_{31} = 208.17$, $p < 0.0001$; AGFI = 0.84; RNI = 0.995; RMSEA = 0.085). The fit is comparable to that of the TAM. Note that the RMSEA for this model is slightly better than that for TAM, suggesting that even when the increased complexity of the TPB is taken into consideration, the fit of the TPB model is at least equivalent to TAM.

The predictive power of the TPB model was roughly comparable to TAM. The addition of normative and control beliefs helped to successfully predict subjective norm and perceived behavioral control ($R^2_{SN} = 0.50$; $R^2_{PBC} = 0.84$), however these variables added only slightly to the explanatory power of behavioral intention ($R^2_{BI} = 0.57$ for TPB, compared with 0.52 for TAM). In addition, the introduction of a monolithic belief structure, incorporating perceived usefulness, ease of use and compatibility did not provide a better prediction of attitude; in this case, the R^2 value decreased relative to TAM ($R^2_A = 0.58$, relative to $R^2_A = 0.73$ for TAM). Most importantly, although $\Sigma c b_k p f_k$ explains the variance in PBC, PBC in turn does not provide greater explanation of behavior ($R^2_B = 0.34$). Thus, the addition of perceived behavioral control does not, in this case, help to better understand usage behavior relative to TAM.

As noted in Figure 4, path coefficients were as hypothesized in each case ($p < 0.01$ in all instances). Attitude and subjective norm were significant determinants of intention, and attitudinal and normative structure were significant determinants of attitude and subjective norm respectively. Of particular interest, the path from PBC to intention and the path from control structure ($\Sigma c b_k p f_k$) to PBC were both significant, as was the path from PBC directly to behavior.

effects indicate the combined effect of any direct path from a given independent construct to the dependent constructs of interest, in this case IT usage behavior and behavioral intention, as well as any indirect effects through other variables. For example, in TPB, PBC has a direct effect on behavior and an indirect effect through behavioral intention. The total effects reflect the combination of these two. In TAM, perceived usefulness has no direct effect on IT usage, but does have indirect effects through attitude and intention, these are reflected in the total effects in Table 4. A significant effect of perceived usefulness on IT usage indicates that usefulness indirectly influences usage.

[12] For RMSEA, a lower number is considered to represent a "better" model.

TABLE 2

Covariance Matrix Used in Analysis[a]

	Assign	Visits	Time	*BI*	PBC	*SN*	Attitude	Usefulness	Compatibility	Ease of Use	Peer	Superior	Self Efficacy	Resource	Technology
Assignments	23.71														
Visits	4.25	1.01													
Time	34.24	7.33	61.43												
BI	3.29	0.85	6.13	2.63											
PBC	1.12	0.30	2.05	0.71	1.21										
SN	0.08	0.03	0.06	0.72	0.11	2.03									
Attitude	0.69	0.13	0.92	0.73	0.39	0.49	0.81								
Usefulness	0.85	0.18	1.35	0.90	0.40	0.57	0.60	1.12							
Compatibility	1.51	0.36	2.71	1.17	0.66	0.61	0.71	0.91	1.74						
Ease of Use	0.25	0.06	0.38	0.08	0.20	0.01	0.12	0.17	0.19	0.26					
Peer	0.26	0.09	0.66	0.58	0.10	1.01	0.25	0.34	0.41	0.02	1.51				
Superior	0.01	−0.02	−0.05	0.69	0.05	1.05	0.37	0.59	0.49	0.03	0.88	2.34			
Self Efficacy	1.47	0.36	2.12	0.60	0.98	0.01	0.31	0.20	0.49	0.26	0.06	−0.27	2.65		
Resource	−0.53	−0.16	−1.16	−0.07	0.13	0.14	0.16	0.20	0.21	0.08	0.05	0.16	0.00	1.01	
Technology	0.77	0.23	1.45	0.31	0.56	0.03	0.30	0.34	0.36	0.26	0.00	0.09	0.80	0.22	2.14

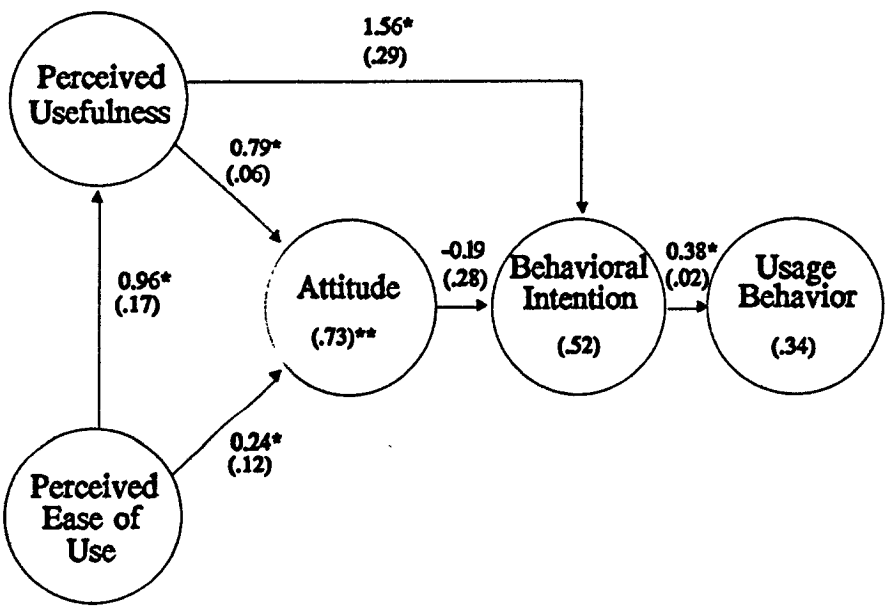
[a] This was converted to an asymptotic covariance matrix to conduct the WLS estimation.

TABLE 3

Fit Indices and Explanatory Power for Each of the Hypothesized Models

	TAM	TPB	Decomposed TPB
FIT			
df	12	31	61
χ^2	98.14*	208.17*	431.45*
A.G.F.I.	0.85	0.84	0.82
R.N.I.	0.998	0.995	0.993
R.M.S.E.A.	0.096	0.085	0.088
R^2_B	0.34	0.34	0.36
R^2_{BI}	0.52	0.57	0.60
R^2_A	0.73	0.58	0.76
R^2_{SN}	–	0.50	0.57
R^2_{PBC}	–	0.84	0.69

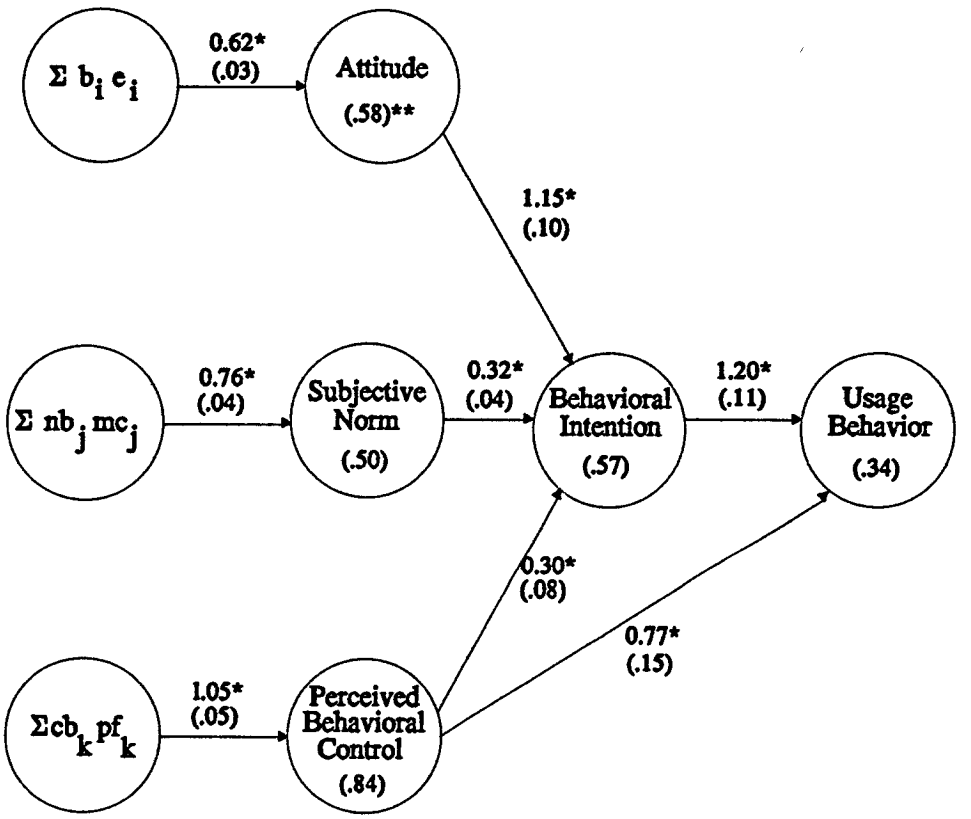
* ($p < 0.01$).



* p < .05

** R^2

FIGURE 3. Path Coefficients for the Technology Acceptance Model (Standard Errors).



* $p < .05$

** R^2

FIGURE 4. Path Coefficients for the Theory of Planned Behavior (Standard Errors).

Table 4 shows that attitude, subjective norm, perceived behavioral control and their antecedent belief conditions all have significant total effects on behavior.

4.3. Model 3—The Decomposed TPB

The decomposed version of the TPB provides essentially the same fit as the pure TPB model ($\chi^2_{61} = 431.45$, $p < 0.0001$; AGFI = 0.82; RNI = 0.993; RMSEA = 0.088). The decomposed TPB provides somewhat better predictive power relative to the TAM and TPB models ($R^2_B = 0.36$; $R^2_{BI} = 0.60$, $R^2_A = 0.76$, $R^2_{SN} = 0.57$; $R^2_{PBC} = 0.69$). In particular, note that there is a slight increase in R^2 for behavioral intention relative to both TAM and pure TPB.

As noted in Figure 5, the path from perceived usefulness to attitude is significant. However, the paths from ease of use and compatibility to attitude are not significant. Both peer and superior influences are significantly related to subjective norm; and self-efficacy and resource-based facilitating conditions (i.e., time and cost related

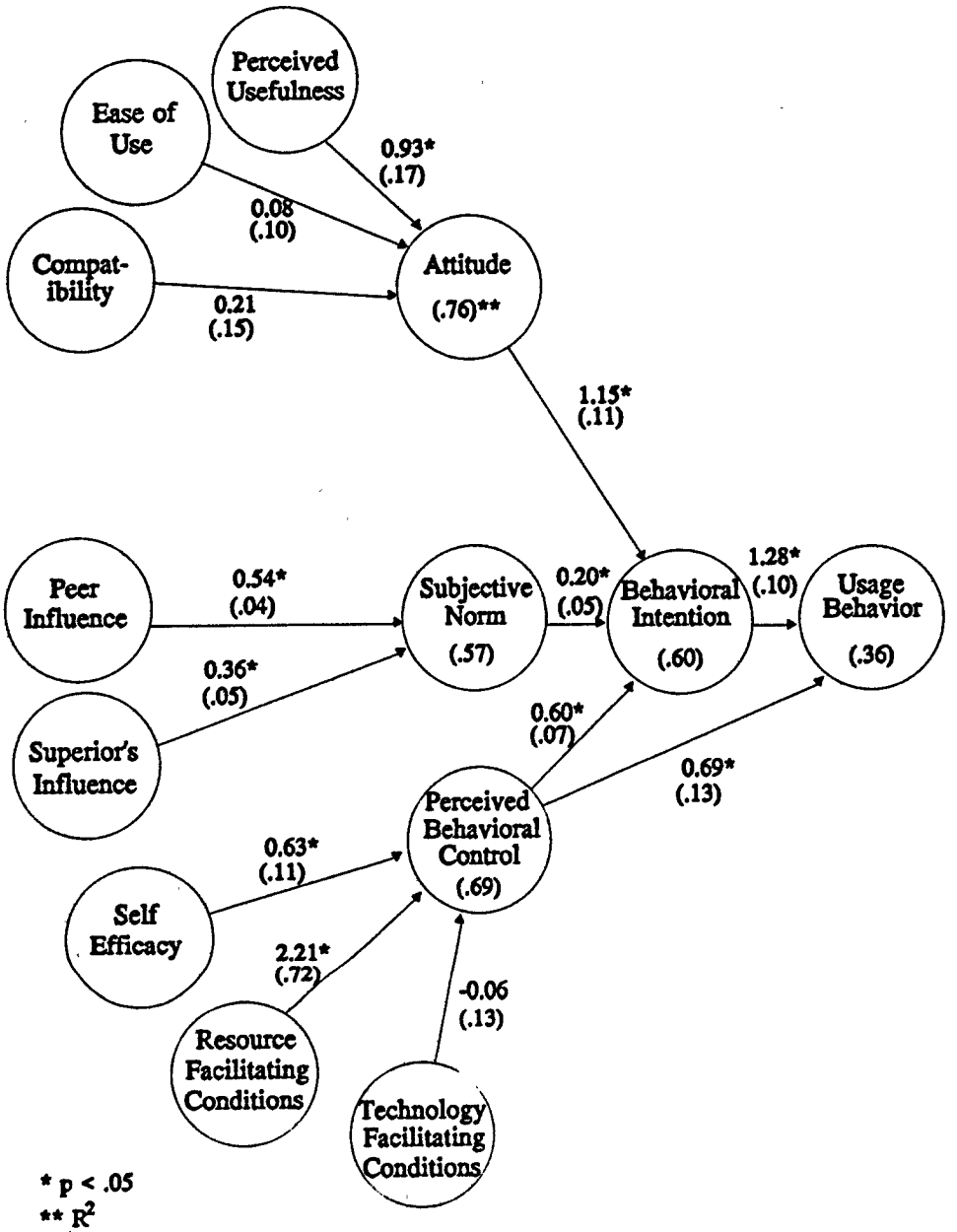


FIGURE 5. Path Coefficients for the Decomposed Theory of Planned Behavior (Standard Errors).

measures) are significant determinants of perceived behavioral control. All three determinants of intention, (i.e., attitude, subjective norm and perceived behavioral control), are significantly related to intention. Finally, both intention and perceived behavioral control are significant determinants of behavior.

Table 4 shows that attitude, subjective norm, and perceived behavioral control all have significant indirect effects on behavior. In addition, relative advantage, the

TABLE 4

*Total Effects on Behavior and Behavioral Intension for Each of the Hypothesized Models**

	TAM	TBP	Decomposed TPB
TO BEHAVIOR			
Perceived Usefulness	0.54[b] (.04)	–	1.36[b] (.27)
Ease of Use	0.50[b] (.09)	–	−0.31 (.22)
$\Sigma b_i e_i$	–	0.85[b] (.10)	–
$\Sigma nb_j mc_j$	–	0.29[b] (.05)	–
$\Sigma cb_k pf_k$	–	1.18[b] (.18)	–
Compatibility	–	–	−0.11 (.15)
Peer Influences	–	–	0.14[b] (.03)
Superior Influences	–	–	0.09[b] (.02)
Self Efficacy	–	–	0.91[b] (.18)
Technology Facilitating Conditions	–	–	−0.09 (.19)
Resource Facilitating Conditions	–	–	3.22[b] (1.07)
Attitude	−0.07 (.11)	1.38[b] (.16)	1.47[b] (.16)
Subjective Norm	–	0.38[b] (.06)	0.26[b] (.06)
Perceived Behavioral Control	–	1.13[b] (.17)	1.46[b] (.15)
TO BEHAVIORAL INTENTION			
Perceived Usefulness	1.41[b] (.10)	–	1.07[b] (.21)
Ease of Use	1.31[b] (.24)	–	−0.25 (.17)
$\Sigma b_i e_i$	–	0.71[b] (.06)	–
$\Sigma nb_j mc_j$	–	0.24[b] (.03)	–
$\Sigma cb_k pf_k$	–	0.31[b] (.08)	–
Compatibility	–	–	−0.09 (.11)
Peer Influences	–	–	0.11[b] (.02)
Superior Influences	–	–	0.07[b] (.02)
Self Efficacy	–	–	0.37[b] (.08)
Technology Facilitating Conditions	–	–	−0.03 (.08)
Resource Facilitating Conditions	–	–	1.32[b] (.46)

[a] Standard errors in parentheses.
[b] $p < 0.05$.

influence of friends and professors as well as self-efficacy and resource facilitating conditions all have significant indirect effects on behavior. The indirect effects of ease of use, compatibility and technical facilitating conditions are not significant to behavior.

5. Discussion

The intent of this study was to compare the Technology Acceptance Model to a traditional version and a decomposed version of the Theory of Planned Behavior in terms of their contribution to the understanding of IT usage. Data from a field study of in excess of 750 potential users of a computing resource center were used to test these models using structural equation modelling. This included behavior data based on approximately 3,700 visits to the resource centre, monitored over a 12-week period.

Overall, all three models provided comparable fit to the data based on the measures presented in Table 3. Given this, it is reasonable to examine the models in terms of path significance and explanatory power. It was anticipated that the TPB model, which adds subjective norm and perceived behavioral control as key determinants of

both intention and IT usage would provide a fuller explanation of behavioral intention and IT usage behavior. Furthermore, we expected the decomposed TPB model which includes detailed attitudinal, social and control influences, would provide the best overall explanation of IT usage behavior. In terms of the ability to explain IT usage behavior, the results show that the TAM and the two TPB models are comparable. However, when behavioral intention is considered, the results show improvement in explanatory power for both the pure and decomposed TPB over the TAM. These two results are explored in detail below.

5.1. *Understanding Behavior*

To interpret these results, it is important to examine how each of the models attempts to explain behavior. In all three models, behavioral intention is the primary, direct determinant of behavior. The TPB adds perceived behavioral control as an additional direct determinant of behavior. In addition, all three models suggest that there are indirect effects on behavior. These indirect effects are from each of attitude (for both TAM and TPB), subjective norm and perceived behavioral control (for TPB only), as well as their antecedent beliefs. Consider first the direct effect of *BI*, which is common to all three models. *BI* has long been recognized as an important mediator in the relationships between behavior and other factors such as attitude, subjective and perceived behavioral control (Ajzen and Fishbein 1980, Ajzen 1985). The path from behavioral intention to behavior was significant in all models. Furthermore, the correlation between *BI* and *B* was 0.54. This is a strong correlation, which is higher than the 0.34 correlation reported by Davis et al. (1989) for the explanation of self reported usage at the end of a term based on an intention measure taken at the start of the term (a situation which is identical to the one reported here, except that our usage is based on actual behavior throughout the term). The correlation is also consistent with the average correlation of 0.53 for the *BI-B* relationship reported in the Sheppard et al. (1988) meta-analysis of 87 studies. The 0.54 correlation implies that *BI* alone explains almost 30% of the variance in behavior.

The importance of *BI* as a mediating variable can be seen when *BI* is omitted from the three models and direct paths are provided to behavior. For TAM, this results in a model with paths from attitude and perceived usefulness directly to behavior. For the TPB and decomposed TPB, this results in paths from attitude, subjective norm and PBC directly to behavior. When this is done, the prediction of behavior decreases substantially (for TAM, $R_B^2 = 0.05$; for TPB, $R_B^2 = 0.14$; for decomposed TPB, $R_B^2 = 0.20$). The drop in predictive power when *BI* is excluded is consistent with Fishbein and Ajzen's (1975) identification of intention as an important mediating variable. Thus, *BI* plays an important substantive role, but is also important pragmatically in predicting behavior. However, it is important to note that *BI* is more predictive of behavior when individuals have had prior experience with the behavior (Taylor and Todd 1995).

An examination of the indirect effects in each model shows that most factors have a significant indirect effect on behavior. First for TAM, the indirect effects of both perceived usefulness and ease of use are significant ($t = 12.35$ and 5.3 respectively, $p < 0.01$). Interestingly, attitude does not have an indirect effect on behavior ($t = -0.69$; $p > 0.10$). This is likely due to the significant effect of usefulness on intention and subsequent behavior. This would appear to support the contention of Davis et al. (1989) that attitude may not be an important determinant of intention

and usage in workplace settings when other factors such as usefulness are independently taken into account. The explanation for such a finding is based on the fact that in work-related settings, performance is key, and intentions will be formed based on performance considerations rather than simply on personal likes or dislikes with respect to performing a behavior (Davis et al. 1989). Our setting provides an excellent example of such effects. The students are motivated in large part by consideration of grades and receive direct and frequent feedback on their performance. A survey of students taken independent of this research indicated that their perception was that quality of presentation was a key determinant of their academic performance. Thus, their decision to use the CRC may be independent of their attitudes towards it. They will use the CRC because they think it will help them to improve, or at least maintain, their grades.

For the pure TPB model, attitude, subjective norm and PBC all had significant indirect effects on behavior, as did the monolithic belief structures (i.e., $\Sigma b_i e_i$, $\Sigma n b_j m c_j$, $\Sigma c b_k p f_k$). Recall though that the variance explained for behavior did not increase for the pure TPB relative to TAM. For the decomposed TPB, the separate belief structures for superior and peer influences (professors and friends), as well as separate control beliefs for self-efficacy and resources, had significant indirect effects on behavior, however they had little effect on the R^2 for behavior relative to TAM and the pure TPB.

In interpreting the contribution of each model to the understanding of behavior, it is important to recognize that behavior is largely driven by behavioral intention, which on its own explains almost 30% of the variance in behavior. Furthermore, it is important to remember that variance explained actually decreases when *BI* is omitted from the model. Overall, the additional explanatory power afforded by the other factors in TAM and TPB are important, though relatively small. They are important in two ways. First, they have a measurable indirect effect on behavior (see Table 4). Second, they provide substantive indicators of the factors that influence behavioral intention, which is itself a key determinant of behavior. By turning to the antecedents of intention, we develop a fuller understanding of IT usage.

5.2. *Understanding Behavioral Intention*

Since behavioral intention is clearly the most important determinant of IT usage behavior in all three models, it becomes important to examine the direct and indirect influences of other factors on behavioral intention. TAM explains 52% of the variance in behavioral intention, pure TPB explains 57% and decomposed TPB 60% of the variance in intention. This indicates that the addition of subjective norm and perceived behavioral control and the decomposition of beliefs provide some additional insight into behavioral intention. Overall, the results are consistent with the meta-analysis of TRA reported by Sheppard et al. (1988) which reports that attitude and subjective norm together explained 44% of the variance in behavioral intention. The results are also similar in magnitude to those reported by Davis et al. (1989), Mathieson (1991) and Hartwick and Barki (1994).

Each of the models employs attitude and beliefs about ease of use and usefulness to explain behavioral intention. TAM differs from the other two models in that it also allows a direct link from perceived usefulness to behavioral intention. It is clear that this direct effect is important. In TAM, the direct effect of perceived usefulness is

significant, while attitude does not have a significant influence on behavioral intention. The reasoning for this was outlined above. In addition, ease of use has a significant total effect on behavioral intention through both perceived usefulness and attitude ($t = 5.3$; $p < 0.01$). In short, TAM employing two factors, ease of use and usefulness, can explain over 50% of the variance in behavioral intention.

The two TPB models both show moderate increases in the ability to explain intention, relative to TAM. Thus, both subjective norm and perceived behavioral control do contribute to the explanation of behavioral intention. The direct effects, as indicated in Figures 4 and 5 are significant in both models. In addition, superior and peer influences, self-efficacy and resource constraints, all have significant indirect influences on *BI*. Thus, while it is reasonable to conclude that all three models provide similar predictions of IT usage behavior, it appears that the TPB models, in this case, provide a more complete understanding of intention than does TAM.

5.3. *Comparison to Prior Studies*

It is important to contrast these results with those of Davis et al. (1989) and Mathieson (1991). In these studies, the TRA and TPB models did not perform as well as TAM in predicting behavioral intention (R^2 for TAM was 0.5 to 0.7 while R^2 for TRA and TPB was between 0.3 and 0.6). In both cases, TAM outperformed TPB in predicting behavioral intention. Our results show somewhat smaller differences in explanatory power, but in the opposite direction to those previously reported, with TPB providing a moderately better explanation of *BI*.

In making any comparisons, the differences in measurement approaches between the studies should be taken into account. However, all of these studies measure the same constructs and each has taken care to establish the validity and reliability of those measurements, This permits us to focus on the substantive similarities and differences between the studies. There are several possible substantive explanations for these results which should be considered. These explanations relate to differences in the contexts which were studied; however, since these models were designed to understand and predict behaviors in general, comparisons across studies are warranted and necessary to develop cumulative knowledge in this area.

First, neither Davis et al. (1989) nor Mathieson (1991) found a significant influence of subjective norm on behavioral intention. We, however, do find such an influence, which provides some contribution to the explanation of *BI*. This result may be due to differences in the nature of the target behavior between the studies. We examined actual use of a computing resource facility that the students use voluntarily over a period of time. Students are likely to be influenced in deciding whether to use the facility by both what their professors may think, due to possible impact on their grades, and by what their peers think due to the competitive nature of the environment. In addition, they are influenced by the need to work in teams with other students. Thus, we believe that the perception of real consequences associated with the behavior causes subjective norm to have a significant influence on *BI*. Indeed, Davis (1993) and Davis et al. (1992) both suggest that subjective norm may be influential in more realistic organizational settings. Furthermore, since subjective norm has been found to be more important in early stages of system development (Hartwick and Barki 1994), our results, with respect to subjective norm, may be due to the fact that our sample included a large number of respondents with no prior use of the CRC. In fact, when the relationship between subjective norm and behavioral intention is compared for those with and

without prior experience in the CRC, we found that while subjective norm was a significant determinant for both groups, it was a more important predictor of intention for those without prior experience (Taylor and Todd 1995).

The naturalistic setting, where actual behavior was monitored, may also have made the subjective norm and perceived behavioral control components of the model more salient to the respondents and thus these constructs may have had a greater influence on the formation of behavioral intention. For example, in this study students were using the CRC to work on actual projects in a variety of courses in a relatively competitive environment. Mathieson (1991, p. 188), by contrast, examined a task where differences in grades and other long term consequences are explicitly *ruled out* as consequences of the behavior.

Third, our decomposition approach and the inclusion of a variety of theoretically based belief constructs may have strengthened the ability of the model to explain intention. The partitioning of normative influences into peer and superior influences, and the inclusion of efficacy and resource factors for PBC likely result in some differences in explanatory power relative to those reported by Davis et al. (1989) and Mathieson (1991) where beliefs in TRA and TPB were treated as monolithic constructs.

Operational differences between the studies may also account for the differences. Constructs which were common to each model were measured in the same fashion for this study, whereas Davis et al. (1989) and Mathieson (1991) used different scales for the attitudinal beliefs included in TRA and TPB. They did not explicitly incorporate the ease of use and usefulness items found in TAM in their operationalizations of the TRA and TPB belief sets. Both of these approaches have merit. The development of measures specific to the models, as was done by Davis and Mathieson, helps to ensure fair operationalizations of the theories. At the same time, it may omit or underrepresent important beliefs such as ease of use and usefulness which are known to influence intention and behavior. Furthermore, when different measures are used, it becomes unclear whether the observed differences are due to substantive concerns or measurement concerns. Our approach narrows the focus to substantive concerns. Differences between the models are not attributable to how we measure common constructs but rather to how the theories represent the relationships between those constructs.

Since TAM has received considerable support in the literature, and receives support in this study as well, in spite of an alternative operationalization of ease of use and usefulness, we would view this alternative approach as a strength of the study. In our view, it complements the approach followed by Davis et al. (1989) and Mathieson (1991). Further, it is consistent with the suggestion by Davis (1993) that alternative operationalizations of the TAM constructs need to be examined to determine the robustness of the model.

5.4. *Comparison and Selection of Models*

In a setting where all three models exhibit a reasonable fit to the data and explain similar amounts of the target behavior, i.e., usage, other criteria must be examined to determine which model is "best". Indeed, the definition of a "best" model in this case may depend on the purpose to which the model is put. Typically, fit statistics and explanatory power being equivalent, the "best" model is the one which is the most parsimonious (Bagozzi 1992). An extensive discussion of parsimony in the history of science and its relationship to structural equation modelling is provided by Mulaik

et al. (1989). By their reasoning, a model that provides good prediction while using the fewest predictors is preferable. Other researchers however, have argued that parsimony, in and of itself, is not desirable but rather is desirable only to the extent that it facilitates understanding (Browne and Cudeck 1993, McDonald and Marsh 1990). Based on this reasoning, we would assert that, assuming reasonable fit and explanatory power, models should be evaluated in terms of both parsimony and their contribution to understanding. For predictive, practical applications of the model, parsimony may be more heavily weighted. In trying to obtain the most complete understanding of a phenomena, a degree of parsimony may be sacrificed. In our case, while all three models are relatively parsimonious, the 5-variable TAM is, in our opinion, more parsimonious than the 13-variable decomposed TPB. In fact, the decomposed TPB with 11 determinants of *BI* and *B* can be considered an order of magnitude more complex than TAM which has only three determinants of behavioral intention and behavior.

First, by comparing the two TPB models, we can examine the trade-off between parsimony and understanding associated with decomposition. The decomposed TPB is a more complex model than the pure TPB by virtue of the additional constructs it includes. However, by decomposing the belief structures, the explanatory power of the model increases somewhat for behavioral intention. More importantly, because of its unidimensional belief constructs, the decomposed TPB model provides better diagnostic value than the original TPB model. It suggests specific beliefs that can be targeted by designers or managers interested in influencing system usage. It also provides greater insight into the factors that influence IT usage. Thus, in comparing the two versions of the TPB, we believe that there is value added as a result of the decomposition, in terms of increased explanatory power and a better, more precise, understanding of the antecedents of behavior. Thus, in our view, the decomposed TPB is preferable to the pure form of the model.

In comparing the decomposed TPB model to TAM, a number of factors need to be considered in making the model selection. Both TAM and the decomposed TPB include specific constructs which provide a detailed understanding of behavioral intention and IT usage behavior. Thus, like the decomposed TPB, TAM is directive. In addition, it is parsimonious. Thus, to make a choice between the two models, it is important to consider the relative trade-off of the moderate increases in explanatory power for behavioral intention and understanding of relevant phenomena against the increased complexity of the decomposed TPB. In making this choice it is important to consider how the model is to be applied.

On the one hand, while the decomposed TPB model has a good fit, and moderately better predictive power, particularly with respect to *BI*, it is not clear that this offsets the increased complexity of the model relative to TAM. It takes the inclusion of seven more constructs in the decomposed TPB model to increase the predictive power of behavior 2% over TAM. However, the decomposed TPB model helps to better understand subjective norm and perceived behavioral control and their role as determinants of behavioral intention. As a result, it provides a better understanding of behavioral intention. In short, if the central goal is to predict IT usage, it can be argued that TAM is preferable. However, the decomposed TPB model provides a more complete understanding of the determinants of intention.

In this regard, the limits of the parsimony argument should be recognized. If we are guided solely by a rule of parsimony then it becomes possible to argue that a

model linking behavioral intention to behavior is most appropriate. Such a model would explain a large part of the variance in behavior relative to either TAM or TPB and would do so with only a single variable. Clearly such a model is undesirable because it tells us little about the factors that influence IT usage. By contrast, both TAM and decomposed TPB provide some very useful and direct indicators of behavioral intention and usage behavior and we would argue that the decomposed TPB provides the richest understanding of these factors. While TAM focuses on system design characteristics and is of particular use as a guide to design efforts, the TPB model includes these design factors, but also draws attention to normative and control factors that an organization can work with to facilitate implementation.

Normative beliefs, self-efficacy, and facilitating conditions, the additional components of the decomposed TPB, provide managers with leverage points from which to manage the successful deployment of IT. Normative beliefs speak to the importance of, and avenues for, communication and user participation. Furthermore they provide an important rationale for the impact of top management support. Self-efficacy places a focus on training as an important mechanism to influence system acceptance. Finally, the impact of facilitating conditions should alert management to possible barriers to use, including those that may be established institutionally through mechanisms such as chargeback schemes or by basic decisions with respect to IT architecture. Overall, the decomposed TPB model should resonate well with those who study systems implementation and recognize that technical and design features are a necessary, but not sufficient, condition for successful implementation. Thus, the decomposed TPB may be particularly relevant to providing guidance during implementation efforts. Moreover it may provide a linkage between the study of individual IT usage and the impact of organizational IT deployment decisions on the value of IT to the firm.

In summary, each model has clear strengths. If the sole goal is the prediction of usage, then TAM might be preferable. However, the decomposed TPB provides a fuller understanding of usage behavior and intention and may provide more effective guidance to IT managers and researchers interested in the study of system implementation.

6. Limitations and Further Research

This study represents a careful and systematic effort to examine three models of IT usage. It incorporates a number of features, including a large sample size, actual measures of behavior collected over time and a realistic setting which lend significant strength to the study. However, it is not without its limitations. First, it is important to recognize that the three models were examined in a student setting where subjective norms and perceived behavioral control may operate differently than in workplace settings. On the one hand, because the measurement of performance and effort expended by the students are perceived to be related, the actual strength of linkages to behavior may be stronger in this setting than in the workplace. In workplace settings, a variety of more ambiguous factors may influence behavior and the linkages between behavior and rewards are not as apparent. At the same time, use of the computing resource center was largely voluntary, in that most students had other options available to them. In workplace settings, usage is more likely to be mandated and thus our results may not hold for such settings. Under conditions of mandatory

usage, different results may be obtained. Thus, caution must be exercised in any attempt to generalize these findings directly to organizational settings.

A second general concern with studies of this type is the issue of self-generated validity (Feldman and Lynch 1988). According to this argument, when survey respondents are asked about issues to which they have given very little prior thought, they are likely to construct responses based on the measurements taken of these issues. Thus, respondents are apt to use answers to earlier survey questions as the bases for responses to later questions, resulting in inflated causal linkages. This may be most problematic for respondents who have no prior experience with the target behavior. While this may have potential implications for the results in this study, we feel that these effects are mitigated for two reasons. First, over half of our sample had previously used the CRC. Second, we monitored actual behavior over time rather than just behavioral intention or self reported usage.

Perhaps one of the most interesting results from this study was that by adding subjective norm and perceived behavioral control constructs to the relatively simple TAM model, the ability of the model to predict IT usage behavior did not increase substantially. This leads us to question: what does account for the approximately 65% of variance in behavior which is unexplained? While TAM accounted for 34% of the variance in behavior, adding predictors such as PBC, efficacy and facilitating conditions in the decomposed TPB model did not increase the variance accounted for in behavior in a substantial way. Similarly, while subjective norm was significant in the model, it did not add any significant amount of explanatory power over and above TAM when only IT usage is considered. This suggests a need for a broader exploration of factors beyond those suggested by the traditional intention and innovations models. For example, Hartwick and Barki (1994) show that participation and involvement in the design process are related to attitude, intention and usage. Prior usage may also be an important determinant (Thompson et al. 1991, Triandis 1979).

Alternatively, it may be that additional general factors do not exist which can be used to systematically explain usage behavior. In other words, it may be that 30% to 40% explained variance is the best that can be done in these settings and that additional factors are highly situation specific. Such an outcome would be consistent with the meta-analytic findings with respect to TRA, indicating an average explanation of about 30% of the variance in behavior (Sheppard et al. 1988). However, even if only 30% of the variance can be accounted for by these models, this still serves to reduce, by a significant amount, the risk of system failure. Nevertheless, further exploration of alternative factors that might influence usage and intention are warranted.

One avenue for exploration is to expand on these findings by more fully examining the relationships among the determinants of attitude, subjective norm and perceived behavioral control. These determinants are not independent of one another, as is suggested in TAM where ease of use impacts directly upon perceived usefulness (Davis 1989, Davis et al. 1989). It might also be reasonable to expect that ease of use and self-efficacy would be related. Table 2 indicates some of these interrelationships for this data set. In this case there are high covariances between perceived usefulness and compatibility, between peer and superior influences and between self-efficacy and technical facilitating conditions. Further investigation into these interrelationships may help to better understand IT usage behavior.

Finally, it should be recognized that there are alternative approaches to the study of IT usage at the workgroup, firm and economic level which should be considered in

assessing information technology usage. The manner in which firms chose to deploy IT resources should have a significant impact on individual IT usage. Thus, in order to truly explain usage and the value of IT more broadly, researchers need to examine the issue at these different levels of analysis and moreover attempt to integrate and reconcile these diverse works. A useful approach would be to examine the impact of firm level factors, which influence IT deployment strategies, on individual beliefs about IT and subsequent usage of systems and to relate all of these factors to worker productivity. This would provide direct evidence on how institutional mechanisms might influence IT adoption and usage and help to integrate this research with the literature which examines IT value.

To conclude, the results of this study demonstrate that while the Technology Acceptance Model is useful in predicting IT usage behavior, the decomposed TPB provides a more complete understanding of behavior and behavioral intention by accounting for the effects of normative and control beliefs. This should help to better manage the system implementation process by focusing attention on social influences and control factors in the organization that influence IT usage.*

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Appendix: Questionnaire Items.

Attitudinal Structure

Perceived Usefulness

b_1 The CRC will be of no benefit to me.
e_1 A service that is of no benefit to me is: (bad/good).

b_2 Using the CRC will improve my grades.
e_2 A service that will improve my grades is: (bad/good).

b_3 The advantages of the CRC will outweigh the disadvantages.
e_3 A service with more advantages than disadvantages is: (bad/good).

b_4 Overall, using the CRC will be advantageous.
e_4 A service that is advantageous is: (bad/good).

Compatibility

b_5 Using the CRC will fit well with the way I work.
e_5 A service that fits well with the way I work is: (bad/good).

b_6 Using the CRC will fit into my workstyle.
e_6 A service that fits into my workstyle is: (bad/good).

b_7 The setup of the CRC will be compatible with the way I work.
e_7 A service that is compatible with the way I work is: (bad/good).

Ease of Use

b_8 Instructions for using equipment in the CRC will be hard to follow.
e_8 Instructions that are hard to follow are: (bad/good).

b_9 It will be difficult to learn how to use the CRC.
e_9 A service that is difficult to learn is: (bad/good).

b_{10} It will be easy to operate the equipment in the CRC.
e_{10} A service with equipment that is easy to operate is: (bad/good).

Normative Structure
Peer Influences
nb_1 My friends would think that I should use the CRC.
mc_1 Generally speaking, I want to do what my friends think I should do.

nb_2 My classmates would think that I should use the CRC.
mc_2 Generally speaking, I want to do what my classmates think I should do.

Superior Influences
nb_3 My professors would think that I should use the CRC.
mc_3 Generally speaking, I want to do what my professors think I should do.

nb_4 I will have to use the CRC because my professors require it.
mc_4 Generally speaking, I want to do what my professors think I should do.

Control Structure
Efficacy
cb_1 I would feel comfortable using the CRC on my own.
pf_1 For me, feeling comfortable using a service on my own is: (unimportant/important).

cb_2 If I wanted to, I could easily operate any of the equipment in the CRC on my own.
pf_2 For me, being able to easily operate equipment on my own is: (unimportant/important).

cb_3 I would be able to use the equipment in the CRC even if there was no one around to show me how to use it.
pf_3 For me, being able to use equipment even if there is no one around to show me how to use it is: (unimportant/important).

Facilitating Conditions—Technology
cb_4 The equipment (printers, computers, etc) in the CRC are not compatible with the other computers I use.
pf_4 For me, a service having equipment that is compatible with the other equipment I use is: (unimportant/important).

cb_5 The software in the CRC is not compatible with the software I use.
pf_5 For me, a service having software that is compatible with the software I use is: (unimportant/important).

cb_6 I will have trouble reading my disks in the CRC.
pf_6 For me, whether or not I have trouble reading my disks is: (unimportant/important).

Facilitating Conditions—Resources
cb_7 There will not be enough computers for everyone to use in the CRC.
pf_7 For me, having enough computers for everyone to use is: (unimportant/important).

cb_8 Printing in the CRC will be too expensive.
pf_8 For me, being able to print for a low price is: (unimportant/important).

cb_9 I won't be able to use a computer in the CRC when I need it.
pf_9 For me, being able to use a computer when I need it is: (unimportant/important).

Attitude
A_1 Using the CRC is a (*bad/good*) idea.
A_2 Using the CRC is a (*foolish/wise*) idea.
A_3 I (*dislike/like*) the idea of using the CRC.
A_4 Using the CRC would be: (*unpleasant/pleasant*).

Subjective Norm

SN_1 People who influence my behavior would think that I should use the CRC.
SN_2 People who are important to me would think that I should use the CRC.

Perceived Behavioral Control

PBC_1 I would be able to use the CRC.
PBC_2 Using the CRC is entirely within my control.
PBC_3 I have the resources *and* the knowledge *and* the ability to make use of the CRC.

Behavioral Intention

BI_1 I intend to use the CRC this term.
BI_2 I intend to use the CRC *to print* projects, papers or assignments this term.
BI_3 I intend to use the CRC *frequently* this term.

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