MIS Quarterly

RESEARCH ARTICLE

THE INTEGRATIVE FRAMEWORK OF TECHNOLOGY USE: AN EXTENSION AND TEST[1]

By: **Sung S. Kim**
Wisconsin School of Business
University of Wisconsin–Madison
975 Univesity Avenue
Madison, WI 53706
U.S.A.
skim@bus.wisc.edu

Abstract

The integrative framework of technology use (IFTU) posits that to fully explain post-adoption phenomena, four mechanisms—namely, reason-oriented action, sequential updating, feedback, and habit—should be taken into account simultaneously in a unified model. Although IFTU sheds light on the four mechanisms underlying technology use, it lacks a coherent theoretical explanation for the underlying force that leads to the four mechanisms. To offer a more generalized and richer description of the four mechanisms, this study extends IFTU by drawing on the process model of memory in cognitive psychology. In addition, based on the extended IFTU paradigm, a three-wave panel model is developed that incorporates not only proximal effects but also distal effects of the four mechanisms on post-adoption phenomena. Three different sets of data (n = 195, 160, and 342, respectively) are used to test the proposed model. The results of data analysis show that, as expected, the four mechanisms have proximal effects on subsequent evaluations and behavior. Furthermore, consistent with the memory perspective, the sequential updating and habit mechanisms are found to have distal effects on post-adoption phenomena even after controlling for their proximal effects. Overall, the findings of this study indicate that the memory perspective offers not only a seamless explanation of the four mechanisms underlying technology use but also yields deeper insights that can be validated only through a three-or-more-wave panel study. This research contributes to the literature by demonstrating that the extended IFTU paradigm has the potential to serve as a coherent theoretical framework on post-adoption phenomena in which prior experiences are internalized into memories, which in turn regulate later experiences.

Keywords: Longitudinal study, panel model, technology use, continued use, theory of planned behavior (TPB), process model of memory, path analysis

Introduction

Much research in information systems has focused on identifying the relationships between individuals' evaluations of a technology application and their use of this application (Davis et al. 1989; Taylor and Todd 1995). Although this stream of research sheds light on various psychological factors affecting technology use, it pays little attention to the dynamic interplay that occurs over time between evaluations and technology use. While pointing out the limitations of such static models, which focus only on the psychological determinants of technology use, Benbasat and Barki (2007) call for research that will advance understanding of the dynamic process through which evaluations and behavior change as individuals gain experience with a technology application. In the IS domain, several groundbreaking studies have examined the mechanisms that underlie continued use after adoption. For example, Bhattacherjee (2001) theorized that the formation of current judgments would involve the

[1]Detmar Straub was the accepting senior editor for this paper. Andrew Burton-Jones served as the associate editor.

referencing of prior judgments as supplemental information (i.e., the evaluation–evaluation relationship). In addition, Bajaj and Nidumolu (1998) demonstrated that past use positively influenced current evaluations of the use of a technology application (i.e., the behavior–evaluation relationship). Similarly, Venkatesh et al. (2000) showed that past use had a direct impact on current use (i.e., the behavior–behavior relationship). A consistent premise of these pioneering works is that prior evaluations and behavior relate, in one way or another, to subsequent evaluations and behavior at the post-adoption stage.

Although post-adoption research has revealed numerous mechanisms that drive post-adoption phenomena, few attempts have been made to integrate the disparate perspectives on the nature of those mechanisms. One exception to those fragmented approaches was a longitudinal study by Kim and Malhotra (2005). In attempting a comprehensive theory of how individuals adjust their evaluations and behavior over time, Kim and Malhotra proposed an integrative framework of technology use (IFTU). In essence, IFTU combines into a unified framework four mechanisms—namely, reason-oriented action (i.e., the evaluation–behavior relationship), sequential updating of judgments (i.e., the evaluation–evaluation relationship), feedback (i.e., the behavior–evaluation relationship), and habit (i.e., the behavior–behavior relationship)—that are believed to play important roles in affecting technology use. In their study, the IFTU paradigm was applied specifically in the form of a two-wave panel model (2WPM) in which the technology acceptance model (TAM), which represents the reason-oriented action framework, is complemented by the other three mechanisms of sequential updating, feedback, and habit. Based on data collected from 189 individual users' of a Web-based application, Kim and Malhotra demonstrated that the TAM-based 2WPM explained technology use better than any of the partial models, thus providing initial support for the conceptual framework.

As a comprehensive model of continued use, IFTU helps to enhance our ability to understand the interplay of the four mechanisms in regulating post-adoption phenomena. However, a number of other theoretical issues remain unresolved. First of all, IFTU mainly focuses on describing how the four mechanisms regulate individuals' evaluations and behavior over time but says little about why the four mechanisms are essential to an explanation of continued use at the post-adoption stage. In particular, it lacks a coherent theoretical explanation for the underlying force that leads to the four mechanisms. As a result, when it comes to explaining post-adoption phenomena, the IS community is still left with several seemingly unrelated viewpoints. Another important issue deserving of attention is the extent to which the effects of current evaluations and behavior carry over across time into subsequent evaluations and behavior. IFTU, in its current form, simply posits the proximal effects of the four mechanisms that refer to the short-term, transitory effects that current evaluations and behavior have on subsequent evaluations and behavior. Yet, it does not offer insight into whether the four mechanisms would have long-term, lingering effects, which are called distal effects hereafter, over and above the proximal effects. For example, one view of the sequential updating mechanism holds that current judgments can be securely stored in the brain, where they will be replaced completely with subsequent judgments as new information becomes available (Bolton and Drew 1991; Oliver 1981). According to this proposition, prior judgments are not expected to have distal effects on subsequent judgments. In contrast, another stream of research suggests that memory is a rather abstract and cumulative record of personal experiences. This contrasting view implies that, through this subjective mental representation, prior judgments would have long-lasting effects on subsequent judgments (Alba and Hutchinson 1987; Babin and Babin 2001; Winn 2004). As evident from the discussion, distal effects imply theoretical and managerial connotations that cannot be captured by proximal effects. Unfortunately, however, IFTU remains silent about the critical issue of proximal versus distal effects.

This study is specifically intended to extend the IFTU paradigm by offering a more generalized and richer description of the four mechanisms underlying post-adoption phenomena. To achieve this objective, this study draws on cognitive psychology and its three-stage processing model of memory (Myers 2004; Winn 2004). Basically, the model of memory illustrates how past experiences such as prior evaluations and behavior are accumulated into memory and how the outcomes of learning stored in memory regulate subsequent evaluations and behavior. The memory perspective is particularly relevant in the development of a longitudinal model of continued use because ultimately memory, either explicitly or implicitly, will be the repository of a person's experiences with a technology application and the source of any subjective viewpoint in the interpretation of new information related to the use of the application. Overall, the memory perspective is expected not only to offer a more complete view of the four mechanisms but also to shed new light on the hidden process that is critical to the discussion of proximal versus distal effects.

In addition to using the memory perspective to develop an extended IFTU paradigm, this study also attempts to empirically test the efficacy of the new theoretical framework. In particular, it evaluates the extended IFTU paradigm, which is specifically represented as a three-wave panel model (3WPM) based on the theory of planned behavior (TPB) (Ajzen 1991). A TPB-based 3WPM is examined because TPB is one of the most dominant conceptual models in the IS domain and because a three-wave context presents the opportunity to thoroughly assess the delicate nuances of the memory perspective (e.g., proximal versus distal effects). This proposed model, along with other competing models, is empirically tested based on three different sets of three-wave panel data that are available in the existing literature in the form of correlations (Morris et al. 2005; Venkatesh et al. 2000). The datasets were formerly examined by a longitudinal model that integrates TPB and the proximal habit mechanism. Nevertheless, this existing model in the literature fails to take into account some critical processes that occur at the post-adoption stage. Thus, it is important in this study to reexamine the three-wave panel data from a new perspective. In general, the finding of this study will help assess the efficacy of the extended IFTU paradigm as a comprehensive and in-depth account of how individuals' evaluations and behavior evolve with experience.

The organization of this paper is as follows: The next section discusses the process model of memory and explains how the memory perspective is relevant in the context of technology use. The third section draws on the memory perspective, extends the IFTU paradigm, and develops a TPB-based 3WPM. The fourth section describes the methodology of this study as well as the results of data analysis. This paper concludes with a discussion of research findings, the limitations of this study, and opportunities for further research.

Process Model of Memory

A large number of IS studies have shown that initial information technology use is determined by individuals' firsthand "on-the-spot" evaluations at the preadoption stage. Specifically, TAM states that individuals' evaluations of a new IT application—as captured by perceived usefulness and perceived ease-of-use—will influence whether they choose to use the application. Similarly, other reason-oriented action frameworks such as TPB emphasize that individuals' behavior is driven by a deliberate evaluation of the situation in question and determined wholly from scratch without reference to prior knowledge or experience. Meanwhile, in the course of the shift of theoretical focus from initial use to sustained usage, more attention has recently been paid to the role of prior evaluations and behavior in regulating subsequent post-adoption phenomena (Bhattacherjee and Premkumar 2004; Kim and Malhotra 2005). This stream of research has repeatedly shown that personal history matters; that is, prior evaluations determine current evaluations (i.e., sequential updating), prior behavior influences current evaluations (i.e., feedback), and prior behavior affects current behavior (i.e., habit). Unfortunately, however, a coherent theoretical account of continued use is still lacking as evidenced by the disparate theories employed to explain different facets of post-adoption phenomena (i.e., sequential updating, feedback, habit).

Continued use of a technology application is not a one-shot effort; it involves one's ongoing interactions with the same application over time. Inevitably, prior evaluations and behavior are likely to be somehow internalized into one's memories, and these memories are assumed to play an important role in regulating subsequent phenomena. Thus, an accurate understanding of memory is essential to developing a theoretical framework of the role of past experiences in changing subsequent experiences. In this sense, the three-stage processing model of memory proposed by Atkins and Schiffrin (1968) offers a unified account of how human experiences are processed in the memory system (Myers 2004). In essence, this theory holds that memories are processed at three different stages and that these three memory processes involve sensory memory, short-term memory, and long-term memory. In addition, contemporary research in cognitive psychology suggests that long-term memory should be further divided into two categories, namely, explicit and implicit memory (Greenfield 1997; Miller and Cohen 2001; Thompson and Kim 1996; Winn 2004). Figure 1 depicts a process model of memory that is a revised version of the original three-stage model. This version emphasizes the difference between explicit and implicit memory mentioned in contemporary research. This process model offers a frame of reference for further discussion on the role of memory in post-adoption phenomena.

Memory is defined as the persistent collection of learning, including concepts, events, and procedures that characterize one's idiosyncratic experiences accumulated over time (Myers 2004). Sensory memory is the first step in the memory system. A number of sensory stimuli such as images and sounds constantly occur. For example, when a new e-mail message is delivered, a sound may be heard or a pop-up message may appear. Such auditory or visual information will be sent to sensory memory for further processing. Sensory memory can store all of the information coming in from the senses, but it can hold the sensations only briefly—no more than a few seconds (Eysenck and Keane 2005; Myers 2004). A small portion of the information that receives attention will be encoded and transferred to short-term memory.

Short-term memory, which is also known as working memory, holds only a few thoughts at a time. It is the place

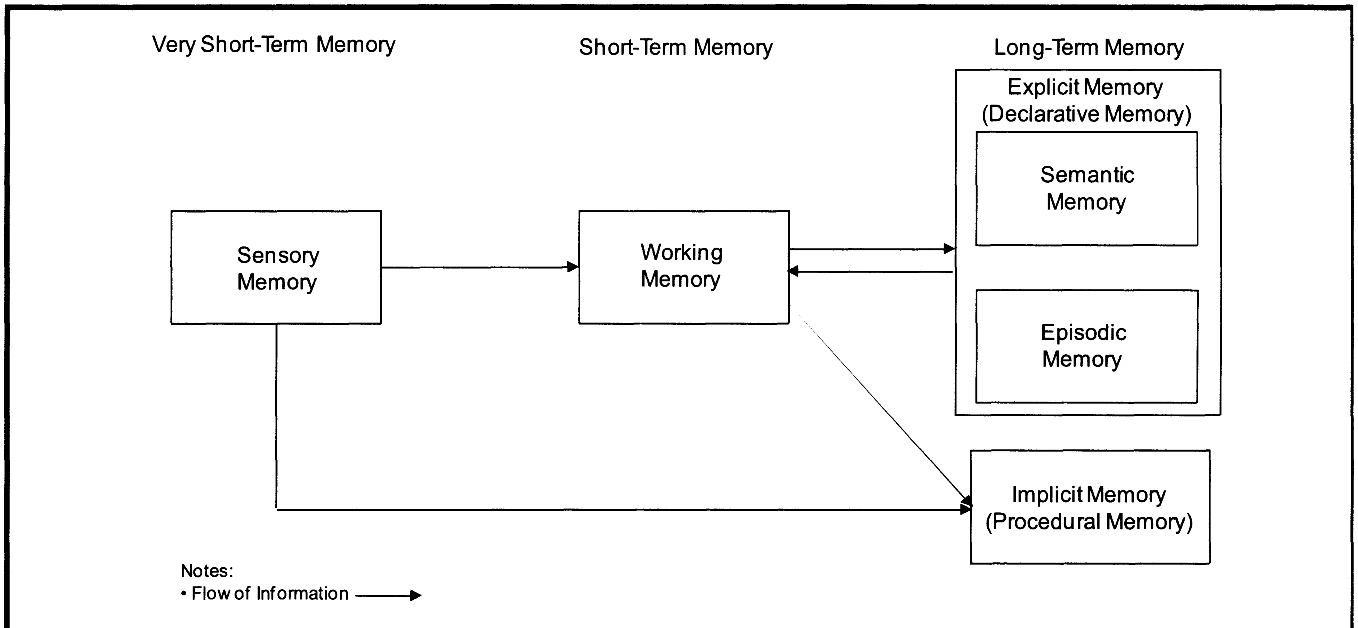

Figure 1. Process Model of Memory

in which conscious effort is exerted for a variety of problem-solving activities. For example, the beliefs and attitudes discussed in the reason-oriented framework are considered the by-products of this process (Ajzen 1991). This is because working memory is believed to process active decision-making tasks, and thus it will be involved in the makings of various judgments (e.g., perceived usefulness, perceived ease-of-use, attitude, subjective norm, perceived behavioral control, etc.). Most of the content in working memory will vanish after 30 seconds, but a tiny piece of content will be encoded and ultimately stored in long-term memory.

Long-term memory refers to the relatively persistent storage function of the memory system. Only a fraction of the data processed in working memory will ultimately be stored in long-term memory, but once stored, this data will remain for a long time (e.g., a few days or even a lifetime). Unlike working memory, which has a strict limitation on storage capacity, long-term memory is essentially unlimited. As mentioned earlier, long-term memory can be broadly classified into two categories, namely, explicit and implicit memory (Thompson and Kim 1996). First of all, explicit memory—also called declarative memory—contains two types of memories, namely, semantic and episodic memories. Whereas semantic memories are associated with memories for concepts concerning "what it is," episodic memories relate to memories for events regarding "what actually occurred." For example, a person's subjective judgments about using a technology application correspond to semantic memories. Meanwhile, episodic memories include when and where the person used the technology application. These semantic and episodic memory stores are referred to collectively as explicit because the person can explicitly declare the concepts and events when the contents are transferred to working memory from the long-term memory stores.

In contrast to explicit memories, which can be transferred back to working memory if necessary, implicit memories can never be retrieved to working memory for conscious processing. Thus, it is impossible for a person to consciously identify the contents of implicit memory. It is widely known that implicit memory—also termed procedural memory—is typically associated with a sequence of actions that are required to perform a task. Taking initial technology use as an example, a person will carefully develop and execute a detailed plan for interaction with a new technology application in order to complete the task at hand. Conscious effort will be required in this case, but the sequence of the actions performed will remain as memory traces in implicit memory. As a person becomes more experienced with the application, the "hard-wired" links in implicit memory will be strengthened (Miller and Cohen 2001). Eventually, when the same person is faced with a similar task, the entire procedure for using the application will be executed unconsciously without recourse to working memory. Thus, implicit memory, as opposed to explicit memory, makes it possible for technology use to occur in the realm of the unconscious.

The process model of memory is well established in cognitive psychology, and its validity has also been demonstrated in numerous neuroscience studies (Miller and Cohen 2001; Myers 2004; Thompson and Kim 1996). Nevertheless, in the IS literature, little attention has been paid to the role of memory in affecting individuals' reactions to an application at the post-adoption stage. The present study contributes to the literature by showing how the various components of memory process, store, and retrieve information in the context of technology use and thereby suggests the applicability of the memory perspective to IS research.

Research Model

This section first discusses a coherent and unified account of IFTU from the perspective of memory processing. Then, the IFTU paradigm is refined with focus on the potential distal, *vis-à-vis* proximal, effects as implied by the memory perspective. This overall discussion concludes with a proposed TPB-based 3WPM that is consistent with the extended IFTU paradigm.

Four Mechanisms Underlying Technology Use

IFTU contends that an explanation of technology use should simultaneously take into account four mechanisms. The four mechanisms are (1) the evaluation–behavior relationship (i.e., reason-oriented behavior), (2) the evaluation–evaluation relationship (i.e., sequential updating), (3) the behavior–evaluation relationship (i.e., feedback), and (4) the behavior–behavior relationship (i.e., habit). Figure 2 depicts a conceptual model that shows a simple application of IFTU to a TPB-based 3WPM.

First, TPB states that three types of evaluation criteria, namely, attitude (ATT), subjective norm (SN), and perceived behavioral control (PBC) influence behavioral intention (BI), which, along with PBC, determines technology usage (USE) (Ajzen 1991). This reason-oriented action mechanism is a driving force that translates into actual use individuals' conscious evaluations of using a technology application. Accordingly, the TPB-based 3WPM in Figure 2 shows that the TPB mechanism represented with a solid arrow—that is, the path from TPB determinants at $t = i$ to USE at $t = i + 1$—will occur over time within the context of technology use.[2]

A key driver of this reason-oriented action mechanism is a deliberate, attribute-based calculation that is required to form conscious evaluations (Wansink and Ray 1996). From the perspective of memory, this intensive mental effort mainly occurs in working memory. Nonetheless, the outcomes of this deliberate evaluation (e.g., ATT, SN, PBC, BI) are likely to be somehow modified and then transferred into explicit memory. In addition, a procedural sequence of technology use, which is initially guided by conscious processing in working memory, will also leave its traces in implicit memory.

Second, one of the central premises of IFTU is that individuals' evaluations at the post-adoption stage are not made from scratch. The rationale for this premise is that individuals tend to take advantage of prior judgments when faced with "nothing-out-of-the-ordinary" issues in familiar environments (Bolton 1998; Hogarth and Einhorn 1992). The sequential updating mechanism refers to this mechanism in which prior evaluations serve as an input to the formation of subsequent evaluations. Consistent with this view, the TPB-based 3WPM in Figure 2 predicts that TPB determinants at $t = i$ affect the same factors at $t = i + 1$. A causal relationship reflecting this sequential updating mechanism is represented with a dashed arrow. It is not difficult to imagine that prior judgments stored in explicit memory would act as anchors, whereas adjustments are made based on new information coming from sensory memory.

In the literature, the notion of schema is often used to refer to the contents of explicit memory (more specifically, semantic memory) that serve as the basis for memory-based evaluations (Myers 2004; Stayman et al. 1992; Winn 2004). A schema is defined as "an organized structure that exists in memory" and "contains the sum of knowledge of the world" (Winn 2004, p. 86). It is an abstract, generalized, and subjective form of knowledge representation, not an exact replica of reality. New information is interpreted through this cognitive structure, and learning also occurs by modifying or extending this mental structure (Babin and Babin 2001; Orth and De Marchi 2007). In this sense, Wansink and Ray (1996) distinguish *piecemeal-based evaluations* in which "attribute beliefs are weighted and combined in a person's evaluation" without relying on an existing schema from *schema-based evaluations* in which an existing schema affects subsequent evaluations (p. 33). As a whole, it can be inferred from this discussion that piecemeal-based evaluations mainly drive the reason-oriented action mechanism, whereas the sequential updating mechanism reflects mostly schema-based evaluations.

Third, Bem's (1972) self-perception theory posits that, especially in a routine environment, individuals do not deliberately assess the pros and cons related to the outcome of

[2]In this present study, USE at $t = i + 1$ is specified to reflect technology usage made between $t = i$ and $t = i + 1$.

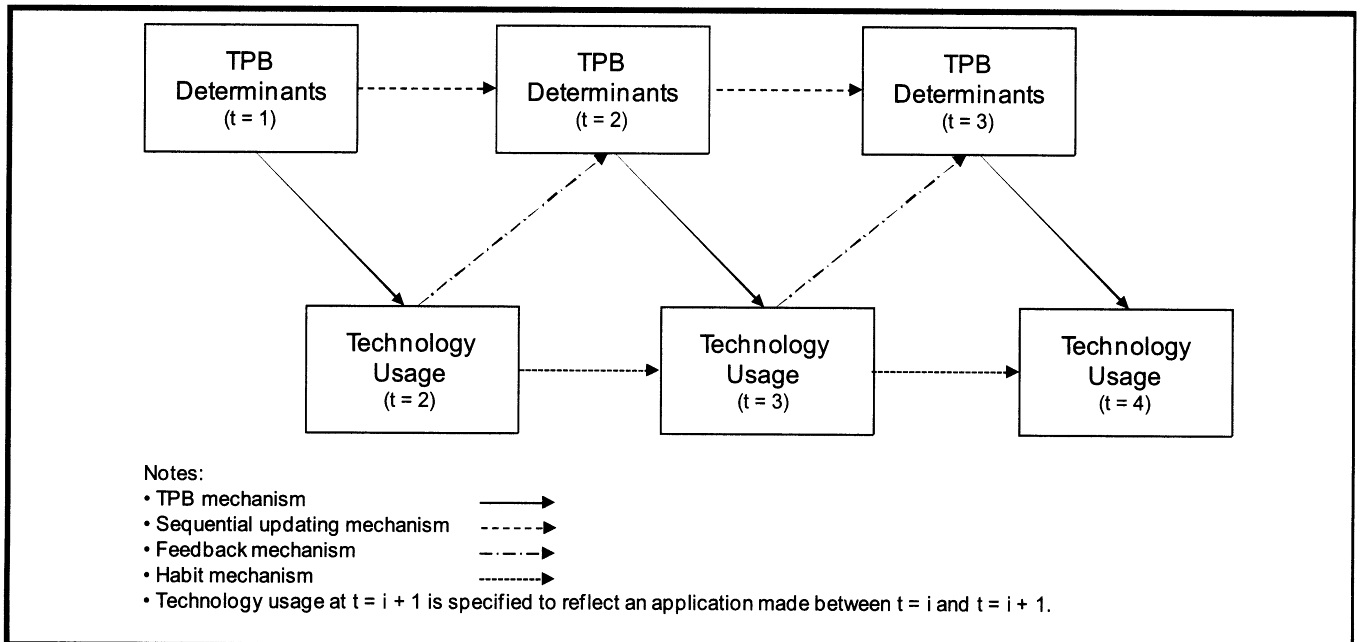

Figure 2. Proximal Effects of Four Mechanisms

their actions. Instead, when questioned by external investigators, respondents tend to infer their judgments directly from past behavior. Accordingly, Bem's theory suggests that at the post-adoption stage this type of heuristic process will lead to the formation of a feedback loop that connects prior behavior with current evaluations (Bajaj and Nidumolu 1998; Kim and Malhotra 2005). Thus, as shown in Figure 2, the TPB-based 3WPM incorporates this feedback mechanism, which is represented with a dot-dash arrow from USE at t = i to TPB determinants at t = i. Note that unlike the previous two mechanisms (i.e., TPB and sequential updating), which emphasize a deliberate decision-making approach, this feedback mechanism implies that individuals employ a "quick-and-dirty" heuristic strategy to arrive at evaluations.

In terms of memory processing, episodic memories, as opposed to semantic memories, seem to take part in this self-perception process. Specifically, to infer their evaluations, people are expected to quickly recall previous incidents of technology use for a certain period of time (e.g., a week, a month). Then, the number of incidents recalled from episodic memories seems to serve as a basis for the formation of current judgments. According to the literature, semantic retrieval is linked with the left hemisphere of the brain, whereas episodic retrieval is associated with the right hemisphere (Tulving 2002). Considering that the right hemisphere, as compared with the left hemisphere, is known to perform more holistic, intuitive processing (Anderson 1990), it is reasonable to argue that the heuristic processing for self-perception relies more on episodic memories than on semantic memories.

Finally, IFTU posits that in the context of automatic use, in addition to the feedback mechanism mentioned previously, another process, called habit, plays a significant role in regulating post-adoption phenomena (Ouellette and Wood 1998; Triandis 1977). The habit literature specifically indicates that with repeated performances, a situational cue automatically activates the behavior without any conscious effort (Aarts and Dijksterhuis 2000; Bargh et al. 2001). This view of automatic behavior is highly consistent with the memory perspective that predicts a direct link between sensory and implicit memory (Figure 1). Similarly, in the IS literature, habit is known to result from the ingrained mental links called script (Jasperson et al. 2005). Habit is also said to drive repeat use and to ultimately produce a strong correlation between past use and subsequent use (Kraut et al. 1999; Venkatesh et al. 2000). Accordingly, the model in Figure 2 incorporates the habit mechanism, which is represented with a dotted arrow from USE at t = i to USE at t = i + 1. Coupled with the heuristic decision-making strategy involved in the feedback mechanism, this type of automaticity is believed to preserve the precious cognitive efforts required for performing occasionally encountered tasks (Bagozzi and Dholakia 1999; Gollwitzer 1996).

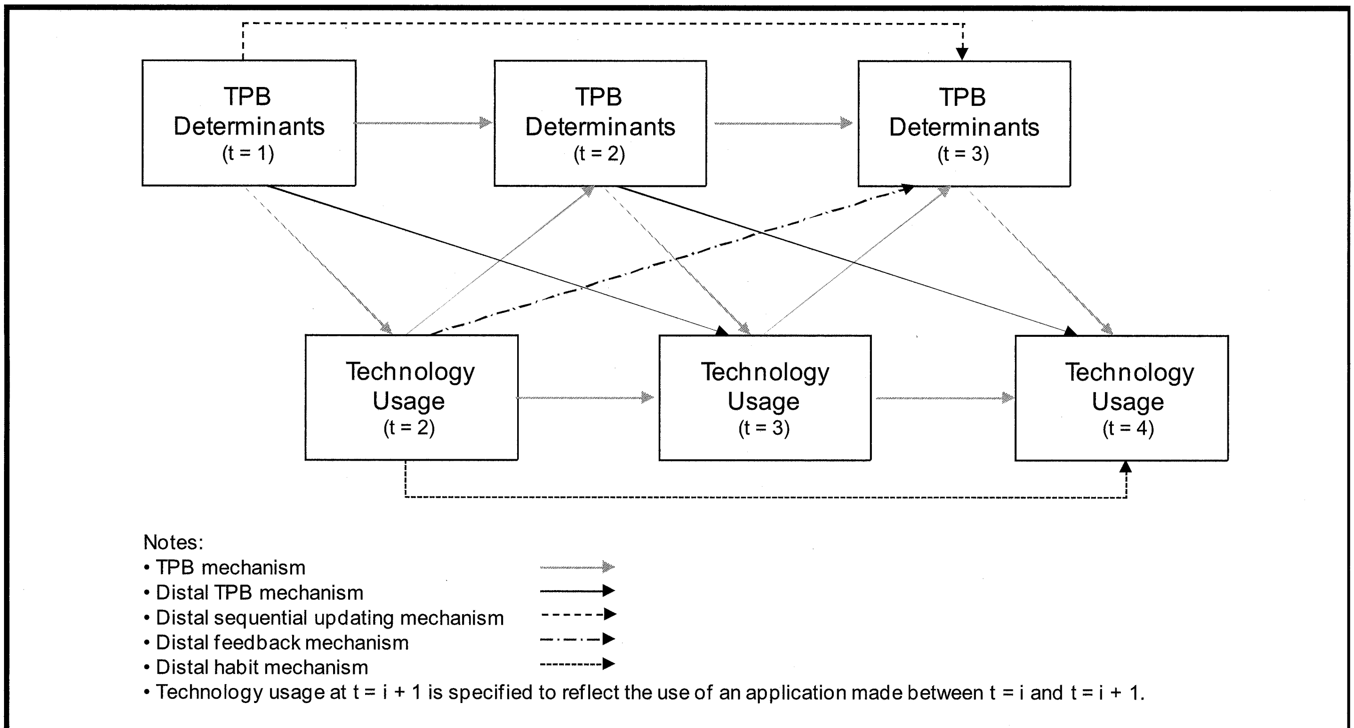

Figure 3. Distal Effects of Four Mechanisms

The model in Figure 2 includes all of the four mechanisms that are considered essential in describing individuals' reactions to a technology application over time as posited by IFTU. It is now apparent from the discussion that the contemporary memory perspective is highly consistent with the propositions of IFTU. In particular, (1) working memory is heavily involved in reason-oriented action; (2) semantic memory is required for sequential updating; (3) episodic memory plays a role in feedback; and (4) implicit memory guides habit at the unconscious realm.

Distal Effects vis-à-vis Proximal Effects

In order to account accurately for continued use, it is vital to consider whether the four mechanisms behind IFTU have distal effects, over and above proximal effects, on post-adoption phenomena. Drawing on the process model of memory, this study offers insight into which mechanisms would entail distal effects and which would not. Figure 3 schematically illustrates four potential distal mechanisms added atop the proximal mechanisms shown in Figure 2.

First, the potential distal TPB mechanism is shown in Figure 3 as represented by the effects of TPB determinants at t = i on USE at t = i + 2 beyond their effects on USE at t = i + 1 (solid arrow). Specifically, this mechanism indicates that subsequent use is a function not only of current judgments but also of previous judgments. However, the proposition that previous judgments, as opposed to current judgments, will affect subsequent use contrasts with the TPB framework. In particular, TPB maintains that current judgments would affect subsequent behavior by fully mediating all other effects (Ajzen 1991; Davis et al. 1989); that is, according to this theory, previous evaluations are unlikely to have distal effects on later use over and above current evaluations (Bamberg et al. 2003). Similarly, the process model of memory also implies that distal effects of TPB on subsequent phenomena are unlikely. As mentioned earlier, the reason-oriented action process relies heavily on working memory, which cannot handle many items at the same time. Thus, two copies of TPB factors—in which each copy in many cases contains almost the same information—are unlikely to simultaneously occupy the most valuable resource in the brain. Accordingly, it is predicted that the distal effects of TPB on technology use will not be statistically significant.

Second, Figure 3 shows the potential distal effects of sequential updating on post-adoption evaluations (dashed arrow). Specifically, the distal sequential updating mechanism implies that TPB variables at t = i affect not only the same variables at t = i + 1 but also those measured at t = i + 2. As discussed earlier, from the perspective of memory, one's judgments about using an application are accumulated into schema in a rather abstract and subjective form. The knowledge accumulated through past experiences in turn provides a basis for interpreting new information in the course of forming subsequent judgments. According to this memory perspective, therefore, the schema related to the use of the particular application is considered as a collection of past experiences, and it is expected to have long-lasting effects on the formation of evaluations over time. Thus, one's judgments made at one point in time are likely not only to have proximal effects but also to have distal effects through the form of schema. That is, it is reasonable to propose that previous evaluations will affect subsequent evaluations over and above current evaluations. Note that this proposition conflicts with the notion of belief updating that suggests that subsequent judgments are updated based on the most recent judgments (Bolton and Drew 1991; Oliver 1981). A major difference between the two perspectives is that whereas the belief updating framework assumes that prior judgments contain all of the information from past experiences, the memory model holds that current evaluations are merely an instance of schema based on a new piece of information. This paper subscribes to the memory perspective and predicts that the sequential updating mechanism will have distal effects on post-adoption phenomena beyond its proximal effects.

Third, the potential distal effects of feedback are depicted in Figure 3, which suggests that USE at t = i has an impact not only on TPB variables at t = i but also on TPB variables at t = i + 1 (dot-dash arrow). Yet, much theoretical and empirical research indicates that such distal effects are unlikely to occur. As mentioned earlier, the feedback mechanism is based on the self-perception process in which current judgments are inferred from past behavior (Bem 1972). This self-perception process is by nature heuristic, not analytical; thus, in an attempt to quickly form their judgments, individuals tend to simply consider their recent behavioral history without attempting to recall an older one unnecessarily. For example, Blair and Burton (1987) found that 75 percent of their respondents did not attempt to recall specific events if the reference period was older than two months. Moreover, according to their study, episodic enumeration was only performed for fewer than 10 events. Given that the self-perception process occurs mostly in a routine environment, the behavior conducive to the feedback mechanism is performed daily or at least weekly (Ouellette and Wood 1998). Thus, in a routine environment that facilitates the feedback mechanism, people are unlikely to try to recall, for example, events of more than two months in the past. For this reason, individuals are expected to infer their judgments from proximally lagged USE, but not from distally lagged USE.

This prediction of the self-perception theory is also consistent with that of the memory model. In particular, from the perspective of memory processing, people rewind episodic memories to instantly count the number of past incidents; in this way, episodic memories are thought to help people make use of their past experiences in order to accurately yet conveniently predict their futures (Wheeler et al. 1997). All things being equal, recent history is the best predictor of what is directly ahead. Thus, to infer their judgment and predict technology use that will occur soon, people are likely to trace the most recent portion of episodic memories. Consistent with this logic, Kim and Malhotra (2005) showed that the feedback mechanism had only proximal effects, *vis-à-vis* distal effects, on subsequent judgments. Taken together, the discussion mentioned previously suggests that the feedback mechanism will not have distal effects beyond proximal effects.

Finally, Figure 3 represents potential distal effects of habit on post-adoption behavior (dotted arrow). In particular, it indicates that the distally lagged USE variable (e.g., USE at t = i) may have a direct impact on later use (e.g., USE at t = i + 2) over and above the proximally lagged USE effect (e.g., USE at t = i + 1). Contemporary research on the subject of habit concurs that habit is strengthened by frequent activation of the same behavior over time (Aarts and Dijksterhuis 2000; Ronis et al. 1989). Specifically, within the framework of memory processing, repeated performances are said to hard-wire in the mental script the procedural steps for performing the behavior. Through this ingrained script, situational cues can automatically activate the well-learned sequence of actions leading to technology use. According to the memory perspective, the strength of habit is directly proportional to the robustness of this script. Given that the script is gradually formulated through repetition over a long period, temporally different measures of past use, rather than a short period of past use, are expected to better represent the nature of habit. Thus, habit (i.e., the robustness of this script) is believed to be a function of both proximally and distally lagged usage factors. In other words, two temporally different measures of past use are likely to contribute jointly to habit formation, and habit will ultimately affect subsequent use. Accordingly, it is proposed that the habit mechanism will have not only proximal effects but also distal effects on subsequent use.

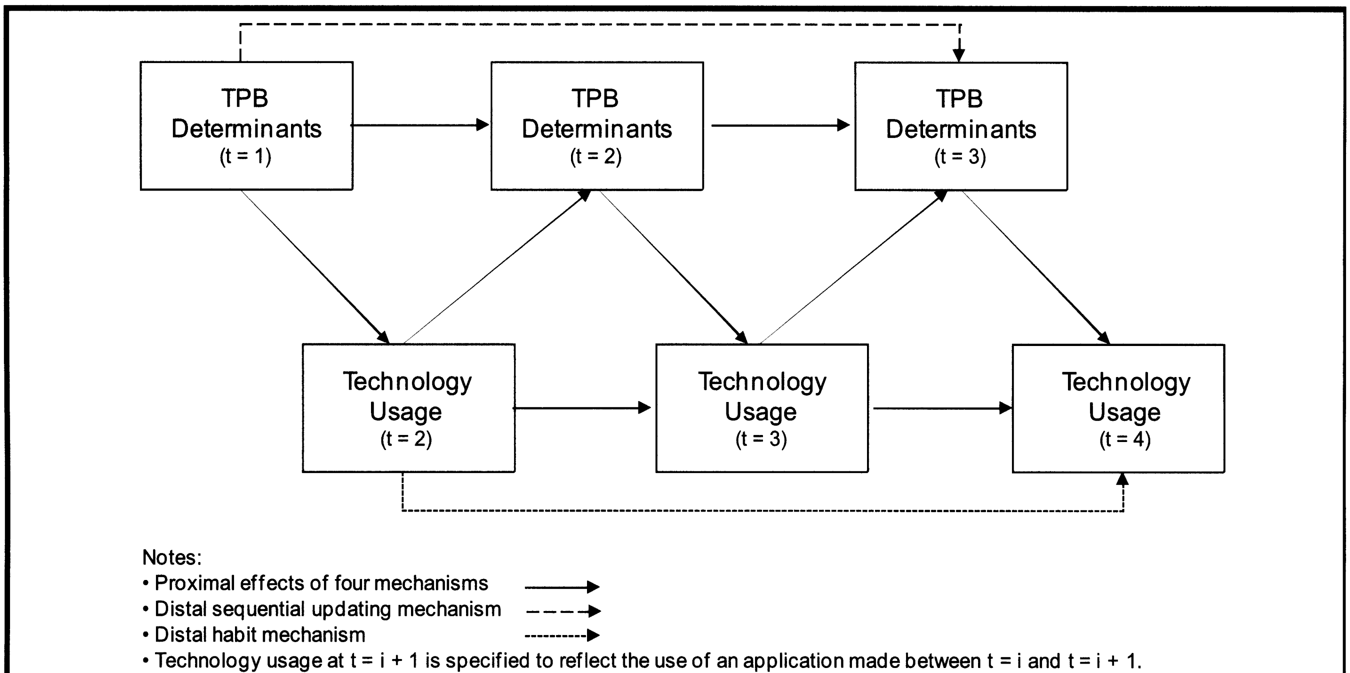

Figure 4. Proposed Model

Proposed Model

The discussion mentioned previously suggests that the distal effects of the four mechanisms have theoretical implications that differ qualitatively from their proximal effects. More important, it indicates that although proximal effects are expected for all of the four mechanisms, distal effects will occur only for the sequential updating and habit mechanisms. Figure 4 depicts the TPB-based 3WPM proposed in this study that includes the proximal effects shown in Figure 2 and two of the distal effects discussed in Figure 3. A careful consideration of distal effects, *vis-à-vis* proximal effects, is a must for a better understanding of post-adoption phenomena that unfold over a long period. In this sense, the longitudinal model of continued use proposed in this study sheds light on the deeper nature of the four mechanisms that are thought to be the most important driving forces of post-adoption phenomena.

Data Analysis and Results

Competing TPB-Based 3WPMs

The efficacy of a model can be better established if the model under scrutiny is shown to be superior to competing models in its fit with the empirical data (Anderson and Gerbing 1988). As a way to examine the comparative validity of the proposed TPB-based 3WPM, this article develops several competing models, each of which highlights a unique, yet partial, perspective on the phenomena underlying technology adoption and sustained usage. These competing models include various proximal and distal effects of the four mechanisms underlying technology use. Consistent with the earlier definition, proximal effects are specified as the relationships between factors temporally adjacent. Meanwhile, distal effects are specified as the relationships between factors temporally remote that go beyond proximal effects. The detailed specifications of the various competing models are described in Table 1.

The first intermediate model, named IM1, is the most parsimonious form of the competing models. In particular, IM1 posits that the TPB framework can succinctly explain technology use, including adoption and sustained usage. Although this approach appears to be extremely naïve and simplistic, it is used often in those studies that collect panel data but only analyze them wave-by-wave without regard for interwave mechanisms. Next, the second intermediate model, called IM2, adds into IM1 the proximal effects of the sequential updating mechanism. Similarly, the third intermediate model, or IM3, integrates into IM1 the proximal

Table 1. Alternative Models and Their Hypothesized Relationships												
	Causal Paths	**Total Paths**	**IM1**	**IM2**	**IM3**	**IM4**	**IFTU1**	**AM1**	**AM2**	**AM3**	**AM4**	**IFTU2**
	Proximal Effects											
The theory of planned behavior	A (t) → BI (t)	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	SN (t) → BI (t)	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PBC (t) → BI (t)	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	BI (t) → USE (t + 1)	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PBC (t) → USE (t + 1)	3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sequential updating	A (t) → A (t + 1)	2		✓			✓	✓	✓	✓	✓	✓
	SN (t) → SN (t + 1)	2		✓			✓	✓	✓	✓	✓	✓
	PBC (t) → PBC (t + 1)	2		✓			✓	✓	✓	✓	✓	✓
	BI (t) → BI (t + 1)	2		✓			✓	✓	✓	✓	✓	✓
Feedback	USE (t) → A (t)	2			✓		✓	✓	✓	✓	✓	✓
	USE (t) → SN (t)	2			✓		✓	✓	✓	✓	✓	✓
	USE (t) → PBC (t)	2			✓		✓	✓	✓	✓	✓	✓
	USE (t) → BI (t)	2			✓		✓	✓	✓	✓	✓	✓
Habit	USE (t) → USE (t + 1)	2				✓	✓	✓	✓	✓	✓	✓
	Distal Effects											
The theory of planned behavior	A (t) → BI (t + 1)	2						✓				
	SN (t) → BI (t + 1)	2						✓				
	PBC (t) → BI (t + 1)	2						✓				
	BI (t) → USE (t + 2)	2						✓				
	PBC (t) → USE (t + 2)	2						✓				
Sequential updating	A (t) → A (t + 2)	1							✓			✓
	SN (t) → SN (t + 2)	1							✓			✓
	PBC (t) → PBC (t + 2)	1							✓			✓
	BI (t) → BI (t + 2)	1							✓			✓
Feedback	USE (t) → A (t + 1)	1								✓		
	USE (t) → SN (t + 1)	1								✓		
	USE (t) → PBC (t + 1)	1								✓		
	USE (t) → BI (t + 1)	1								✓		
Habit	USE (t) → USE (t + 2)	1									✓	✓

Notes:

- A = attitude; SN = subjective norm; PBC = perceived behavioral control; BI = behavioral intention; USE = technology usage
- ✓ = path included in a model

effects of the feedback mechanism. In addition, the fourth intermediate model, IM4, is designed to combine the proximal effects of the habit mechanism with the TPB framework. In this particular study, the model that combines all of the four types of the proximal effects is called IFTU1. IFTU1 is a straightforward application of the 2WPM by Kim and Malhotra (2005) to the three-wave context. It is expected to perform better than the four intermediate models that do not control for some of the important interwave mechanisms.

Four more alternative models are also developed by incorporating four different types of distal effects into IFTU1. The first alternative model, named AM1, adds to IFTU1 the distal effects of TPB. The second alternative model, AM2, incorporates into IFTU1 the distal effects of sequential updating. The third alternative model, AM3, predicts that past behavior will influence proximal judgments and distal judgments. AM4 integrates the notion of the distal habit mechanism and IFTU1. Finally, the proposed model in

Figure 4 is considered IFTU2. IFTU2 extends IFTU1 by incorporating the distal effects of sequential updating and habit. IFTU2 is expected to explain reality significantly better than the competing models.

Methodology

Secondary data from past research were used to test the competing models. A thorough literature review was performed to identify past studies that conducted a TPB-based three-wave panel study and reported data in the form of correlations. As a result, two data sets in Venkatesh et al. (2000) and one by Morris et al. (2005) were identified. These multiple sets of secondary data present an excellent opportunity to evaluate the competing models. The use of secondary data is expected to minimize subjective biases that theory developers may acquire in the course of their data collection. Moreover, because of the multiple datasets available for model testing, the results of this research are likely to yield more reliable inferences than those based on a single dataset. However, because the original studies did not measure the use of information in memory, they are unsuitable for use in tests of the underlying mechanisms related to memory processing. Despite this limitation, the secondary data are considered valuable for an initial assessment of whether the memory perspective merits further consideration for a better understanding of continued use.

Appendix A contains a summary of research objectives, data collection procedures, and sample characteristics in the original studies. In the study by Venkatesh et al., a total of 355 complete responses across all points of measurements were collected. The sample was divided into two groups according to gender; and the samples for men and women, respectively, consisted of 195 and 160 data points. Meanwhile, in the study by Morris et al., the three-wave panel data were collected from 342 workers. In Morris et al.'s study, the correlation matrix was reported based on the pooled data. Thus, data analysis was conducted based on the pooled dataset reported as a form of correlations. For the sake of convenience, the male sample in Venkatesh et al. is called Sample A (n = 195), the female sample is Sample B (n = 160), and the pooled sample in Morris et al. is Sample C (n = 342).

The timing of observations is said to influence the results of a longitudinal study (Collins and Graham 2002). In this sense, the temporal design by Venkatesh et al. and by Morris et al. seems appropriate for testing the proposed model. In particular, the duration of their studies (i.e., at least five months after initial training) is long enough to observe both conscious and automatic use (Limayem and Hirt 2003). Besides, in view of the volatility of individuals' behavior during the technology adoption stage, a short interval deems desirable at the initial stage (i.e., one month between t = 1 and t = 2). Finally, long intervals at the post-adoption stage (i.e., at least two months between t = 2 and t = 3 and between t = 3 and t = 4) are considered appropriate in order to examine the distal, *vis-à-vis* proximal, effects.

Venkatesh et al. and Morris et al. used the same questionnaire items to measure TPB constructs such as attitude, subjective norm, perceived behavioral control, and intention to use. Survey questionnaire items are shown in Appendix B. All scales were shown to be highly reliable because Cronbach alpha estimates exceeded 0.80. In addition, the convergent and discriminant validity of the scales were successfully established through high factor loadings (more than 0.80) and low cross-loadings (less than 0.25) from exploratory factor analyses. However, the two studies differ in how they measured actual usage. In the Venkatesh et al. study, actual usage was measured by the number of information queries made through system logs within a specified period. Morris et al. used the duration of technology use, measured by average hours of use per week, to capture actual usage. For more details on the original studies, readers are referred to Venkatesh et al. (2000) and Morris et al. (2005).

Results of Path Analyses

Each set of the data includes correlation coefficients between 15 variables (i.e., five factors per wave × three waves). All of the intermediate, alternative, and IFTU models were estimated on each set of data using path analysis implemented in LISREL 8 (Jöreskog and Sörbom 1996). To assess model-data fit, four commonly used fit measures were employed: the consistent Akaike information criterion (CAIC), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). CAIC is known to be one of the most effective indices in comparing competing (nested or non-nested) models (Diamantopoulos and Siguaw 2000; Lin and Dayton 1997; Steenkamp and Baumgartner 1998). Meanwhile, the other fit indices (i.e., CFI, RMSEA, and SRMR) are recommended for evaluating model fit in general (Diamantopoulos and Siguaw 2000; Hu and Bentler 1999). A model is said to be moderately acceptable if CFI $\geq$ .90, RMSEA $\leq$ .08, and SRMR $\leq$ .10 (Chin et al. 1997, Hu and Bentler 1999). To be more conservative, the use of stringent criteria such as CFI $\geq$ .95, RMSEA $\leq$ .06, and SRMR $\leq$ .08 is also recommended (Hu and Bentler 1999). For CAIC, a

Table 2. Summary of the Results			
Tests of the Proposed Model (IFTU2)	**Results for Each Sample**		
	Sample A	**Sample B**	**Sample C**
IFTU2 fits the data better than the nine competing models[1]	Yes	Yes	Mixed
IFTU2 explains a significant percentage of the variance in the determinants of IT usage intention and IT usage behavior[2]	Yes (SMCs range from 0.23 to 0.43)	Yes (SMCs range from 0.25 to 0.42)	Yes (SMCs range from 0.25 to 0.46)

Notes:
1. The detailed statistics regarding model fit are in Appendix C.
2. The detailed statistics regarding path coefficients and explained variance are in Appendix D.

lower value is considered an indication of better fit without specific cutoffs (Steenkamp and Baumgartner 1998). Besides, χ^2 difference tests were conducted to formally compare the nested models between IFTU1 and other competing models such as intermediate models, alternative models, and IFTU2. Table 2 shows the summary of the results obtained from the three samples. As indicated in Table 2, the proposed model is generally shown to be a reasonable approximation of technology use over time. The detailed fit statistics for the 10 competing models as well as the results of model comparisons are presented in Appendix C. In addition, path estimates and squared multiple correlations (SMC) for selected models are shown in Appendix D.

Intermediate Models and IFTU1

Intermediate Model 1. IM1 is the base model, which represents only the causal flows explicitly postulated by TPB. Although it has been applied successfully to numerous IS studies, TPB, at least in its original form, apparently fails to describe how individuals' evaluations and behavior evolve over time. As shown in Appendix C, the fit of this unembellished TPB model is nowhere near satisfactory, even if less stringent criteria are applied. As Appendix D shows, IM1 explains little of the variance in BI and USE. For example, SMC for BI is as low as 0.15 for Sample A, 0.18 for Sample B, and 0.17 for Sample C. Similarly, SMC for USE is as low as 0.26 for Sample A, 0.24 for Sample B, and 0.24 for Sample C. Overall, the results strongly indicate that IM1, which is a simple application of the original TPB to a three-stage context, does not properly reflect technology use.

Intermediate Model 2. IM2 integrates the sequential updating mechanism and IM1. The results revealed that although IM2 fit the three sets of the data considerably better than IM1 [$\Delta\chi^2$ (8) = 230.41, $p < 0.001$, for Sample A; $\Delta\chi^2$ (8) = 183.85, $p < 0.001$, for Sample B; $\Delta\chi^2$ (8) = 568.99, $p < 0.001$, for Sample C], it nevertheless was unsatisfactory. For example, all the fit indices for IM2 were considerably closer to cutoff values than were those for IM1 (Appendix C). However, although comparatively superior to the base model, IM2 fit the data unsatisfactorily, even if less stringent criteria were used. Therefore, although the notion of intertemporal updates was shown to be helpful, IM2 still seemed to leave much room for improvement.

Intermediate Model 3. IM3 combines feedback effects and IM1. The difference in fit between IM3 and IM1 was strikingly large [$\Delta\chi^2$ (8) = 166.38, $p < 0.001$, for Sample A; $\Delta\chi^2$ (8) = 165.95, $p < 0.001$, for Sample B; $\Delta\chi^2$ (8) = 340.40, $p < 0.001$, for Sample C]. All of the fit indices consistently and unambiguously pointed out that IM3 represented the data better than IM1 did. Nevertheless, the addition of feedback into TPB was not enough to bring model fit to an acceptable level. Thus, these results suggest that although organizational users might employ self-perception processing, post-adoption phenomena involve extra processes other than self-perception.

Intermediate Model 4. IM4 adds the past use–current use relationship into the original TPB. This model is similar to the longitudinal model used by Venkatesh et al. (2000) and by Morris et al. (2005) in that both are designed to reflect repeated behavioral patterns in addition to the process represented by TPB. Appendix C shows that as with IM2 and IM3, IM4 exhibits significantly better fit than IM1 [$\Delta\chi^2$ (2) = 75.11, $p < 0.001$, for Sample A; $\Delta\chi^2$ (2) = 64.28, $p < 0.001$, for Sample B; $\Delta\chi^2$ (2) = 193.07, $p < 0.001$, for Sample C]. Nevertheless, controlling for habit effects yielded less substantial improvement than when sequential updating or feedback mechanisms were added into TPB. Thus, although habit has recently received much attention from researchers, it seems to be merely one of many mechanisms that influence post-adoption phenomena.

IFTU1. Appendix C shows that IFTU1, which integrates all of the four mechanisms into a coherent three-wave panel structure, achieved statistically significant improvement over the intermediate models. In addition, IFTU1 was found to explain the data more than adequately from the viewpoint of a liberal standard; however, when subjected to rigorous criteria, the model still was unacceptable and required further refinement. Appendix D shows path estimates and SMC for IFTU1. Where path estimates were concerned, most of the relationships representing the three interwave processes (i.e., sequential update, feedback, and habit mechanisms) were statistically significant. Specifically, out of 18 (non-TPB) causal relationships, 14 paths (78 percent) were significant in Sample A, 13 paths (72 percent) in Sample B, and 16 paths (90 percent) in Sample C. In contrast, out of fifteen TPB relationships, only nine (60 percent), eight (53 percent), and thirteen (87 percent) paths were significant, respectively, in Samples A, B, and C. Thus, each of the three interwave mechanisms appeared to be as important, if not more so, as the widely recognized TPB mechanism. In addition, Appendix D shows that compared with the base model (i.e., IM1), IFTU1 explains at least 10 percent (at t = 2 for Sample A) and even as much as 22 percent (at t = 3 for Sample B) more variance in BI during the post-adoption stage. Likewise, IFTU1, as compared with the base model, increases SMCs for continued use by 11 percent (at t = 3 for Sample A) to 19 percent (at t = 4 for Sample C). Overall, IFTU1, as compared with the intermediate models, was considered a more reasonable representation of technology use. In addition, the propositions about the proximal effects found strong support in the three-wave settings.

Alternative Models and IFTU2

Alternative Model 1. AM1 incorporates into IFTU1 eight paths reflecting distal TPB effects. As shown in Appendix C, the fit of AM1 does not generally appear to be better than that of IFTU2. In fact, CAIC suggested that compared with RM1, IFTU1 explained the data more succinctly. The results of χ^2 difference tests also indicated that the eight paths incorporated into the model did not help improve fit with one exception in Sample C [$\Delta\chi^2$ (8) = 8.42, p = ns, for Sample A; $\Delta\chi^2$ (8) = 4.65, p = ns, for Sample B; $\Delta\chi^2$ (8) = 16.99, $p < 0.05$, for Sample C]. This exception seemed to occur mainly because of the sensitivity of the χ^2 test to the large sample size (n = 342). If the sample size had been smaller (i.e., about 200), the outcome of the test would have been the same as found in the other samples. In fact, a careful inspection of the LISREL output revealed that, out of eight paths added on top of IFTU1, only one path was significant, and it was negative, which suggests that the unexpected outcome might result from a random fluctuation. Taken together, it seems reasonable to conclude that the effects of prior evaluations on technology use were fully mediated by current evaluations.

Alternative Model 2. This paper proposed that intertemporal updates would occur not only between the judgments temporally proximal but also between those temporally distal. To formally test this proposition, AM2 was designed to explicitly include the path from each of the TPB variables to the same variable measured not only at one period later but also at two periods later. As expected, the results were found to be consistent with the proposition. For example, the fit of AM2 was significantly better than that of IFTU1 [$\Delta\chi^2$ (4) = 29.70, $p < 0.001$, for Sample A; $\Delta\chi^2$ (4) = 31.41, $p < 0.001$, for Sample B; $\Delta\chi^2$ (4) = 52.67, $p < 0.001$, for Sample C]. In addition, other fit indices such as CAIC, CFI, RMSEA, and SRMR also indicated that AM2 explained actual phenomena better than IFTU1. These results imply that the notion of distal sequential updating effects would enhance our understanding of technology use over time.

Alternative Model 3. AM3 is the amalgamation of IFTU1 and the lagged effects of feedback. This alternative model was developed primarily to examine whether people arrive at their judgments from both distally lagged USE and proximally lagged USE. Results from the model demonstrated that extra paths indicating distally lagged USE effects were largely redundant in the description of post-adoption phenomena. Specifically, the distal effects of feedback were found to be nonsignificant in Samples A and B, but they were significant in Sample C [$\Delta\chi^2$ (4) = 6.19, p = ns, for Sample A; $\Delta\chi^2$ (4) = 8.67, p = ns, for Sample B; $\Delta\chi^2$ (4) = 9.85, $p < 0.05$, for Sample C]. The LISREL output indicated that in Sample C, only one path was significant out of the four added. This observation suggests that the unexpected outcome in Sample C could be attributed to its large size; were it not for the large sample size, the result would have been different. Overall, these results provided empirical support for the proposition that the feedback mechanism would have both proximal and distal effects on post-adoption phenomena.

Alternative Model 4. AM4 adds into IFTU1 the new idea of the distal effects of USE on later usage. The results of path analysis showed that the addition of a relationship from USE (t = 2) to USE (t = 4) significantly increased fit with one exception that occurred in Sample C [$\Delta\chi^2$ (1) = 7.12, $p < 0.01$, for Sample A; $\Delta\chi^2$ (1) = 7.49, $p < 0.01$, for Sample B; $\Delta\chi^2$ (1) = 3.14, p = ns, for Sample C]. However, a careful inspection of the LISREL output indicated that the relationship between USE (t = 2) and USE (t = 4) was actually significant at the 0.01 level in Sample C ($\beta = 0.15$, $p < 0.01$). Therefore, as a whole, the results of AM4 supported the proposition that the habit mechanism would have both proximal and distal effects on subsequent use. That is, the notion of habit would be better represented by a series of past USE measures than by only one measure of recent past usage.

IFTU2. IFTU2 is the proposed model in this study and is depicted in Figure 2. The results of path analysis revealed that model performance improved considerably with the addition of five paths representing the distal effects of sequential updating and habit. As Appendix C shows, IFTU2 is significantly better than IFTU1 in terms of fit. Moreover, IFTU2 yielded a fit that finally met stringent criteria for Samples A and B; specifically, except for CFI in Sample A (0.93), fit indices for both sets of data were well within the satisfactory ranges. However, the fit of IFTU2 in Sample C was still marginal.

Appendix D shows path estimates for IFTU2 for the three samples. The structural paths representing the two distal mechanisms are generally significant for the three samples. Specifically, with the exception of the path from SN (t = 1) to SN (t = 3) in Samples A and C, all of the new paths added into the model were significant. Consistently, SMC for BI (t = 3) increased by 2 percent to 6 percent. These amounts of increase in explained variance correspond to the effect sizes of 0.03 to 0.10—which are considered small-to-medium according to Cohen's (1988) operational definition. Therefore, the distal sequential updating mechanism is believed to help researchers and practitioners to more accurately predict behavioral intention. Meanwhile, SMC for USE (t = 4) increased by 1 percent to 3 percent, and the effect sizes were found to range from 0.02 to 0.05. Although the effect sizes were minimal in this particular study, however, it seems premature to conclude that the distal habit mechanism is all but meaningless. This is because the respondents in the original studies had less than a year of experience with the application, and thus, their habits might not be completely stabilized. To better predict technology usage, researchers and practitioners may still want to use a distally lagged usage measure in addition to a proximally lagged usage measure. This suggestion is especially relevant if individuals already have ample experience with an application in question. Overall, in conjunction with the improved model fit found previously, these results indicated that the proposed model (i.e., IFTU2) surpassed competing models as an effective representation of continued use. Specifically, this study suggests that to gain a better understanding of how individuals adjust their evaluations and behavior over time, the distal sequential updating and habit mechanisms should be taken into account in addition to the proximal effects of the four mechanisms.[3]

[3]To assess the degree of credibility that can be placed on the results of path analyses in this study, common method variance (CMV) and statistical power were examined. The detailed procedures and results of data analyses are described in Appendix E. In short, CMV was not found to be a serious concern in this study, and sample sizes were sufficient to detect false null hypotheses.

Discussion and Conclusion

The major objective of this study is to extend IFTU by adding the notion of memory processing and test the TPB-based 3WPM derived from the extended paradigm. Three different sets of data (n = 195, 160, and 342, respectively) were used to test the proposed model. The results of data analysis show that, as expected, the four mechanisms identified in IFTU, namely, reason-oriented action, sequential updating, feedback, and habit, have proximal effects on post-adoption phenomena. Furthermore, consistent with the memory perspective, the sequential updating and habit mechanisms are found to have distal effects on post-adoption phenomena even after controlling for their proximal effects. Overall, the findings of this study indicate that the memory perspective offers not only a seamless explanation of the four mechanisms underlying technology use but also yields deeper insights that can be validated only through a three-or-more-wave panel study. This research contributes to the literature by demonstrating that the extended IFTU paradigm has the potential to serve as a coherent theoretical framework on post-adoption phenomena in which prior experiences are internalized into memories, which in turn regulate later experiences.

Theoretical Contributions

Technology Use from the Perspective of Memory Processing

The role of memory in individuals' reactions to an application has been relatively ignored in technology adoption research. Accordingly, little was known about how memory is involved in transforming prior experiences into subsequent judgments and behavior. A major contribution of this study is to introduce the notion of memory processing into the explanation of technology use that unfolds over time. Specifically, this study draws on the process model of memory and shows that four categories of memory in the brain—short-term memory (i.e., working memory) and three different types of long-term memory (i.e., semantic, episodic, and implicit memory)—work closely together to guide conscious and automatic technology use. In addition, this study sheds light on how working, semantic, episodic, and implicit memory relate to, respectively, the four mechanisms of reason-oriented action, sequential updating, feedback, and habit. More important, this study suggests that the implications of the memory perspective lie far beyond the notion of the four mechanisms and could provide a richer description of post-adoption phenomena. The process model of memory is well established in cognitive psychology, and its validity has also been demonstrated in numerous neuroscience studies (Miller and Cohen 2001; Myers 2004; Thompson and Kim 1996). Thus, the memory perspective has enormous potential to reveal the hidden nature of the behaviors behind technology use that heretofore has been overlooked in IS research.

Theoretical Refinement of IFTU by Examining Distal Effects Beyond Proximal Effects

An interesting finding of this study is that current judgments are formed based on judgments that are both proximally and distally lagged. This finding differs from the theory that claims that prior judgment serves as an anchor and that the anchor is successively adjusted as new information becomes available (Helson 1964; Hogarth and Einhorn 1992). Within this anchor-adjustment framework, an implicit assumption is that prior judgment can be saved intact and that it can also be retrieved in its original form. According to this perspective, therefore, the effect of prior judgment on subsequent judgment will be fully mediated by current judgment. Contrary to this anchor-adjustment framework, the schema theory suggests that semantic memories can be stored only in a subjective and abstract form (Winn 2004). Thus, a series of prior judgments are required to accurately represent this schema structure, which in turn affects subsequent judgments. A piece of empirical evidence supporting the distal sequential updating mechanism can be found in a three-wave study by Bolton and Drew (1991) of customers' perceptions of service quality within the context of telephone service. Although Bolton and Drew did not formally test the distal sequential updating mechanism, the correlation matrix reported in their study shows that the distal sequential updating mechanism is significant, even after controlling for other relevant variables that included the proximal sequential updating mechanism. This finding suggests that the distal effects of sequential updating are a more or less general phenomenon and not something specific to technology use.

Meanwhile, although numerous studies show that past behavior relates to later behavior, few have examined how two temporally different measures of past behavior jointly affect later behavior. As indicated in the literature, the key notion of habit lies in mental script that is established through repeated performance. According to this script theory, habit is represented by an accumulation of prior use over time; thus in a routine environment, all things being equal, prior use will affect subsequent use over and above current use. The present study is meaningful because it is one of the first studies to confirm the important premise behind habitual use by showing the distal effects of past behavior on later behavior in the context of technology use. In fact, much research in other disciplines also implies the existence of script. For example, Bagozzi (1981) found from a study of blood donation that past behavior influenced distal behavior over and above proximal behavior. In addition, LaBarbera and Mazursky (1983) showed within the context of product purchase that prior purchases at two different periods collectively affected later purchases. Thus, to the extent that a behavior in question is routinized within everyday life (e.g., online purchase of products or services, online community activities, etc.), past behavior is expected not only to have short-term effects but also to have long-term effects on later behavior.

Overall, this study makes a major contribution to the literature by showing that IFTU requires further elaboration on long-time (in addition to short-time) effects of individuals' evaluations and behavior on post-adoption phenomena. Specifically, the findings of this study indicate that the sequential updating and habit mechanisms have temporally distal effects on post-adoption phenomena but the reason-oriented action and feedback mechanisms do not. Furthermore, we learn from the process model of memory that the distal effects of the sequential updating and habit mechanisms are made possible, respectively, through internalized knowledge representations from schema in semantic memory and from script in implicit memory. These findings are important because as long as the schema and script endure, the distal effects are likely to continue to be observed in four-or-more-wave contexts. In this sense, the present study, which theoretically draws on the memory perspective and empirically employs three-wave panel data, makes an important step toward a deeper understanding of continued use that is rarely revealed in past research.

Validation of IFTU as a General Conceptual Framework

This study shows that IFTU can generalize straightforwardly from TAM to TPB (i.e., base theory), from a two-wave setting to a three-wave setting (i.e., periods in time), from personal use to organizational use (i.e., type of technology use), and from a Web-based portal to a software program (i.e., target application). Because the four mechanisms identified in IFTU describe generic decision-making and action processes, their applications seem more wide ranging than the two specific forms mentioned previously. For example, Venkatesh et al. (2003) have developed a model called the unified theory of acceptance and use of technology (UTAUT) that is strongly rooted in the reason-oriented action framework (Jasperson et al. 2005). It is a fairly straightforward exercise to develop a UTAUT-based multistage panel model because UTAUT only needs to be complemented with the other three mechanisms (i.e., the sequential updating, feedback, and habit mechanisms). That is, UTAUT can serve as a basis for other longitudinal models of technology use if investigators believe that UTAUT represents the reason-oriented action mechanism better than other models (e.g., TAM, TPB). Thus, it is important to note that the IFTU paradigm is a general conceptual framework for understanding continued use while transcending a particular form of panel model with predefined factors.

Salience of the Four Mechanisms Underlying Continued Use

The findings of this study reveal that three interwave processes such as sequential updating, feedback, and habit mechanisms were at least as important as the TPB mechanism, if not more so. These findings suggest that an exclusive focus on the reason-oriented action mechanism can easily result in biased inferences. For example, researchers in IS have often discretely analyzed panel data wave-by-wave without taking a holistic view. Yet an important and noteworthy implicit assumption of this discrete procedure is that interwave mechanisms (e.g., sequential updating, feedback, and habit mechanisms) are irrelevant to the actual phenomena under scrutiny. Contrary to this implicit assumption, this study demonstrated that the unembellished TPB model (i.e., IM1), fit the data poorly, suggesting flaws in the common approach to analyzing panel data.

Meanwhile, the superiority of the TPB-based 3WPM proposed in this present study is noteworthy in comparison with IM4, which closely resembles the one used by Venkatesh et al. (2000) and by Morris et al. (2005). Recall that although Venkatesh et al. and Morris et al. explicitly controlled for the past use–current use relationship, they paid little attention to sequential updating and feedback mechanisms that may be vital, especially at the post-adoption stage. Given that neither sequential updating nor feedback mechanisms are supposed to have direct impact on technology use, these processes can be ignored if the objective of a study is to predict system usage in particular. However, if one wants to *explain* actual phenomena in general, omission of these mechanisms is likely to distort our understanding of reality. In general, this study contributes to the literature by showing that each of the four mechanisms in the IFTU paradigm is a critical driver of technology use, and thus, lack of attention to any one of them is likely to lead to biased conclusions.

Managerial Implications

After investigating numerous field practices, McAfee (2003) points out that "when people have a choice, they may well ignore a new technology, especially if it affects a core task or is highly novel" (p. 86). This observation indicates that mental inertia is one of the key barriers to the success of a new technology. Interestingly, the theoretical framework presented in this study provides practitioners with insights into the property of mental inertia and how to help workers overcome it. In particular, the findings of this study suggest that whereas the schema in semantic memory acts as a strong anchor, the adjustment made by the TPB mechanism is not substantial. These findings indicate that individuals tend to keep making similar decisions despite the presence of new information. The schema structure that is deeply seated in semantic memory is believed to be a psychological basis for why people often overlook the potential benefits of the new feature or application. Nevertheless, existing schemas can be also used to facilitate the use of a new feature or application. For example, research shows that if the existing schema is congruent with a new use situation, people tend to have favorable attitudes toward the new experience (Wansink and Ray 1996). Such a phenomenon is called a *halo effect*. This halo effect can be manipulated in practice in a number of ways. For example, organizations have recently been trying to implement business intelligence (BI) tools for their workers (Carte et al. 2005). From the perspective of memory, an effective way to enhance the utilization of the new tools would be to relate the BI tools to the old technology. This is because when the old and new technologies are similar, the schema and script used for the old technology are likely to be evoked again for the new technology. In fact, practitioners recognize that to facilitate sustained usage, BI capabilities should be implemented within the existing enterprise applications such as enterprise resource planning; this is because the workers feel more comfortable with BI capabilities embedded within the familiar applications than with those from new vendors (Daniel 2008). This suggestion is consistent with the IFTU paradigm that highlights the mental inertia resulting from schema.

Another important finding of this study is the significant effect of distally lagged usage on current usage over and above proximally lagged usage. This finding implies the presence of a mental script that is strengthened over time with repeated performance. Without such mental script leading to automatic use, even a simple task would require considerable cognitive effort that otherwise could be directed to other important tasks (Kuutti 1996; Vallacher and Wegner 1987). Thus, to enhance organizational productivity, it is important for managers to help their workers develop a habit of using desirable technology features (Louis and Sutton 1991). On the other hand, it is important to note that habit often leads to mindless repetition of the same routine even when this routine is no longer effective in performing the task at hand. Such a form of habit is detrimental to work performance, and, therefore, managerial interventions should be considered to disrupt the unproductive routine. The literature suggests several intervention methods that could be effective in attracting individuals' attention. For example, explicit directives from upper-level managers could influence workers to revert from automatic to conscious control of technology use (Jasperson et al. 2005). In addition, to make workers pay attention to the drawbacks of the current routine, the benefit of innovative use, *vis-à-vis* the current use, needs to be made apparent to them through training and education. This is because individuals who are faced with contrasting information tend to employ deliberate evaluations, and, as a result, their recall of the new attribute is often better (Wansink and Ray 1996). This awareness program is believed to be effective not only as a way to disrupt habitual behavior but also to overcome the mental inertia discussed previously.

To summarize, managers will benefit from viewing the effective management of technology post-adoption essentially as an issue of managing human memory. With a rich account of technology use, the conceptual framework proposed in this study is expected to give the practitioners useful insights in how to deploy a new technology into their organizations.

Limitations of the Study

Several potential limitations of this study deserve mentioning. First of all, it should be noted that the original studies did not take into account measurement errors when factor correlations were calculated. Inevitably, the results of the present study, which relied on the reported correlation matrices, are unlikely to be free of measurement errors. Despite the potential for bias, the scales in the original studies were shown to be highly reliable and, consequently, any measurement errors in them were likely to be minor. Thus, any bias resulting from measurement errors is expected to be minimal. Meanwhile, the correlations in the original studies were reported only at the factor level, and as a result, autocorrelation—which refers to "correlation between error terms for the same variables over time" (Jöreskog and Sörbom 1996, p. 228)—was not explicitly controlled for. Kim and Malhotra (2005) reported that out of 12 interwave paths examined over a month, three paths in the sequential updating mechanism exhibited autocorrelation. This finding suggests that autocorrelation is not necessarily omnipresent, but it could affect the inferences that are drawn from a longitudinal study. Hence, caution is advised in view of the possibility that this study overestimates some of the mechanisms.

Although survey questionnaire items were the same across the original studies, actual usage measures were not identical (e.g., frequency and duration). This discrepancy in behavioral measures could potentially affect the results of this study. As a matter of fact, although the fit of the proposed model was found to be satisfactory on Samples A and B, it was not so on Sample C. Considering that the frequency measure was used for Samples A and B, the poor fit for Sample C could be attributed to the duration measure used to tap actual usage in the study by Morris et al. Although the results of this study were, for the most part, comparable regardless of the usage measures, readers are advised to consider them with this potential shortcoming in mind. Meanwhile, it is important to point out that the use of secondary data in this study made it difficult to capture the various aspects of technology usage that lie beyond frequency or duration. A growing number of IS studies have revealed that technology usage is more complex than mere frequency or duration and that its nuances cannot be fully understood without examining other characteristics such as integrative use, extended use, and emergent use (Ahuja and Thatcher 2005; Burton-Jones and Straub 2006; Saga and Zmud 1994). Thus, caution should be taken in any attempts to generalize the findings of this study beyond the lean usage measures examined in it.

Another limitation of this study is that it did not consider moderating effects in the course of its maintaining a focus on the linear relationships between research variables. A number of moderators have been identified in the literature and include, but are not limited to, age, gender, habit, cultural background, voluntariness, and task characteristics (Limayem et al. 2007; Sun and Zhang 2006; Venkatesh et al. 2003). In addition, technology usage is known to have not only a main effect on subsequent use but also a moderating effect on the relationship between usage intention and subsequent use (Kim et al. 2005). Unfortunately, such potential moderating effects were not examined in this study. Further research is required to incorporate diverse moderators into a conceptual model for a more nuanced examination of post-adoption phenomena.

The original memory model by Atkins and Schiffrin (1968) has been used as a conceptual basis for much of contemporary cognitive psychology research. However, the three-stage processing model of memory is criticized as oversimplified (Eysenck and Keane 2005). To overcome the limitation of the original three-stage processing model (Atkins and Schiffrin 1968), the present study reviews recent development in memory research and then offers an extended model with a more detailed account of long-term memory. Accordingly, the extended memory model in Figure 1 is believed to be a parsimonious yet reasonable model of memory that can guide the development of longitudinal models of technology use. Nevertheless, contemporary research suggests that sensory memory and working memory consist of several qualitatively distinct components and, thus, they do not operate in a simple and linear way (Thompson and Kim 1996). Therefore, although the extended memory model (Figure 1) serves well for this particular study, it should not be considered a complete account of memory processing.

Although this study adds further confirmation to IFTU and the model of memory processing, it should not be treated as direct evidence for validation of the major claim that the different components of memory give rise to the four mechanisms underlying post-adoption phenomena that ultimately cause the relationships as proposed in the panel model. For example, this study posits that implicit (i.e., procedural) memory results in habit, which in turn causes the relationship between current use and subsequent use. Yet it is possible that the repeated behavioral pattern observed in this study was caused by forces other than habit (e.g., moral norms, self-identity) (Ajzen 2002). Hence, further research needs to systematically compare the theoretical framework proposed in this study with alternative explanations.

Avenues for Further Research

The integrative view of technology adoption and sustained usage opens up several exciting avenues of research. One interesting topic for further research is the delicate nature of schema in the evaluation process. For example, according to the literature, new experience is known to lead to the formation of new schema; as long as subsequent experiences do not deviate significantly from the initial representation, the original schema is said to be maintained (Stayman et al. 1992; Winn 2004). Then we can expect that, all things being equal, initial evaluations, as compared with those performed later, have stronger effects on the subsequent evaluation process as a whole. In contrast, the literature also suggests that, when existing schema is not congruent with incoming information, people develop a different set of schema to assimilate the new piece of information. In such an unstable environment (i.e., system update, malfunction, etc.), prior judgments are likely to become less relevant than recent judgments. In addition to these propositions, a variety of other interesting hypotheses can be developed using the schema theory (e.g., Alba and Hutchinson 1987). As such, the concept of schema is expected to have great potential to broaden our knowledge of individuals' evaluative processes within the context of technology use. In a similar vein, further research can examine how the lagged patterns of repeated behaviors vary with respect to user experience. Although habit can be described as a function of both distally lagged usage and proximally lagged usage, the weight of those variables is likely to be unequal. As with the case of schema, in-depth analysis of script in implicit memory may help us to develop specific hypotheses related to this habit issue. Taken together, the IFTU paradigm, along with the memory perspective, is believed to offer a number of interesting ideas for further research and to provide insights into how individuals' evaluations and behavior unfold over time.

Another fertile area for research would be the role of user experience in regulating individuals' evaluations and behavior. To assess the moderating role of user experience, past research usually divided a sample into groups with respect to user experience (e.g., preadoption, post-adoption) (Karahanna et al. 1999) or employed a dummy variable representing different time periods (Venkatesh et al. 2003) (for a review, see Sun and Zhang 2006). However, past findings are open to further scrutiny because a variety of mechanisms underlying post-adoption phenomena (e.g., sequential updating, feedback, habit) were not taken into account simultaneously. In contrast, the panel model proposed in this study has the potential to address the shortcomings of the traditional methods because it allows investigators to assess the role of user experience within a more general conceptual framework. For example, to examine how the reason-oriented action mechanism varies with user experience, one can compare the relationships between BI and USE across time. In particular, this line of reasoning can be legitimately tested by comparing the path from BI at $t = i$ to USE at $t = i + 1$, the path from BI at $t = i + 1$ to USE at $t = i + 2$, and the path from BI at $t = i + 2$ to USE at $t = i + 3$. Assuming that the time intervals are all equal, the change in the BI-USE path across time can be attributed to user experience. It is hoped that future research can rigorously test the moderating effect of experience on individuals' evaluations and behavior in the manner described here while taking into account both proximal and distal effects of the mechanisms underlying post-adoption phenomena.

Finally, it is important to note that the proposed conceptual framework and its propositions regarding proximal and distal effects are not specific to certain time intervals. Put simply, the conceptual model proposed in this study is expected to apply regardless of the different time intervals that may be chosen in a longitudinal study (e.g., weeks, years). In this particular study, for example, the time intervals between waves were designed to be a couple of months. Thus, it will be interesting to see whether the proximal and distal effects of the four mechanisms behave as observed in this study despite the different time intervals that are employed in other studies. Meanwhile, researchers are also encouraged to extend the test of IFTU by using different numbers of periods. In the three-wave context examined in this particular study, each mechanism is associated with two sets of proximal effects and a set of distal effects. However, if data collection occurs over a larger number of periods, the operationalization of these effects would be more complex. In the case of a four-wave context, for example, each mechanism corresponds to three sets of proximal effects and three sets of distal effects. Interestingly, this four-wave context allows researchers to test various distal effects that cannot be examined in a two- or three-wave context. In summary, because of the flexibility of IFTU, its operationalization can vary with different time intervals over different numbers of periods. As the results of different versions of IFTU are accumulated in the future, the validity of IFTU can be better assessed.

Conclusion

Although the IS literature has revealed that a variety of mechanisms are involved in technology use, this same literature lacks a unifying account of those mechanisms. The present study fills the void in the literature by presenting a coherent and comprehensive theory from the new perspective of memory processing. The memory perspective is rich in theoretical depth and well-grounded in cognitive psychology; thus, it will help to pose and answer numerous challenging questions related to post-adoption phenomena. It is hoped that the conceptual framework presented in this study will be helpful in this important line of inquiry.

Acknowledgments

The author thanks the senior editor for his thoughtful guidance over the course of the review process involved with this paper. The associate editor's valuable comments contributed to substantial improvement of this paper and are deeply appreciated, as are the generous efforts to improve the paper that were made by the three *MIS Quarterly* reviewers. An earlier version of this paper was presented at the DIGIT conference and benefited greatly from the comments received from anonymous referees and the workshop participants. The author is grateful for valuable comments on the paper by Ramon J. Aldag at the University of Wisconsin. The author would also like to thank J. Stanford Fisher for his editorial help.

References

Aarts, H., and Dijksterhuis, A. 2000. "Habits as Knowledge Structures: Automaticity in Goal-Directed Behavior," *Journal of Personality and Social Psychology* (78:1), pp. 53-63.

Ahuja, M. K., and Thatcher, J. B. 2005. "Moving Beyond Intentions and Toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use," *MIS Quarterly* (29:3), pp. 427-459.

Ajzen, I. 1991. "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes* (50), pp. 179-211.

Ajzen, I. 2002. "Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives," *Personality and Social Psychology Review* (6), pp. 107-122.

Alba, J. W., and Hutchinson, J. W. 1987. "Dimensions of Consumer Expertise," *Journal of Consumer Research* (13:4), pp. 411-454.

Anderson, J. C., and Gerbing, D. W. 1988. "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach," *Psychological Bulletin* (103:3), pp. 411-23.

Anderson, J. R. 1990. *Cognitive Psychology and Its Implications* (3rd ed.), New York: W. H. Freeman and Company.

Atkins, R. C., and Schiffrin, R. M. 1968. "Human Memory: A Proposed System and its Control Processes," in *The Psychology of Learning and Motivation: Advances in Research and Theory*, Volume 2, K. W. Spence and J. T. Spence (eds.), New York: Academic Press, pp. 89-195.

Babin, B. J., and Babin, L. 2001. "Seeking Something Different? A Model of Schema Typicality, Consumer Affect, Purchase Intentions and Perceived Shopping Value," *Journal of Business Research* (54), pp. 89-96.

Bagozzi, R. P. 1981. "Attitudes, Intentions and Behavior: A Test of Some Key Hypotheses," *Journal of Personality and Social Psychology* (41:4), pp. 607-627.

Bagozzi, R. P., and Dholakia, U. 1999. "Goal Setting and Goal Striving in Consumer Behavior," *Journal of Marketing* (63:Special Issue), pp. 19-32.

Bajaj, A., and Nidumolu, S. R. 1998. "A Feedback Model to Understand Information System Usage," *Information and Management* (33), pp. 213-224.

Bamberg, S., Ajzen, I., and Schmidt, P. 2003. "Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action," *Basic and Applied Social Psychology* (25:3), pp. 175-187.

Bargh, J. A., Gollwitzer, P. M., Lee-Chai, A., Barndollar, K., and Trötschel, R. 2001. "The Automated Will: Conscious Activation and Pursuit of Behavioral Goals," *Journal of Personality and Social Psychology* (81:6), pp. 1,014-1,027.

Bem, D. 1972. "Self-Perception Theory," in *Advances in Experimental Social Psychology*, L. Berkowitz (ed.), New York: Academic Press, pp. 1-62.

Benbasat, I., and Barki, H. 2007. "Quo Vadis TAM?," *Journal of the Association for Information Systems* (8:4), pp. 211-218.

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), pp. 351-370.

Bhattacherjee, A, and Premkumar, G. 2004. "Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test," *MIS Quarterly* (28:2), pp. 229-254.

Blair, E., and Burton, S. 1987. "Cognitive Processes Used by Survey Respondents to Answer Behavioral Frequency Questions," *Journal of Consumer Research* (14:2), pp. 280-288.

Bolton, R. N. 1998. "A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction," *Marketing Science* (17:1), pp. 45-65.

Bolton, R. N., and Drew, J. H. 1991. "A Longitudinal Analysis of the Impacts of Service Changes on Customer Attitudes," *Journal of Marketing* (55:1), pp. 1-9.

Burton-Jones, A., and Straub, D. W. 2006. "Reconceptualizing System Usage: n Approach and Empirical Test," *Information Systems Research* (17:3), pp. 228-246.

Carte, T. A., Schwarzkopf, A. B., Shaft, T. M., and Zmud, R. W. 2005. "Advanced Business Intelligence at Cardinal Health," *MIS Quarterly Executive* (4:4), pp. 413-424.

Chin, W. W., Gopal, A., and Salisbury, W. D. 1997. "Advancing the Theory of Adaptive Structuration: The Development of a Scale to Measure Faithfulness of Appropriation," *Information Systems Research* (8:4), pp. 342-67.

Cohen, J. 1988. *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.), Hillsdale, NJ: Erlbaum Associates.

Collins, L. M., and Graham, J. W. 2002. "The Effect of the Timing and Spacing of Observations in Longitudinal Studies of Tobacco and Other Drug Use: Temporal Design Considerations," *Drug and Alcohol Dependence* (68), pp. 85-96.

Daniel, D. 2008. "Four Tips for Better Business Intelligence in 2008," *CIO*, January 8 (available online at www.cio.com/article/170201).

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. 1989. "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Management Science* (35:8), pp. 982-1,003.

Diamantopoulos, A., and Siguaw, J. A. 2000. *Introducing LISREL*, London: Sage Publications.

Dunlap, W. P., Xin, X., and Myers, L. 2004. "Computing Aspects of Power for Multiple Regression," *Behavior Research Methods, Instruments, and Computers* (36:4), pp. 695-701.

Eysenck, M. W., and Keane, M. T. 2005. *Cognitive Psychology: A Student's Handbook* (5th ed.), Hove, UK: Psychology Press.

Gollwitzer, P. M. 1996. "The Volitional Benefits of Planning," in *The Psychology of Action: Linking Cognition and Motivation to Behavior*, P. M. Gollwitzer and J. A.. Bargh (eds.), New York: The Guilford Press, pp. 287-312.

Greenfield, S. 1997. *The Human Brain: A Guided Tour*, New York, NY: Basic Books.

Helson, H. 1964. *Adaptation-Level Theory*, New York: Harper & Row.

Hogarth, R. M., and Einhorn, H. J. 1992. "Order Effects in Belief Updating: The Belief Adjustment Model," *Cognitive Psychology* (24:1), pp. 1-55.

Hu, L., and Bentler, P. M. 1999. "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives," *Structural Equation Modeling* (6:1), pp.1-55.

Jasperson, J., Carter, E. C., and Zmud, R. W. 2005. "A Comprehensive Conceptualization of the Post-Adoptive Behaviors Associated with IT-Enabled Work Systems," *MIS Quarterly* (29:3), pp. 525-557.

Jöreskog, K., and Sörbom, D. 1996. *LISREL8: User's Reference Guide*, Chicago, IL: Scientific Software International.

Karahanna, E., Straub, D. W., and Chervany, N. L. 1999. "Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs," *MIS Quarterly* (23:2), pp. 183-213.

Kim, S. S., and Malhotra, N. K. 2005. "A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Postadoption Phenomena," *Management Science* (51:5), pp. 741-755.

Kim, S. S., Malhotra, N. K., and Narasimhan, S. 2005. "Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison," *Information Systems Research* (16:4), pp. 418-432.

Kraut, R., Mukhopadhyay, T., Szczypula, J., Kiesler, S., and Scherlis, B. 1999. "Information and Communication: Alternative Uses of the Internet in Households," *Information Systems Research* (10:4), pp. 287-303.

Kuutti, K. 1996. "Activity Theory as a Potential Framework for Human-Computer Interaction Research," in *Context and Consciousness: Activity Theory and Human Computer Interaction*, B. A. Nardi (ed.), Cambridge, MA: MIT Press, pp. 17-44.

LaBarbera, P., and Mazursky, D. 1983. "A Longitudinal Assessment of Consumer Satisfaction/Dissatisfaction: The Dynamic Aspect of the Cognitive Process," *Journal of Marketing Research* (20), pp. 393-404.

Limayem, M., and Hirt, S. G. 2003. "Force of Habit and Information Systems Usage: Theory and Initial Validation," *Journal of the Association for Information Systems* (4), pp. 65-97.

Limayem, M., Hirt, S. G., and Cheung, C. M. K. 2007. "How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance," *MIS Quarterly* (31:4), pp. 705-737.

Lin, T. H., and Dayton, C. M. 1997. "Model Selection Information Criteria for Non-Nested Latent Class Models," *Journal of Educational and Behavioral Statistics* (22:3), pp. 249-264.

Lindell, M. K., and Whitney, D. J. 2001. "Accounting for Common Method Variance in Cross-Sectional Research Designs," *Journal of Applied Psychology* (86:1), pp. 114-121.

Louis, M. R., and Sutton, R. I. 1991. "Switching Cognitive Gears: From Habits of Mind to Active Thinking," *Human Relations* (44:1), pp. 55-76.

MacCallum, R. C., Browne, M. W., and Sugawara, H. 1996. "Power Analysis and Determination of Sample Size for Covariance Structure Modeling," *Psychological Methods* (1:2), pp. 130-149.

Malhotra, N. K., Kim, S. S., and Patil, A. 2006. "Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research, *Management Science* (52:12), pp. 1,865-1,883.

McAfee, A. 2003. "When Too Much IT Knowledge is a Dangerous Thing," *MIT Sloan Management Review* (44:2), pp. 83-89.

Miller, E. K., and Cohen, J. D. 2001. "An Integrative Theory of Prefrontal Cortex Function," *Annual Review of Neuroscience* (24), pp. 167-202.

Morris, M. G., Venkatesh, V., and Ackerman, P. A. 2005. "Gender and Age Differences in Employee Decisions about New Technology: An Extension to the Theory of Planned Behavior," *IEEE Transactions on Engineering Management* (52:1), pp. 69-84.

Myers, D. G. 2004. *Psychology* (7th ed.), New York: Worth Publishers.

Oliver, R. L. 1981. "Measurement and Evaluation of Satisfaction Processes in Retail Settings," *Journal of Retailing* (57:3), pp. 25-48.

Orth, U. R., and De Marchi, R. 2007. "Understanding the Relationships Between Functional, Symbolic, and Experiential Brand Beliefs, Product Experiential Attributes, and Product Schema: Advertising–Trial Interactions Revisited," *Journal of Marketing Theory and Practice* (15:3), pp. 219-233.

Ouellette, J. A., and Wood, W. 1998. "Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior," *Psychological Bulletin* (124:1), pp. 54-74.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology* (88:5), pp. 879-903.

Ronis, D. L., Yates, J. F., and Kirscht, J. P. 1989. "Attitudes, Decisions, and Habits as Determinants of Repeated Behavior," in *Attitude Structure and Function*, A. R. Pratkanis, S. J. Breckler, and A. G. Greenwald (eds.), Hillsdale, NJ: Lawrence Erlbaum Associates, pp. 213-239.

Saga, V. L., and Zmud, R. W. 1994. "The Nature and Determinants of IT Acceptance, Routinization, and Infusion," in *Diffusion, Transfer and Implementation of Information Technology*, L. Levine (ed.), Amsterdam: North-Holland, pp. 67-86.

Stayman, D. M., Alden, D. L., and Smith, K. H. 1992. "Some Effects of Schematic Processing on Consumer Expectations and Disconfirmation Judgments," *Journal of Consumer Research* (19:2), pp. 240-255.

Steenkamp, J. E. M., and Baumgartner, H. 1998. "Assessing Measurement Invariance in Cross-National Consumer Research," *Journal of Consumer Research* (25:1), pp. 78-90.

Sun, H., and Zhang, P. 2006. "The Role of Moderating Factors in User Technology Acceptance," *International Journal of Human-Computer Studies* (64), pp. 53-78.

Taylor, S., and Todd, P. A. 1995. "Understanding Information Technology Usage: A Test of Competing Models," *Information Systems Research* (6:2), pp. 144-176.

Thompson, R. F., and Kim, J. J. 1996. "Memory Systems in the Brain and Localization of a Memory," Colloquium Paper, *Proceedings of the National Academy of Sciences of the United States of America* (93:24), pp. 13438-13444.

Triandis, H. C. 1977. *Interpersonal Behavior*, Monterey, CA: Brooks/Cole.

Tulving, E. 2002. "Episodic Memory: From Mind to Brain," *Annual Review of Psychology* (53), pp. 1-25.

Vallacher, R.V., and Wegner, D. M. 1987. "What Do People Think They're Doing? Action Identification and Human Behavior," *Psychological Review* (94:1), pp. 3-15.

Venkatesh, V., Morris, M. G., and Ackerman, P. L. 2000. "A Longitudinal Field Investigation of Gender Differences in Individual Technology Adoption Decision-Making Processes," *Organizational Behavior and Human Decision Processes* (83:1), pp. 33-60.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.

Wansink, B., and Ray, M. L. 1996. "Advertising Strategies to Increase Usage Frequency," *Journal of Marketing* (60:1), pp. 31-46.

Wheeler, M. A., Stuss, D. T., and Tulving, E. 1997. "Toward a Theory of Episodic Memory: The Frontal Lobes and Autonoetic Consciousness," *Psychological Bulletin* (121:3), pp. 331-354.

Winn, W. 2004. "Cognitive Perspectives in Psychology," in *Handbook of Research for Educational Communications and Technology* (2nd ed.), D. H. Jonassen (ed.), Manwah, NJ: Lawrence Erlbaum, pp. 79-112.

About the Author

Sung S. Kim is an associate professor of operations and information management at the University of Wisconsin–Madison. He holds a B.S. in electronic engineering from Yonsei University, Seoul, Korea; an M.S. in information systems from the University of Wisconsin–Madison; and a Ph.D. from the Georgia Institute of Technology in information technology management with a minor in industrial and systems engineering. His primary research focuses on automaticity in IT use, online consumer behavior, information privacy, and philosophical and methodological issues. His research appears in *Management Science*, *Information Systems Research*, *MIS Quarterly*, *Journal of the Association for Information Systems*, and *Decision Sciences*. He currently serves as an associate editor for *Information Systems Research*.

Appendix A

Comparisons of the Original Studies

	Venkatesh et al. (2000)	Morris et al. (2005)
Objective	Gender differences in IT adoption decision-making processes	Gender and age differences in IT adoption decision-making processes
Setting	Organizations implementing a new technology application in part or all of the organization	Organizations implementing a new technology application in part or all of the organization
Number of organizations	4	5
Respondents	355 (195 men and 160 women)	342 (186 men and 156 women)
Target application	Enterprise-wide system for data and information retrieval	Enterprise-wide Windows-based system for data and information retrieval
Methodology	Three-wave panel study	Three-wave panel study
First data collection (t=1)	The first TPB set was measured immediately after initial training.	The first TPB set was measured immediately after initial training.
Second data collection (t=2)	The second set of TPB data, along with actual usage, was measured one month after the initial data collection.	The second set of TPB data, along with actual usage, was measured one month after the initial data collection.
Third data collection (t=3)	The second set of TPB data, along with actual usage, was measured two months after the second data collection.	The second set of TPB data, along with actual usage, was measured two months after the second data collection.
Final data collection (t=4)	Actual usage was measured once more two months after the third data collection.	Actual usage was measured once more three months after the third data collection.
Survey questionnaire items	Shown in Appendix B	Shown in Appendix B
Actual usage	Actual usage was measured by the number of information queries made through system logs within a certain period.	The duration of technology use, measured by average hours of use per week, was used to capture actual usage.
Samples	Sample A (the male sample) Sample B (the female sample)	Sample C (the pooled sample)

Appendix B

Questionnaire Items

Intention to Use (7-point Likert scale)
- Assuming I had access to the system, I intend to use it.
- Given that I had access to the system, I predict that I would use it.

Attitude Toward Using (7-point semantic differential scale)
- Using the system is a (bad/good) idea.
- Using the system is a (foolish/wise) idea.
- I (dislike/like) the idea of using the system.
- Using the system is (unpleasant/pleasant).

Subjective Norm (7-point Likert scale)
- People who influence my behavior think that I should use the system.
- People who are important to me think that I should use the system.

Perceived Behavioral Control (7-point Likert scale)
- I have control over using the system.
- I have the resources necessary to use the system.
- I have the knowledge necessary to use the system.
- Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system.
- The system is not compatible with other systems I use.

Appendix C

Model Fit

	Fit Indices	Intermediate Model				IFTU1	Alternative Model				IFTU2
		1	2	3	4		1	2	3	4	
Sample A											
Model Fit	χ^2	510.73	280.32	344.35	423.08	143.54	135.12	113.84	137.35	136.42	106.39
	df	87	79	79	85	69	61	65	65	68	65
	CAIC	717.74	537.52	601.55	642.43	463.46	505.23	458.86	482.36	462.61	457.68
	CFI	0.48	0.72	0.62	0.58	0.88	0.89	0.92	0.89	0.89	0.93
	RMSEA	0.16	0.12	0.13	0.14	0.075	0.080	0.063	0.076	0.073	0.059
	SRMR	0.22	0.16	0.16	0.21	0.090	0.090	0.078	0.083	0.087	0.075
Model Com-parison	$\Delta\chi^2$	367.19	136.78	200.81	279.54		(-)8.42	(-)29.70	(-)6.19	(-)7.12	(-)37.15
	Δdf	18	10	10	16		8	4	4	1	5
	p-value	<0.001	<0.001	<0.001	<0.001		ns	<0.001	ns	<0.01	<0.001
Sample B											
Model Fit	χ^2	431.10	247.25	265.15	366.82	121.30	116.65	89.89	112.63	113.81	81.85
	df	87	79	79	85	69	61	65	65	68	64
	CAIC	631.59	496.33	514.23	579.45	431.13	475.08	424.02	446.76	429.71	422.06
	CFI	0.54	0.72	0.68	0.63	0.90	0.90	0.95	0.91	0.91	0.96
	RMSEA	0.16	0.12	0.12	0.15	0.070	0.076	0.050	0.069	0.066	0.042
	SRMR	0.23	0.17	0.16	0.21	0.093	0.091	0.075	0.082	0.089	0.071
Model Com-parison	$\Delta\chi^2$	309.80	125.95	143.85	245.52		(-)4.65	(-)31.41	(-)8.67	(-)7.49	(-)39.45
	Δdf	18	10	10	16		8	4	4	1	5
	p-value	<0.001	<0.001	<0.001	<0.001		ns	<0.001	ns	<0.01	<0.001
Sample C											
Model Fit	χ^2	1139.51	570.52	799.11	946.44	300.02	283.08	247.35	290.17	296.88	245.38
	df	87	79	79	85	69	61	65	65	68	64
	CAIC	1365.05	850.75	1079.34	1185.66	648.60	686.29	623.26	666.08	652.29	628.13
	CFI	0.42	0.68	0.54	0.52	0.84	0.84	.087	0.84	0.84	0.87
	RMSEA	0.19	0.14	0.16	0.17	0.100	0.10	0.09	0.10	0.10	0.09
	SRMR	0.24	0.16	0.17	0.22	0.079	0.091	0.065	0.073	0.077	0.063
Model Com-parison	$\Delta\chi^2$	839.49	270.50	499.09	646.42		(-)16.99	(-)52.67	(-)9.89	(-)3.14	(-)54.64
	Δdf	18	10	10	16		8	4	4	1	5
	p-value	<0.001	<0.001	<0.001	<0.001		<0.05	<0.001	<0.05	ns	<0.001

Notes:

- ns = Not significant
- Model comparison was made with IFTU1

Appendix D

Completely Standardized Path Estimates and Squared Multiple Correlations

Hypothesized Mechanisms	Causal Paths	Sample A			Sample B			Sample C		
		IM1	IFTU1	IFTU2	IM1	IFTU1	IFTU2	IM2	IFTU1	IFTU2
The theory of planned behavior	A (t = 1) → BI (t = 1)	0.43***	0.043**	0.43***	0.12	0.12	0.12	0.31***	0.31***	0.31***
	SN (t = 1) → BI (t = 1)	0.06	0.06	0.06	0.46***	0.46***	0.46***	0.26***	0.26***	0.26***
	PBC (t = 1) → BI (t = 1)	0.09	0.09	0.09	0.28***	0.28***	0.28***	0.12*	0.12*	0.12*
	PBC (t = 1) → USE (t + 2)	0.05	0.05	0.05	-0.01	-0.01	-0.01	0.14**	0.14**	0.14**
	BI (t = 1) → USE (t + 2)	0.50***	0.50***	0.50***	0.50***	0.05***	0.05***	0.62	0.62***	0.62***
	A (t = 2) → BI (t = 2)	0.36**	0.24**	0.24***	0.29***	0.18*	0.18*	0.34***	0.22***	0.22***
	SN (t = 2) → BI (t = 2)	0.10	0.08	0.08	0.08	0.04	0.04	0.15**	0.09	0.09
	PBC (t = 2) → BI (t = 2)	0.11	0.02	0.02	0.28***	0.20**	0.20**	0.18***	0.12***	0.12***
	PBC (t = 2) → USE (t = 3)	0.17**	0.13*	0.13*	0.10	0.06	0.06	0.14**	0.10*	0.10*
	BI (t = 2) → USE (t = 3)	0.47	0.31***	0.31***	0.47***	0.35***	0.35***	0.44***	0.25***	0.25***
	A (t = 3) → BI (t = 2)	0.35***	0.22***	0.23***	0.10	0.03	0.01	0.36***	0.26***	0.26***
	SN (t = 3) → BI (t = 2)	0.13	0.11*	0.08	0.04	0.04	0.00	0.06	0.02	0.00
	PBC (t = 3) → BI (t = 2)	0.06	-0.06	-0.06	0.45***	0.36***	0.37***	0.21***	0.12*	0.11*
	PBC (t = 3) → USE (t = 3)	0.20***	0.14*	0.12*	0.06	-0.03	-0.05	0.19***	0.11*	0.10*
	BI (t = 3) → USE (t = 3)	0.49***	0.34**	0.01***	0.45***	0.35***	0.31***	0.43***	0.24***	0.22***
Sequential updating	A (t = 1) → A (t = 2)		0.25***	0.25***		0.22**	0.22**		0.24***	0.24***
	SN (t = 1) → SN (t = 2)		0.16*	0.16*		0.14	0.14		0.46***	0.46***
	PBC (t = 1) → PBC (t = 2)		0.30***	0.30***		0.33***	0.33***		0.35***	0.35***
	BI (t = 1) → BI (t = 2)		0.32***	0.32***		0.22**	0.22**		0.27***	0.27***
	A (t = 2) → A (t = 3)		0.20**	0.16*		0.21**	0.16*		0.22***	0.15*
	SN (t = 2) → SN (t = 3)		0.19**	0.17*		0.20**	0.17*		0.50***	0.48***
	PBC (t = 2) → PBC (t = 3)		0.24***	0.17*		0.20**	0.14		0.37***	0.28***
	BI (t = 2) → BI (t = 3)		0.42***	0.34***		0.34**	0.26***		0.13*	0.07
Feedback	USE (t = 2) → A (t = 2)		0.21**	0.21**		0.31***	0.31***		0.25***	0.25***
	USE (t = 2) → SN (t = 2)		0.09	0.09		0.16	0.16		0.06	0.06
	USE (t = 2) → PBC (t = 2)		0.11	0.11		0.18*	0.18*		0.12*	0.12*
	USE (t = 2) → BI (t = 2)		0.15*	0.15*		0.15	0.15		0.17	0.17**
	USE (t = 3) → A (t = 3)		0.31***	0.27***		0.14	0.10		0.26***	0.18***
	USE (t = 3) → SN (t = 3)		0.06	0.04		0.20**	0.14		0.05	0.04
	USE (t = 3) → PBC (t = 3)		0.18*	0.17**		0.30***	0.28***		0.18***	0.15**
	USE (t = 3) → BI (t = 3)		0.13	0.07		0.06	0.01		0.27***	0.24***
Habit	USE (t = 2) → USE (t = 3)		0.40***	0.40***		0.35***	0.35***		0.46***	0.46***
	USE (t = 3) → USE (t = 4)		0.37***	0.29***		0.42***	0.33***		0.48***	0.40***
Distal sequential updating	A (t = 1) → A (t = 3)			0.17*			0.22**			0.29***
	SN (t = 1) → SN (t = 3)			0.09			0.22**			0.05
	PBC (t = 1) → PBC (t = 3)			0.23**			0.17**			0.25***
	BI (t = 1) → BI (t = 3)			0.24***			0.26***			0.16
Distal habit	USE (t = 1) → USE (t = 4)			0.18**			0.21**			0.15**
Squared multiple correlations	BI (t = 1)	0.23	0.23	0.23	0.40	0.40	0.40	0.25	0.25	0.25
	USE (t = 2)	0.26	0.26	0.26	0.25	0.25	0.25	0.44	0.44	0.44
	BI (t = 2)	0.16	0.31	0.31	0.18	0.28	0.28	0.17	0.34	0.34
	USE (t = 3)	0.26	0.40	0.40	0.26	0.37	0.37	0.24	0.42	0.42
	USE (t = 4)	0.15	0.37	0.41	0.24	0.36	0.42	0.18	0.30	0.32
		0.29	0.41	0.43	0.24	0.38	0.41	0.26	0.45	0.46

Notes:
- A = attitude; SN = subjective norm; PBC = perceived behavioral control; BI = behavioral intention; USE = technology usage
- $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$ (two-tailed)

Appendix E

Common Method Variance and Statistical Power

This study used data collected over time (i.e., three times) using multiple methods (i.e., subjective and objective measures). Hence, compared with other studies that rely exclusively on a survey questionnaire for data collection, this particular study is less susceptible to common method variance (CMV) (Podsakoff et al. 2003). Nevertheless, the occurrence of CMV within survey data collected at the same point in time cannot be ruled out. The marker–variable technique, which allows researchers to estimate the extent of CMV from factor correlations (Lindell and Whitney 2001, Malhotra et al. 2006), was used to assess this potential problem. In particular, the smallest correlation among the variables measured at the same time was considered as a proxy for CMV, given the lack of a marker variable prepared explicitly beforehand. This approach would give us a rather conservative estimate because TPB factors are theorized to be correlated significantly. An inspection of the correlation matrix in each of the three samples indicated that the correlation inflated by CMV was not significant, and its magnitude was 0.10 or less. These results are highly consistent with the finding of Malhotra et al. (2006) that in IS research the inflated correlation resulting from CMV is typically on the order of 0.10 or less. Taken together, it seems reasonable to argue that CMV did not significantly contaminate the results of this study.

The power of statistical tests was examined in terms of fit and effect size. First, power for the test of not-close fit—the probability of rejecting the (false) null hypothesis that fit is mediocre (i.e., RMSEA $\geq$ 0.10)—was assessed given the degrees of freedom, the sample size, and the observed fit. MacCallum et al.'s (1996) procedure was followed to calculate power for this test of not-close fit. The results indicated that with the 64 degrees of freedom associated with IFTU2, the power was 0.99 in Sample A (given the sample size of 195 and the RMSEA value of 0.059), 1.00 in Sample B (given the sample size of 160 and the RMSEA value of 0.042), and 0.39 in Sample C (given the sample size of 342 and the RMSEA value of 0.090). Because of the marginal fit of the model (i.e., RMSEA = 0.09), power was relatively low in Sample C (i.e., 0.39); yet, in the other two samples, power was found to be more than adequate (i.e., $\geq$ 0.99). Subsequently, power for the test of no effect—the probability of rejecting the (false) null hypothesis that effect size is 0—was examined given the number of predictors, the sample size, and the observed effect size. Dunlap et al.'s (2004) procedure, which is shown to be more reliable than the well-known method by Cohen (1988), was employed to calculate power for this test of no effect. The results showed that power values were 0.99 or higher for all BI and USE variables in each of the samples. Thus, power was considered to be excellent for the test of effect size. Overall, a series of power analyses indicated that sample sizes were sufficient for the model to reasonably detect false null hypotheses concerning fit and effect size.