An Empirical Investigation of Habitual Usage and Past Usage on Technology Acceptance Evaluations and Continuance Intention

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Abstract

Although much research has examined information technology (IT) usage that involves deliberate evaluation and decision-making, we know less about automatic use that occurs spontaneously with little conscious effort. In this study we have investigated this issue by studying how habitual usage and past usage may influence the predicting power of perceived ease of use (PEOU) and perceived usefulness (PU) on intention. Using 232 cross-sectional responses from subjects who have continuously used the Google search engine, the results show that as individuals get into the habit of continuously using a system, the predicting power of PU and PEOU on intention is diluted by the addition of either habitual usage or past usage. This indicates that the stronger the habitual use of the Google search engine, the less conscious planning is involved, and the relationship between subjects' evaluations of PU/PEOU and their intention to use weakens. Furthermore, our study shows that past usage, often employed as a proxy of habitual usage, demonstrates a similar effect but differs in the predicting power from habitual usage. This result suggests that researchers may employ habitual usage for studies of post-adoption phenomenon concerning continuous information system usage.

ACM Categories: H.1.2, H.3.3

Keywords: Automaticity, Habit, Habitual usage, Past usage, Self-perception, Technology acceptance model

Introduction

Prior IS research has largely sought to explore how users come to adopt a particular IS. Among these theories are the technology acceptance model (TAM) (Davis, 1989), the innovation diffusion theory (Moore & Benbasat, 1991), the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), and the theory of planned behavior (TPB) (Ajzen, 1991). Most of these models are variants of social psychology theories that focus primarily on the role of intentions in predicting future behavior.

However, compared with potential adopters, users' system usage evaluations are likely to be based on their past experience (Karahanna et al., 1999), and their decision-making process changes (Kim et al., 2005). According to the self-perception account, system users may rely on their own overt behaviors or environmental cues to infer their inner states or thoughts, because they may have little direct introspective access to their own higher order cognitive processes (Nisbett & Wilson, 1977) or they may lack the motivation or ability to process information (Kim & Malhotra, 2005). In accordance with self-perception theory, prior work has demonstrated that IS past usage has a significant impact on evaluations of usefulness and intention and acts as a principal predictor of future behavior (Davis & Venkatesh, 2004; Kim & Malhotra, 2005; Venkatesh et al., 2000). In this line of reasoning, self-perception can be extended to account for why past behavior, or IS habit, would interfere with analytical information processing conducted to evaluate usefulness and to form intention. Thus, contemporary researchers have begun to explore the impact of habitual, automatic use in IS post-adoption context (Jasperson et al., 2005; Limayem et al., 2007). Frequently performed behavior is said to become habitual over time (Kim & Malhotra, 2005; Ouellette & Wood, 1998). Several previous studies used past behavior as a measure of habit (Bergeron et al., 1995; Kim & Malhotra, 2005). Nevertheless, the divergent conceptual definitions and measurements may cause controversial conclusions in theory development. More specifically, Limayem et al. (2007) gave a thorough review of past studies on habit and found that the theoretical roles of habit can either be direct, mediated through intention on future behavior, or moderated between intention and behavior. In order to gain further theoretical understanding of decision-making processes in IS post-adoption, it is important to disentangle the conceptually distinct notions of past behavior and habit.

The main purpose of this study aims to (1) investigate to what extent evaluations of usefulness and ease of use (i.e., PU, PEOU) toward system usage are influenced by the user's past behavior and habit; (2) examine what the dominant factors are affecting web-based application continuance intention; and (3) empirically verify the conceptual distinction of habitual and past usage and their impacts on evaluations and intention towards web-based application usage. In doing so, we seek to contribute to the growing body of knowledge concerning how and to what extent IS habitual usage and past usage influence the evaluations and intention of system usage under IS post-adoption context.

The paper proceeds as follows. In the next section, theoretical background is provided and the research model and hypotheses are proposed. This is followed by the description of survey procedures, data analysis, and results. In the final section, we discuss the implications of our research findings, identify the limitations of the study, and suggest directions for further research.

Theoretical background

In this section, a brief overview of technology acceptance model (TAM) is presented, followed by an introduction about self-perception to gain insight into how past experience may play a significant role in IS continuance situation. Next, to better understand the core concept of habit, the various dimensions of automaticity (i.e., lack of awareness, mental efficiency and hard to control) are described, and the theoretical conceptualization and empirical operationalization of habit are clarified. Finally, the differences between past system usage and habitual usage are discussed.

Technology Acceptance Model (TAM)

Determinants of specific behaviors are guided largely by a reasoned action approach that assumes that people's behavior follows their beliefs, attitudes, and intentions (Ajzen, 2002). A great deal of the contemporary IS usage research concerning the influence of attitudes on behavior has been conducted within this conceptual framework (Jasperson et al., 2005; Seddon, 1997). In this line of research, most studies hold the assumption that IT usage is rational behavior, driven mainly by analytical, reflective, and deliberate cognitive processing. Among the intention-based models, TAM is considered to be the most parsimonious and powerful theory for describing user acceptance of information systems (Lee & Lee, 2003; Venkatesh & Morris, 2000). According to this theory, IS usage behavior is predominately explained by behavioral intention that is formed as a result of conscious decision-making processes. Behavioral intention, in turn, is determined by two belief factors, namely, perceived usefulness (PU) and perceived ease of use (PEOU). Note that perceived ease of use also has a direct impact on perceived usefulness.

Self-perception Theory

As opposed to the reasoned action approach, Nisbett and Wilson (1977) have asserted that individuals may have little direct introspective access to their own higher order cognitive processes. People's reports of why they behave a certain way are assumed to be based on *a priori*, implicit causal theories, or judgments about the extent to which a particular stimulus is a plausible cause of a given response. In other words, people are likely to rely on the observation of overt behaviors (verbal, actions and otherwise) in order to make causal attributions about these behaviors. This is in line with Bem's (1972) self-perception theory, which states that "individuals come to 'know' their own attitudes, emotions, and other internal states partially by inferring them from observations of their own overt behavior and/or the circumstances in which this behavior occurs." "To the extent that internal cues are weak, ambiguous, or uninterpretable, the individual is functionally in the same position as an outside observer, an observer who must necessarily rely upon those same external cues to infer the individuals' inner states" (Bem, 1972, p. 2). In short, when we observe another person, we rely on that person's overt behaviors to induce his or her motives without having access to his or her internal states or thoughts.

While the self-perception position has received only modest attention in the IS literature (Bajaj & Nidumolu, 1998; Kim & Malhotra, 2005; Melone, 1990), over the years it has been applied to various phenomena, including change following counter-attitudinal behavior (Bem, 1965), emotional experience (Duclos et al., 1989; Schachter & Singer, 1962), self-evaluations (Comer & Laird, 1975), foot-in-the-door compliance procedure (Freedman & Fraser, 1966), money donation (Holland et al., 2002), appearance on self-perceptions (Kellerman & Laird, 1982), information system usage (Kim & Malhotra, 2005), insomnia (Storms & Nisbett, 1970), premenstrual syndrome (Schnall et al., 2002), and preferences for pictures (Valins, 1966). The studies employing self-perception theory clearly suggest that people do ascribe attributes to themselves on the basis of the kinds of behavioral information that would lead an outside observer to make the same attributions. For example, Holland et al.'s (2002) study showed that participants' attitudes were significantly influenced by their donation behavior among participants with weak attitude. Duclos et al. (1989) demonstrated that mood states could be induced by changes in people's bodily activities. In their study, the behaviors necessarily preceded and produced the feelings. People who were induced to adopt facial expressions or postures of various emotions felt the corresponding emotions. In Valins' (1966) study, subjects' preferences for certain pictures were induced from the rapidly increased heart rates which were experimentally manipulated rather than genuine. These research findings echo Nisbett and Wilson's (1977) viewpoint in that individuals may have little direct introspective access to their own higher order cognitive processes. Instead, their reasoning about inner state is cued by overt behaviors.

In IS post-adoption context, Karahanna et al. (1999) compared the differences of attitude beliefs between potential adopters and users. Contrary to their expectations, potential adopters tried to articulate pros and cons and thus had richer set of attitude beliefs than familiar users, who might just rely on their past experience to simplify the inference about their inner attitude instead of looking for lots of information to form a judgment. That is, people rarely retrieve all the information that may be relevant to a judgment and instead truncate the search process as soon as "enough" information has come to mind to form a judgment with sufficient subjective certainty (Bodenhausen & Wyer, 1987; Higgins, 1996). In a similar vein, Kim and Malhotra (2005) argued that in routine environments individuals form attitudes and continuance intention using rule of thumb (i.e., past system usage) when they lack the motivation or ability to process information. This is because highly accessible information is accompanied by a metacognitive experience of fluent processing, which lends additional credibility and weight to the information (Schwarz, 2004). As consequence, the more frequent is past usage, the better the recall is about the usage experiences and, hence, the use practices serve as the dominant baseline for judgment. Consistent with prior post-adoption studies, we expect that past system usage is used as an important environmental cue about inner attitudes and IS continuance intention.

Furthermore, self-perception may interfere with individuals' information processing. Once individuals have formed the habit of using an IS, they may not pay much attention to benefit-evaluation when deciding to continue to use an IS. That is, under the influence of habitual automaticity, information processing is so quick that individuals almost bypass evaluative information to form their IS continuance intention (Kim et al., 2005). Thus, habits may directly influence intention toward continuance usage directly rather than be mediated by deliberate evaluations in IS post-adoption context. In this way, self-perception of using an IS would not only be used as an inference about inner attitude but would also impact the procedure of information processing.

Automaticity: The Core Concept of Habit

Automaticity is characterized as lack of awareness, efficiency, and lack of control (Bargh, 1994; Verplanken & Orbell, 2003). First of all, research on automaticity (Banaji & Greenwald, 1995; Bargh & Williams, 2006; Wegner & Bargh, 1998) has shown that several different forms of social representations become automatically activated in the course of social perception, triggered by the presence of their corresponding features in the environment. To understand how contexts cue social behaviors spontaneously, the priming paradigm was developed and used to manipulate the level of awareness. Priming effects are subtle so that participants usually cannot detect the experimental manipulation. For example, subtle priming of the stereotype of the elderly (including the notions that the elderly are forgetful, as well as physically slow and weak) may cause college students to walk more slowly when leaving the experimental session and to subsequently have poorer memory for the features of a room (Dijksterhuis & Bargh, 2001). In another study, participants who have been unobtrusively primed with instances of the concept “rude” are considerably more likely to interrupt a subsequent conversation than were those primed with the concept “polite” (Bargh et al., 1996). Another potential mechanism by which the social environment can directly influence social behavior is through the activation and operation of goal representations that have become strongly associated with a particular situation (Bargh & Williams, 2006). Even when the goal is activated outside of the participant’s awareness, the same outcomes can be obtained. For instance, in one study, subliminal priming of a cooperation goal produced the same increase in cooperative behavior as did explicit, conscious instructions to cooperate (Bargh et al., 2001). More importantly, the participants were not aware of the activation of the goal or of its operation over time to guide their behavior.

In addition, performance efficiency accompanies habitual automaticity. Wood et al. (2002) have employed the diary methodology to access people’s thoughts and emotions while performing habitual behaviors and non-habitual behaviors. The results show that when engaged in habitual behavior, participants are likely to think about other issues unrelated to their behavior, which indicates that habit performance is characterized by cognitive economy and performance efficiency. Habit performance is not likely to deplete self-regulatory resources and this may allow people to conserve regulatory strength for important decisions. In another diary study, Neal and Wood (2005) have explored the regulatory demands of habitual and non-habitual behaviors. Across four days they monitored people’s daily performance of a range of personally important behaviors (e.g., attending the gym, getting up on time). For two of the four days people’s self-control capacity was reduced by requiring them to use their non-dominant hand for a range of activities (an effortful task that drains will-power). When self-control was lowered, people were less likely to perform non-habitual behaviors but continued to perform habits successfully. They not only maintained beneficial habits, but also maintained bad habits. Thus, habits represent a double-edged sword; desirable habits are easy to perform when one is depleted, but undesirable habits are difficult to inhibit.

Even when one wants to, automaticity is still difficult to suppress. Aarts and Dijksterhuis’ (1999) study shed light on the difficulty of holding back automatic habitual responses related to travel mode choices. Participants were presented with familiar travel destinations. Under severe time pressure, they were asked to mention which mode of traveling they would use (the inclusion condition). Other participants were instructed to mention travel mode options that they would not use for the presented destinations (the exclusion condition). In addition, half of the participants worked while their mental capacity was overloaded. It was found that when overloaded, it was more difficult to suppress responses (i.e., more mistakes in the exclusion condition) that were related to the automatic habitual choices than the non-habitual choices. In another study (Verplanken et al., 1997), participants made travel mode choices in response to 27 imaginary trips. In the experimental condition, the participants’ attention was focused on the importance of the information they acquired. In the control condition, the participants’ attention was focused on irrelevant aspects or no additional procedures. As expected, participants with a strong habit acquired less information about the context of the trips than did participants with a weak habit. In the enhanced-attention condition, participants with a strong habit initially acquired the same amount of information as participants with a weak habit. However, the level of information search of participants with a strong habit dropped to the level of control participants with a strong habit. That is, although the attention manipulation was effective in initially raising the level of information search among participants with a strong habit, they soon relapsed to a default level of search.

Taken as a whole, habit automaticity is characterized by minimal awareness, in the sense that people do not need to attend closely to what they are doing when they act habitually, and thus automatically repeat prior behavior. Efficiency is evident in that habitually practiced actions are performed quickly, easily, with little effort, and in parallel with other behaviors. Finally, some habits are characterized by a lack of control, meaning that it is difficult to avoid initiating the behavior or performing it in the same way as in the past (Betsch et al., 2004; Heckhausen & Beckmann, 1990; Verplanken, 2006). In short, the automatic activation of well-practiced responses is a key to the persistence of habits.

Habit: Theoretical Conceptualization and Empirical Operationalization

Past research on the relationship between attitude and behavior shows that the role of habit has always been elusive (Ajzen & Fishbein, 2005; Ouellette & Wood, 1998). A major problem is the way habit has been conceptualized and measured. Triandis (1980, p. 204) defines habit as "situation-behavior sequences that are or have become automatic, so that they occur without self-instruction." Verplanken and Aarts (1999, p. 104) describe habit as "learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end-states." They conceive habit as "learned goal-directed automatic responses." Adapting habit to IS usage, Limayem et al. (2007, p. 709) define IS habit as "the extent to which people tend to perform behaviors (use IS) automatically because of learning." Although all of the aforementioned researchers acknowledge that automaticity is the essential core notion of habit, the ways they measure habit are divergent, including past behavioral frequency (Landis et al., 1978; Sheeran et al., 2005; Triandis, 1980), behaviors performed out of habit (Limayem & Hirt, 2003; Saba & Di Natale, 1998; Towler & Shepherd, 1991-1992), response frequency measure (Aarts & Dijksterhuis, 1999; Klockner et al., 2003; Verplanken et al., 1994), and self-report habit index (SRHI) (Honkanen et al., 2005; Verplanken, 2006; Verplanken & Orbell, 2003). The definition of a measure of habit is so complex that it still requires attention in future research (Saba & Di Natale, 1998). More importantly, it is possible that by adapting a different definition, the influence of habit could change its importance in the prediction models (Tuorila & Pangborn, 1988).

A number of researchers consider habitual behavior as an interesting form of automaticity (Bargh, 1990; Bargh & Gollwitzer, 1994; Chaiken et al., 1996; Ouellette & Wood, 1998; Ronis et al., 1989). Habit is conceived as a form of goal-directed automatic response. As goals are pursued regularly, the need to pay conscious attention to details dwindles (Anderson, 1982; Newell & Rosenbloom, 1981). When people select the same actions more often and when these actions lead to goal achievement in a satisfactory manner, the actions become mentally linked to the goal. That is, selecting and performing the same goal-directed behavior frequently and consistently results in associations between the goal and the instrumental actions (i.e., to the formation of a habit). Hence, activation of these goals spreads automatically to the associated actions (Anderson, 1993; Mäntylä, 1993). The exhibition of habits, then, is the result of the automatic and immediate activation of the habitual action on the instigation of a goal (Aarts & Dijksterhuis, 2000). For example, instead of asking someone else or going to a bookstore/library, a person who chose to use a search engine for the sake of a quick response (i.e., goal), when encountering a puzzle-solving or an information-gathering situation, would eventually, over time, come to use it (i.e., goal-directed action) without having to think or consciously decide to.

In IS continuance contexts, this goal-activation response instigates persistent system usage until there is some environmental interruption. Thus, when you ask someone, "Why do you use this search engine," it will not be surprising to get the answer, "The search engine is useful to accomplish my task (i.e., goal)." Note that this is not to say that positive evaluation of system use is not important. In fact, past experiences are now turned to become goal-directed automatic responses to system use when encountering the same situation.

Nevertheless, it is useful to have an instrument to measure habit strength that is not based on estimates of behavioral frequency, especially when we wish to establish the contribution of habit in addition to behavioral frequency. The use of behavioral frequency as a measure of habit, valid as it might sometimes be, is clearly only a proxy for a true measure of habit strength. In addition, behavioral frequency measures do not tap the heart of habit concept: automaticity.

One might be suspicious of a self-report instrument that attempts to tap qualities like the extent to which a behavior is automatic (Nisbett & Wilson, 1977). Are people able to reflect on how habitual a particular behavior is? Asking such a question directly (e.g., "To what extent is Behavior X a habit?") would likely yield responses that lack validity and reliability, because participants have to provide simultaneously both an estimate of behavioral frequency and an indication of the degree to which behavior is habitual in one response. In order to accommodate to that notion, Verplanken and Orbell (2003) presented a self-report measure of habit (i.e., SRHI), which included subjective experiences of repetition as well as automaticity. Although SRHI measures subjective experiences of repetition that form a core element of habits, this subjective perception of repetition is different from the measurement of self-reported frequency of past behavior in that subjective perception of repetition may vary while self-reported behavior frequency remains constant (Verplanken & Orbell, 2003). For instance, two individuals with identical behavior frequency of using a target IS may differ in their subjective perception of repetition, especially when one of them has alternative IS choices. Thus, a measure not based on behavioral frequency estimates is critical for monitoring habit strength. Finally, SRHI showed good psychometric properties, and showed content, discriminant, and predictive validity for various studies on habitual behavior (Honkanen et al., 2005; Verplanken, 2006; Verplanken et al., 2005; Verplanken & Orbell, 2003).

IS Habitual Usage versus Past Usage

If one accepts Verplanken and Orbell's (2003) definitions of habit (as discussed above), which include both the elements of repetition and automaticity, it follows that a measure of past behavior or a measure of behavior performed out of habit is not a sufficiently valid measure of habit. Habits are learned sequences of acts that have become automatic responses to specific situations, and are functional in obtaining certain goals or end-states (Hull, 1943; James, 1890; Triandis, 1980; Watson, 1914). Furthermore, Verplanken and Aarts (1999) emphasized that habit is not equal to "past behavior", although in the literature the terms are often used as synonyms (Limayem et al., 2007; Ouellette & Wood, 1998). A behavior that has been performed many times is no guarantee that it has been habituated (Ajzen, 2002). Past behaviors, only when sufficiently and satisfactorily repeated, may turn into automatic responses to specific situations, and thus become habits (Ronis et al., 1989). As outlined by Ouellette and Wood (1998), past behaviors may influence future behaviors in two ways, i.e., through deliberate processes (e.g., the formation of behavioral intentions), or directly as an automatic process. In the latter case, past behavior is a habit.

Previous findings also show that habit is distinct from past behavior. In Verplanken's (2006) study, habit and frequency of occurrence share a good deal of variance. This reflects the history of repetition, which is a necessary condition for a habit to develop. However, the results demonstrate that habit has an independent contribution, after controlling for the theory of planned behavior variables and past behavioral frequency, in the prediction of the criterion variables (i.e., unhealthy snacks consumed and negative thinking). Similarly, Honkanen et al. (2005) employ the SRHI instrument to measure food consumption habit and show that both habit and past behavior have significant influences on intention, suggesting that neither habit nor past behavior should be disregarded as empty constructs in studies of behavior.

In IS post-adoption context, past usage is often measured by system usage time and frequency during a fixed period of time (Jasperson et al., 2005; Kim & Malhotra, 2005; Limayem & Hirt, 2003). IS continuous usage can be guided either by conscious deliberation or by automatic reliance on well-established routines. Recent studies have demonstrated that past usage is the most powerful predictor of future usage (Kim et al., 2005; Venkatesh & Morris, 2000). Kim et al.'s (2005) study point out that in a stable environment past system usage is likely to be a good proxy for the concept of habitual usage and a reliable predictor of future use. They empirically demonstrated that when taken past use into account, the belief of behavior consequence on behavioral intention vanishes. However, the most prominent features of habit automaticity are the lack of awareness and efficiency. In addition, habit strength may vary while past usage remains constant. Therefore, it is critical to consider habit as a psychological construct (Verplanken, 2006) that has a number of facets, rather than simply defining habit as past behavior. Of greater importance, by adapting different definitions, the influence of habit could change its importance in the prediction models.

Research model and hypotheses. Figure 1 depicts our research models and hypotheses. Human reasoning is accompanied by metacognitive experiences, most notably the ease or difficulty of recall and thought generation and the fluency with which information can be processed (Schwarz, 2004). These experiences are informative in their own right. They can serve as a basis of judgment in addition to, or at the expense of, declarative information and can qualify the conclusions drawn from recalled content (Schwarz & Bless, 2007).

This is evident in Holland et al.'s (2002) experiment, which shows that strong attitudes will guide later behavior and later attitudes, whereas weak attitudes are significantly influenced by their overt donation behavior in accordance with the self-perception principle. In line with Holland et al.'s (2002) study, we conceive that, in the post-adoption context, user's evaluations and intention will be affected by both deliberate consideration and past experience. Therefore, we propose two competing research models based on TAM (Davis, 1989) and the self-perception theory (Bem, 1972). Model 1 (see Figure 1a), which employs the construct of past usage, and Model 2 (see Figure 1b), which employs the construct of habitual usage, are constructed in such a way as to allow us to compare and contrast the influences of habitual usage and past usage on PU and PEOU evaluations and IS continuance intention.

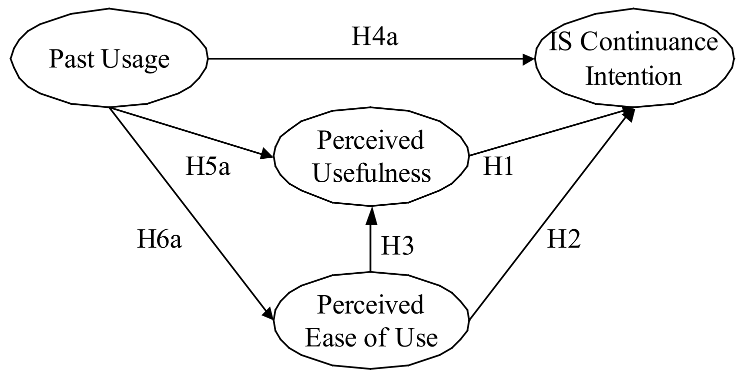


Figure 1a: Model 1. TAM + Past Usage

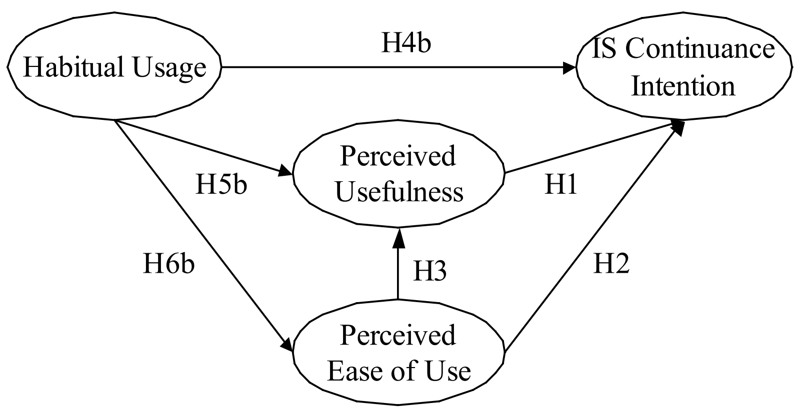


Figure 1b: Model 2. TAM + Habitual Usage

Figure 1. Research Model and Hypotheses

In Figure 1a, TAM presumes that intention is formed as a result of conscious decision-making processes. The model specifies two belief factors that are most salient in the context of IS adoption: perceived usefulness (PU) and perceived ease of use (PEOU). PU is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance,” while PEOU refers to “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989) . According to TAM, PEOU has a positive impact on PU, and both factors positively affect continuance intention (Venkatesh & Davis, 2000). The following hypotheses are therefore proposed:

H1: Perceived usefulness is positively associated with continuance intention.

H2: Perceived ease of use is positively associated with continuance intention.

H3: Perceived ease of use is positively associated with perceived usefulness.

Melone (1990) points out IS researchers hold the common bias that behavior is completely determined by beliefs and attitudes. He then demonstrates the existence of reversed causal relationship from behavior to beliefs and attitudes. This is in line with self-perception theory (Bem, 1972): People observe their overt behaviors to infer their inner attitudes and states. Ouellette and Wood (1998) provide an extensive review of previous research on the role of past behavior in predicting future intentions and behavior and find substantial empirical evidence supportive of a direct relationship between past behavior and intentions regarding future behavior. In other words, people consider direct behavioral experiences as reliable information that is highly reflective of their attitudes toward the given object or behavior. In fact, past behavior might function as a priming effect on future intention, making past behavior a predictor of intention to perform behavior later (Conner & Armitage, 1998). Trafimov (1999) reasons that performing a behavior increases its cognitive accessibility, which affects intentions to perform the behavior again in the future. In addition, past usage itself could be a basis for the formation of user evaluations at a subsequent stage and could demonstrate a positive feedback loop from past behavior to PEOU and PU (Bajaj & Nidumolu, 1998; Kim & Malhotra, 2005). Recently, the study by Kim and Malhotra (2005) further supports that self-perception process plays an important role in the formation of judgments and intentions. Consequently, the more past usage there is, the more likely the user forms favorable evaluations and intention (Kim & Malhotra, 2005; Melone, 1990; Ouellette & Wood, 1998). The following three hypotheses are therefore formulated:

H4a: Past usage is positively associated with continuance intention.

H5a: Past usage is positively associated with perceived usefulness.

H6a: Past usage is positively associated with perceived ease of use.

Several studies in various contexts have shown that habit influences intentions over and above attitudes (Bamberg et al., 2003; Ouellette & Wood, 1998; Saba & Di Natale, 1998). Furthermore, Burton-Jones and Hubona (2005) indicate that PEOU and PU will only partially mediate the influence of external variables on IT usage behavior. According to Gefen's (2003) study, experienced online shoppers' intentions to continue using a website depend not only on PU and PEOU, but also on habit, which alone can explain a large proportion of the variance of continued use of a website. In the context of IS continuance, using web-based applications or services (e.g., email or search engine) may give rewards such as efficiency, quality and novelty, which further give rise to IS habitual usage. More importantly, because most habits are functional in obtaining certain goals and rest on actions in the past that have positive consequences, many habits may be associated with positive attitudes toward the habitual responses (Verplanken & Aarts, 1999). In addition, as habitual behavior accompanies cognitive economy and performance efficiency, habit is less likely to deplete self-regulatory resources, and allows people to do things in parallel with habitually practiced actions. Thus, we formulate the following hypotheses:

H4b: Habitual usage is positively associated with continuance intention.

H5b: Habitual usage is positively associated with perceived usefulness.

H6b: Habitual usage is positively associated with perceived ease of use.

Research method

Data Collection

Searching is a pervasive behavior on the Internet. For example, the study by Jupiter Media Matrix shows that the top two popular web services are email and search engine (Jupiterresearch, 2007), indicating that using a search engine has become a regular and inevitable online activity. In another report accessed April, 2007 (Insightxplorer, 2007), states that in Taiwan more than 84% of Internet users are actively using a search engine, and more than 70% of users express that they rely on searching the Internet for product information gathering as the basis of shopping or services, implying that the Internet has been changing consumers' behaviors and lifestyles. Because our study aims to understand automatic IS usage, we have chosen Google search as our target application.

A survey instrument was developed based primarily on established scales from the literature. We have employed a web-based survey to collect data. A convenience sampling method based on voluntary participation was used. Volunteers were recruited from the Internet with money rewards (NT$50) to complete the questionnaire. After two weeks, a total of 232 valid and complete responses were collected. Table 1 shows the demographic profiles of the respondents.

Measures

Table 2 lists the measures used in this research. We have employed items that had been validated by prior research, but modified the wording of the questionnaire in order to fit this particular context of Google search usage. The first item of behavioral intention was anchored with "unlikely" and "likely," whereas the second item was anchored with "uncertain" and "certain." All items except past usage are measured on a seven-point scale anchoring from "strongly disagree" to "strongly agree," while past usage is measured by two self-reported items with respect to behavior frequency and usage time.

Table 1. Demographic Profiles of the Respondents

Variables	Categories	Total (N=232)	Statistics (%)
Gender	Male	140	60.3 %
	Female	92	39.7 %
Age	Younger than 20	28	12.1 %
	21 ~ 25 years	77	33.2 %
	26 ~ 30 years	65	28.0 %
	31 ~ 35 years	36	15.5 %
	36 ~ 40 years	17	7.3 %
	41 ~ 45 years	4	1.7 %
	46 ~ 50 years	2	0.9 %
	51 years or older	3	1.3 %
Internet Experience	1 ~ 2 years	1	0.4 %
	2 ~ 3 years	5	2.2 %
	3 ~ 4 years	9	3.9 %
	4 ~ 5 years	15	6.5 %
	6 years or more	202	87.1 %
Target system Experience	Less than 3 months	18	7.8 %
	3 ~ 6 months	2	0.9 %
	6 ~ 12 months	15	6.5 %
	1 ~ 2 years	27	11.6 %
	2 ~ 3 years	40	17.2 %
	3 ~ 4 years	41	17.7 %
	5 years or more	89	38.4 %

Data Analysis

The analysis was conducted with partial least squares (PLS), which is capable of modeling latent constructs under conditions of non-normality and small to medium sample sizes (Chin, 1998). It allows the researcher to specify both the relationships among the conceptual factors of interest and the measures underlying each construct. When using PLS, the researchers simultaneously analyzes how well the measures relate to the associated construct and whether the hypothesized relationships at the theoretical level are empirically verified. PLS's ability to include multiple measures for each construct also provides accurate estimates of the paths among constructs, which are typically biased downward by measurement error when using techniques such as multiple regression. Tests of significance for all paths were performed using the bootstrap resampling procedure (Cotterman & Senn, 1992). The number of samples in the bootstrap procedure is set to 200 (Chin et al., 2003).

Reliability and Convergent Validity

Table 3 presents the loadings of the measures of our research model. The composite reliability (CR) measures and the average variance extracted (AVE) provide support for reliability and convergent validity, with all reliability indices being greater than 0.70 and average variance shared between the construct and measures to be above 0.50, as recommended by Chin (1998).

Table 2. List of Measures

Construct	Item	Source
Perceived ease of use		
PEOU1 PEOU2 PEOU3 PEOU4	Interacting with (Google search) is clear and understandable. Interacting with (Google search) does not require a lot of mental effort. I find (Google search) easy to use. I find it easy to get (Google search) to do what I want it to do.	Davis (1989), Kim et al. (2005)
Perceived usefulness		
 PU1 PU2 PU3 PU4	When I use Google to search information, I will be better organized on searching what I want. I will increase my effectiveness on the search job. I will spend less time on searching what I want. I will increase the quality of searching consequences.	Davis (1989), Compeau and Higgins (1995)
Behavioral intention		
BI1 BI2	Would you intend to use (Google search) in the next month? How certain are your plans to use (Google search) within the next month?	Davis (1989), Kim et al. (2005)
Past Usage		
USE1 USE2	On average, how frequently have you use (Google search) over the past one month? Seven categories were given for this item (1 = never; 2 = less than once a week; 3 = once a week; 4 = 2 or 3 times a week; 5 = a few times a week; 6 = about once a day; 7 = several times a day). On average, how much time do you spend each time using (Google search) over the past one month? Seven categories were given for this item (1 = less than 10 mins; 2 = 10 ~ 20 mins; 3 = 20 ~ 30 mins; 4 = 30 mins ~ 1 hr; 5 = 1 ~ 1.5 hrs; 6 = 1.5 ~ 2 hrs; 7 = 2 hrs or more)	Kim et al. (2005)
Habitual Usage		
 HA1 HA2 HA3 HA4 HA5 HA6 HA7 HA8 HA9 HA10	When I need to search information, I use (Google search) frequently. I use (Google search) automatically. I use (Google search) without having to consciously remember. It makes me feel weird if I do not use (Google search). I use (Google search) without thinking. It would require effort not to use (Google search). Using (Google search) belongs to my routine. I start use (Google search) before I realize I'm using it. I would find hard not to use (Google search). I have no need to think about using (Google search).	Verplanken and Orbell (2003) Repetition: item 1, 7 Awareness: item 2, 3, 8 Efficiency: item 5, 6, 10 Control: item 4, 9

Table 3. Means, Standard Deviation, Construct Loadings, Composite Reliability and Average Variance Extracted

				Model 1 (TAM + Past Usage)			Model 2 (TAM + Habitual Usage)		
Construct	Item	Mean	Standard Deviation	Standard Loading	CR	AVE	Standard Loading	CR	AVE
Perceived Ease of Use (PEOU)	PEOU1	5.70	1.378	0.891	0.95	0.84	0.891	0.95	0.84
	PEOU2	5.73	1.367	0.930			0.930		
	PEOU3	5.88	1.317	0.917			0.918		
	PEOU4	5.77	1.250	0.925			0.925		
Perceived Usefulness (PU)	PU1	5.32	1.141	0.847	0.93	0.76	0.846	0.93	0.76
	PU2	5.56	1.034	0.912			0.912		
	PU3	5.41	1.269	0.859			0.860		
	PU4	5.40	1.180	0.873			0.872		
Behavioral Intention (BI)	BI1	6.20	1.200	0.973	0.97	0.95	0.973	0.97	0.95
	BI2	6.10	1.289	0.973			0.973		
Past Usage (USE)	USE1	5.22	1.861	0.978	0.74	0.61	—	—	—
	USE2	3.44	1.862	0.511			—		
Habitual Usage (HA)	HA1	5.91	1.485	—	—	—	0.886	0.98	0.80
	HA2	5.74	1.566	—			0.951		
	HA3	5.75	1.537	—			0.949		
	HA4	4.93	1.757	—			0.838		
	HA5	5.46	1.700	—			0.950		
	HA6	4.74	1.767	—			0.613		
	HA7	5.58	1.623	—			0.957		
	HA8	5.58	1.634	—			0.965		
	HA9	5.45	1.664	—			0.878		
	HA10	5.38	1.756	—			0.918		

While our results pass the more technical criteria put forward by the literature, the standard loading of past usage volume (i.e., USE2) is moderate (i.e., 0.511). As pointed out by Burton-Jones and Hubona (2006), usage volume is influenced by more factors than frequency, and thus many previous studies used only frequency measure. However, Venkatesh and Morris (2000) suggested employing the duration of usage along with frequency of use to more completely capture the intensity of use. In addition, in three previous studies, the average variances extracted from past usage were 0.53 (Kim et al., 2005, Sample A), 0.61 (Kim et al., 2005, Sample B) and 0.69 (Kim & Malhotra, 2005) respectively. (Note that item loadings for past usage were absent in these three studies.) In our study, the average variance extracted from past usage is 0.61 which is compatible with prior work.

Table 4. Correlations between Constructs
(Diagonal elements are square roots of the average variance extracted)

	Perceived Ease of Use	Perceived Usefulness	Behavioral Intention	Past Usage	Habitual Usage
Perceived Ease of Use	0.92	0.53	0.58	—	0.55
Perceived Usefulness	0.53	0.87	0.51	—	0.55
Behavioral Intention	0.58	0.51	0.97	—	0.71
Past Usage	0.40	0.29	0.57	0.78	—
Habitual Usage	—	—	—	—	0.89

Notes: Correlations below the diagonal are for Model 1 (TAM + Past Usage); correlations above the diagonal are for Model 2 (TAM + Habitual Usage).

Overall, these results provide empirical support for the convergent validity of the scales of our research model.

Discriminant Validity

A satisfying level of discriminant validity is achieved when the square root of AVE for a particular construct is larger than the correlations between itself and the other constructs (Chin, 1998). As shown in Table 4, the discriminant validity of the measurement model is verified, indicating that each construct shares greater variance with its own block of measures than with the other constructs representing a different block of measures. In order to further assess the validity of our measurement instruments, a cross-loadings table (Appendix A) was constructed. It can be seen that each item loading in the table is higher on its assigned construct than on the other constructs, supporting adequate convergent and discriminant validity (Chin, 1998).

Common Method Bias

As with all self-reported data, there is a potential for common method biases resulting from multiple sources such as consistency motif and social desirability (Podsakoff et al., 2003). We conducted two statistical analyses to assess the existence of common method bias. First, a Harmon one-factor test (Podsakoff & Organ, 1986) was conducted on the four conceptually crucial variables in our theoretical model including PEOU, PU, BI, and past usage (Model 1) or habitual usage (Model 2). For model 1, the four factors explained 82.6% of the variance in the data, with the first extracted factor accounting for 27.8% of the variance. For model 2, the four factors explained 82.7% of the variance in the data, with the first extracted factor accounting for 36.3% of the variance. Given that more than one factor was extracted from the analysis and the first factor was accountable for much less than 50% of the variance, common method bias is unlikely to be a significant issue with the collected data.

Next, following Podsakoff et al. (2003) and Williams et al. (2003), we incorporated in the PLS model a common method factor whose indicators included all the principal constructs' indicators and calculated each indicator's variances substantively explained by the principal construct and by the method (Liang et al., 2007). As shown in Appendix B, for Model 1, the results demonstrate that the average substantively explained variance of the indicators is 0.791, while the average method based variance is 0.010. The ratio of substantive variance to method variance is about 79:1. For Model 2, the results demonstrate that the average substantively explained variance of the indicators is 0.807, while the average method based variance is 0.024. The ratio of substantive variance to method variance is about 34:1. In addition, most method factor loadings are not significant. Given the small magnitude and insignificance of method variance, we contend that the method is unlikely to be a serious concern for this study.

Results

Figure 2 presents the results of testing our research model using PLS analysis. The standardized estimated path effects are given along with the associated t-value. All significant paths ($p < 0.001$) are indicated with an asterisk. Note that we have checked the effect of target system experience (TEXP) on intention because respondents' technical capability and literacy might influence continuance intention.

The testing results show that the path coefficients of TEXP-Intention are 0.113 (t-value = 1.64, non-significant) and 0.098 (t-value = 1.47, non-significant) in Model 1 and Model 2 respectively, suggesting that in the current study the target system experience is a non-critical determinant of IS continuance intention. That is, the research models that exclude the control variable (i.e., TEXP) are qualitatively equivalent to models that include the control variable, with significant levels of all paths remaining the same and not biasing research findings. Therefore, the following results are discussed based on the four core variables in our theoretical model (i.e., PEOU, PU, BI and past usage in Model 1 or habitual usage in Model 2).

Assessing the results in terms of paths, we find that five of the six proposed hypotheses are supported in each model (Table 5). In Model 1 (see Figure 2a), perceived usefulness (H1), perceived ease of use (H2), and past usage (H4a) all have significant effects on behavioral intention, explaining 51.2% variance. Perceived ease of use (H3) exerts a significant effect on perceived usefulness while past usage (H5a) does not, explaining 28.9% variance. Past usage (H6a) has a significant effect on perceived ease of use, explaining 16.1% variance.

However, when past usage is replaced by the construct of habitual usage in Model 2 (see Figure 2b), perceived usefulness is no longer a significant determinant of behavioral intention (H1 not supported). Perceived ease of use (H2), and habitual usage (H4b) explain 55.9% variance. Meanwhile, perceived ease of use (H3) and habitual usage (H5b) have significant effects on perceived usefulness, explaining 37.7% variance. Habitual usage (H6b) has a significant effect on perceived ease of use, explaining 30.2% variance.

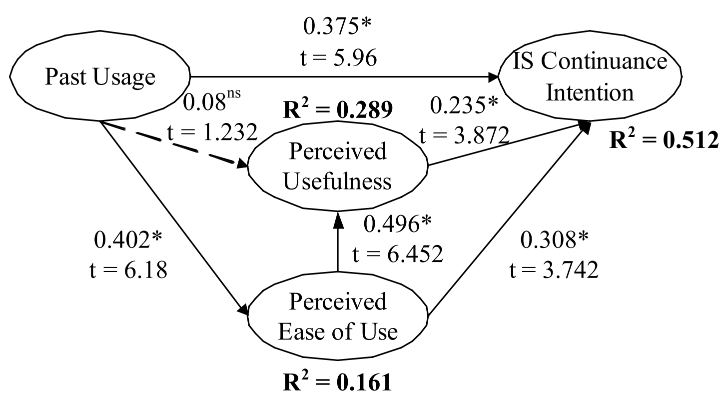


Figure 2a: Model 1. TAM + Past Usage

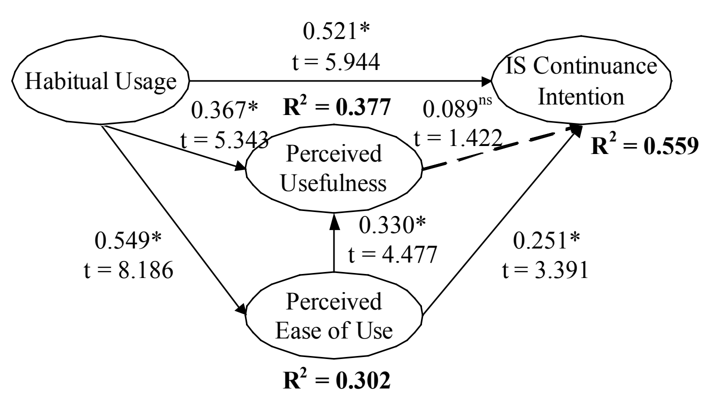


Figure 2b: Model 2. TAM + Habitual Usage

ns: non-significant, *: $p < 0.001$

Figure 2. Results of Hypotheses Testing

Table 5. Results of Hypotheses Testing

Model 1. TAM + Past Usage				Model 2. TAM + Habitual usage			
No.	Path	Path Coefficient	Supported?	No.	Path	Path Coefficient	Supported?
H1	PU->BI	0.235*	Y	H1	PU->BI	0.089^{ns}	N
H2	PEOU->BI	0.308*	Y	H2	PEOU->BI	0.251*	Y
H3	PEOU->PU	0.496*	Y	H3	PEOU->PU	0.330*	Y
H4a	USE->BI	0.375*	Y	H4b	Habit->BI	0.521*	Y
H5a	USE->PU	0.08^{ns}	N	H5b	Habit ->PU	0.376*	Y
H6a	USE->PEOU	0.402*	Y	H6b	Habit ->PEOU	0.549*	Y

ns: non-significant, *: $p < 0.001$

To further examine the predictive power of the proposed models, we have compared both models and their variants to TAM in terms of R^2 adjusted, using Cohen's (1988) formula for calculating effect size (f^2) where 0.02, 0.15, and 0.35 have been suggested as small, medium, and large effects, respectively. Table 6 shows the results. Excluding the past usage leads to a significant reduction in R^2 with medium-to-large effect size, while dropping the habitual usage significantly reduces the R^2 toward IS continuous intention with large effect size.

To sum up, the results reveal that when compared with the basic TAM model, the coefficients for the path of PU-Intention and PEOU-Intention are diluted significantly by habitual usage or past usage (see Table 6), indicating that users' direct hands-on experiences are the main predictors of continuance intention in post-adoption phases. Moreover, in TAM, PU and PEOU combined explain 39.5% variance in continuance intention.

Table 6. Results of Structural Models

Effects	Causes	TAM	TAM + Past Usage	TAM + Habitual Usage
INT		(39.5%)	(51.2%)	(55.9%)
	PU	0.275*	0.235*	0.089^{ns}
	PEOU	0.438*	0.308*	0.251*
	USE		0.375*	
	Habit			0.521*
PU		(28.3%)	(28.9%)	(37.7%)
	PEOU	0.532*	0.496*	0.330*
	USE		0.08^{ns}	
	Habit			0.367*
PEOU			(16.1%)	(30.2%)
	USE		0.402*	
	Habit			0.549*
$\triangle R^2$			0.117*	0.164*
Effect size			$f^2 = 0.24$ Medium-Large	$f^2 = 0.37$ Large

ns: non-significant, *: $p < 0.01$
Each construct's effect size (f^2) can be calculated by the formula (R^2_{full} - $R^2_{partial}$) / (1 - R^2_{full}) (Chin et al., 2003). Multiplying f^2 by (n-k-1), where n is the sample size (232) and k is the number of independent variables, provides a pseudo F test for the change in R^2 with 1 and n-k degrees of freedom. An effect size of 0.02 is small, 0.15 is medium, and 0.35 is large (Cohen, 1988).

By taking past usage and habitual usage into account, the explained variances in intention are raised by 11.7% and 16.4%, respectively, demonstrating that a measure of either habit or past usage contributes significantly to IS continuance intention. Thus, in IS post-adoption context, the relation between prior and later behavior may not be fully mediated by the variables of reasoned-action theories like TAM. In other words, to better explain continued use in the post-adoption context, the self-perception process plays an important role in the formation of intention and is a viable explanation of the residual variance problem (Ajzen, 2002).

Furthermore, past usage and habitual usage collectively explain 52.0% variance of Intention (see Figure 3a). We use hierarchical regression to predict intention from past usage (step1, see Figure 3b with R^2 = 32.7%) and habitual usage (step2, with ΔR^2 = 19.3%), as well as from habitual usage (step1, see Figure 3c with R^2 = 50.2%) and past usage (step2, with ΔR^2 = 1.8%). These comparisons allow us to calculate the unique variance accounted for by past usage and habitual usage, which are 1.8% and 19.3%, respectively. This analysis supports the claim that habitual usage surpasses past usage in explaining IS continuance intention.

Figure 2b shows that the coefficient for the path of PU-Intention becomes insignificant when habit is included as antecedent, suggesting that habitual usage is not only conceptually but also empirically distinct from past usage. As shown in Table 6, the mediating role of PU and PEOU decreases more as the model employs habitual usage than does past usage. Although the means of evaluations of usefulness and ease for IS usage remain high, their predicting power is strongly influenced by the construct of habit in contrast with the construct of past usage. Hence, equating these two constructs (i.e., past usage to habitual usage) is problematic, since habit is comprised of a number of facets that past use does not include.

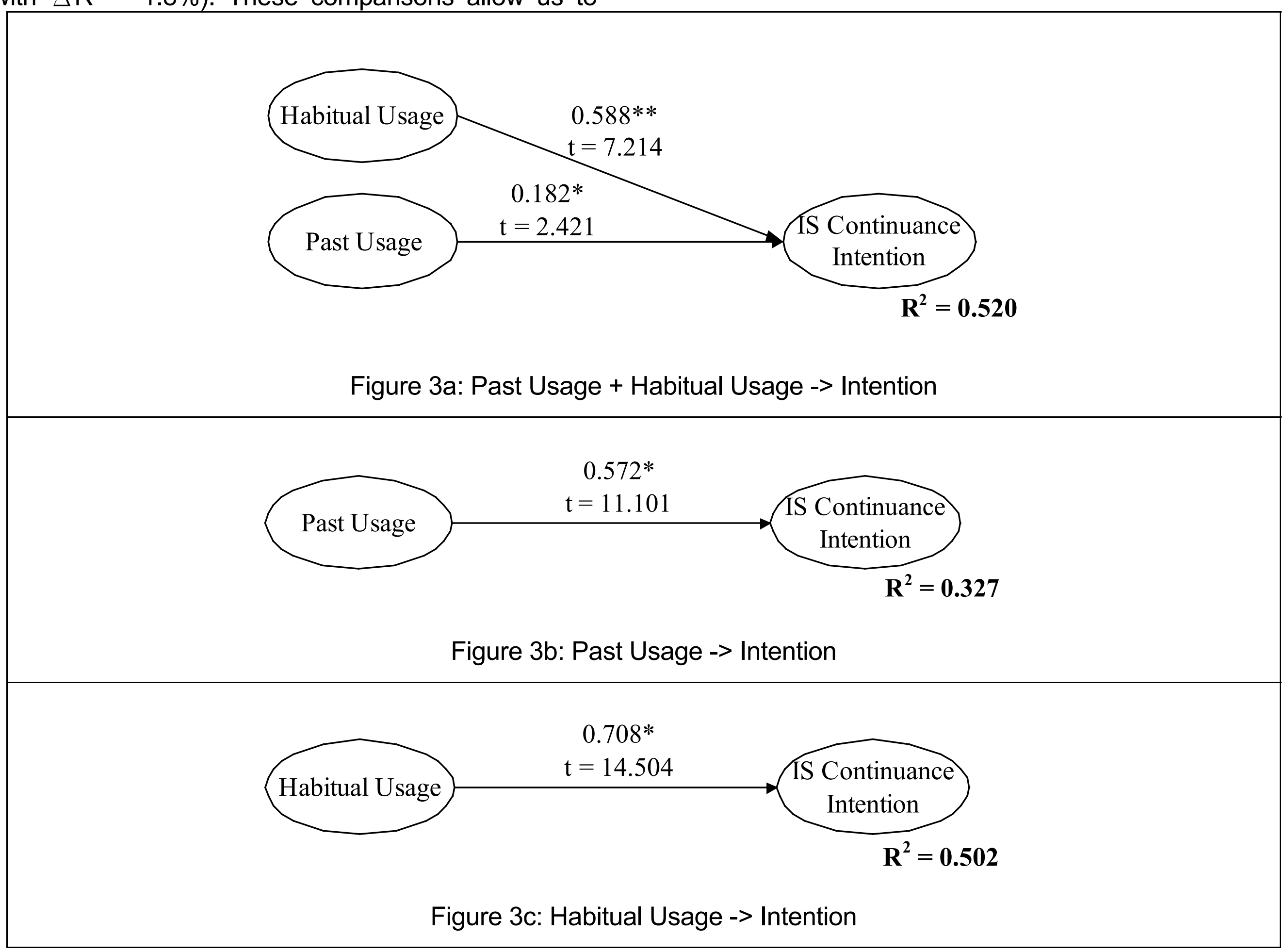


Figure 3a: Past Usage + Habitual Usage -> Intention

Figure 3b: Past Usage -> Intention

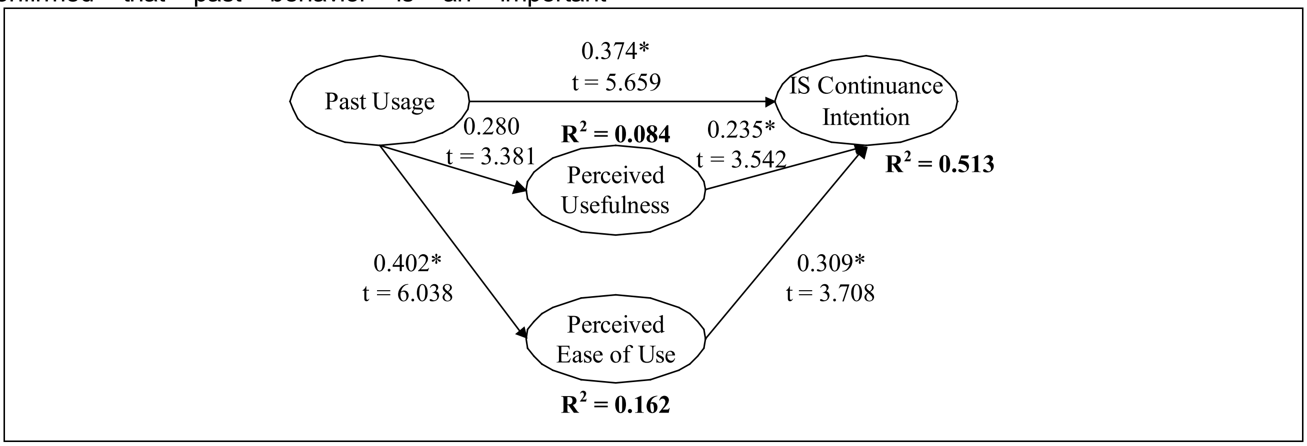
Figure 3c: Habitual Usage -> Intention

ns: non-significant, *: p < 0.01, **: p < 0.001

Figure 3. Variance of Intention Explained by Past Usage and Habitual Usage

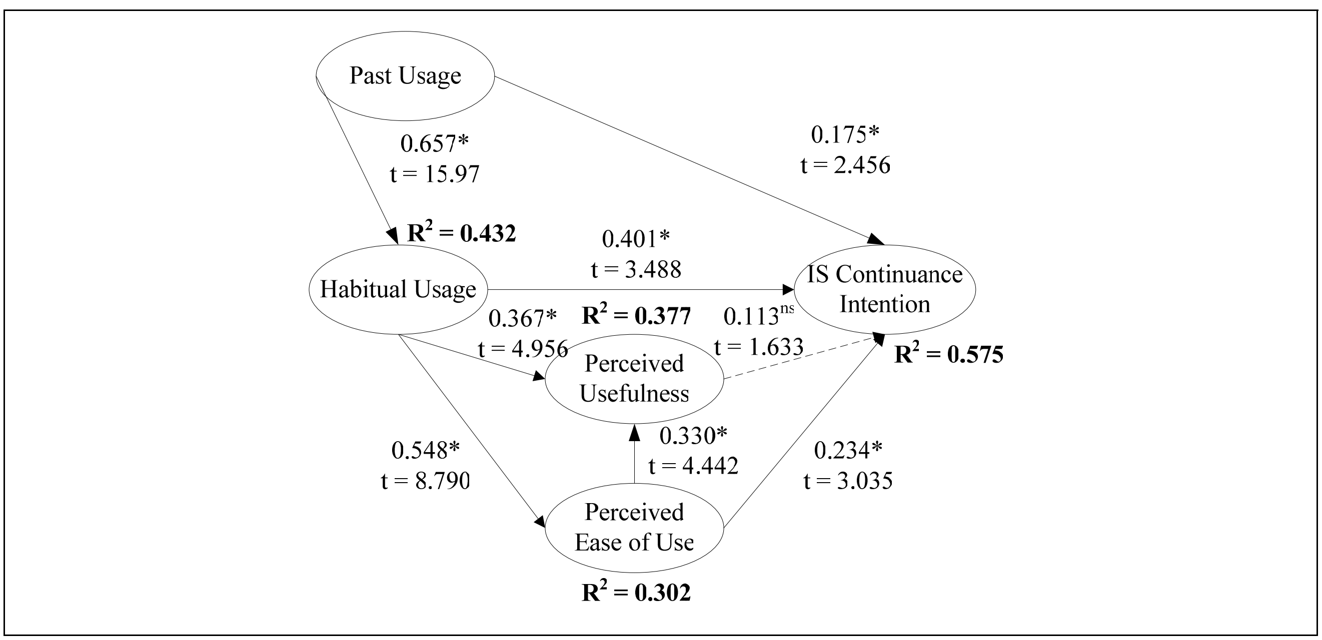
Note that the path coefficient of past usage-PU is not significant even though past usage is supposed to positively affect PU. Additional analysis directed at resolving this anomaly is shown in Figure 4: after removing the association of PEOU-PU, the path coefficient of past usage-PU was significant (see Figure 4). This suggests that the past usage-PU relationship is completely mediated by PEOU in our study. Thus, habit differs from past usage not only conceptually but also exerts empirically different impacts on evaluations and on the relationship between evaluations and intention.

In addition, the study by Limayem et al. (2007) has confirmed that past behavior is an important antecedent of IS habit. To further investigate if this causal effect between past usage and habitual usage in the current study, we incorporate the construct of past usage into the research model in Figure 2b. The results are shown in Figure 5. In accordance with Limayem et al. (2007), past usage has a significant influence on habit. However, there is only a slight increase in explaining the variance of Intention (R^2 increases from 0.559 to 0.575), while the relationship of past usage-Intention is partially mediated by habitual usage, with the path coefficient dropping from 0.375 to 0.175. All other path relationships resemble those in Figure 2b.



ns: non-significant, *: p < 0.01

Figure 4. Results of Research Model 1 after Removing the Path of PEOU-PU



ns: non-significant, *: p < 0.01

Figure 5. Results of Research Model Combining Habitual Usage and Past Usage

Discussion

In the present study we have examined the roles of habitual usage and past usage in relation to IS continuance intention in the post-adoption context. Both habitual usage and past usage are shown to have strong influence on intention. The respective predicting power of PU and PEOU on intention is considerably diluted by the addition of habitual usage or past usage, implying that the residual effect indeed exists. The habitual usage explains half of the variance of IS continuance intention. This may indicate that the formation of the intention does not rely on reasoned, analytical information process when users psychologically perceive the target system as habitual usage.

Our study is important to IS research in studies of post-adoption behaviors. In 1980s when TAM was initially proposed, microcomputers were just invented and people, unfamiliar with the technology, might rely on critical, reasoned thinking to determine if they would adopt IT. Today, not only have information systems permeated almost every corner of societies in developed countries, they also serve a variety of purposes—i.e., functional, social, and hedonic—in the Web 2.0 environment. Habitual usage has gradually become a norm. Thus, theorists may wish to explore models and related constructs from the perspective of self-perception.

In addition, understanding the theoretical bases of habit is important for managers who wish to change the behavior or the behavioral intentions of their clients. Because people with a strong habit may suppress how much information they acquire before they make decisions (Verplanken et al., 1997), messages or policies directed toward changing behavior through changing evaluations or attitudes by means of persuasive communication would not be effective for these people. An alternative strategy is to focus directly on breaking undesirable habits and replacing these with new behaviors. One approach would be to use implementation intentions, which form links between cues in the environment and specific actions. Since habits are goal-directed automatic responses, the goal-response association makes them difficult to control, especially when lacking cognitive resources (e.g., time pressure) or motivations. Implementation intentions thus try to develop a new thinking route that links new actions to the existing goal. However, such interventions seem only feasible in the form of small-scale projects. Verplanken and Wood (2006) suggest that interventions plus environmental changes would be more effective, because the changes in the context not only disrupt habits but also challenge habitual mind-sets and increase openness to new information and opportunities. In other words, contextual changes impair the automatic cuing of well-practiced responses, thereby enabling the performance of new actions.

Implications for research

This study has several implications. First and foremost, habit leads to “tunnel vision” (Verplanken & Orbell, 2003) and attenuates the amount of information acquired and utilized before the decision is made (Aarts et al., 1998). Consistent with prior research (Trafimow, 2000; Tyre & Orlikowski, 1994), our findings support the notion that habitual usage overshadows the effects of evaluations on intention and becomes a principal predictor of future behavioral intention under post-adoption context. To some extent, our findings imply that if a person is in the habit of continuously using a particular IS, they will be less likely perform the deliberate and reasoned judgment assumed by any of the intentional behavior models. Simultaneously, echoing the perspective of automatic use, as past usage increases, the influence of users’ evaluations on usage intention decreases (Kim et al., 2005). This finding suggests that with repeated system usage the overall role of evaluation diminishes in importance as a determinant of behavioral intention.

Second, our findings suggest that the construct of habitual usage differs from that of past usage, although past usage may contribute to the formation of habitual usage, as suggested by self-perception theory (Kim & Malhotra, 2005; Melone, 1990). Many studies have empirically supported the feedback processes (Bagozzi et al., 1992; Conner & Armitage, 1998). Our study shows that the path of PU-Intention remains statistically significant when past usage is employed (Model 1) but becomes insignificant when replaced by habitual usage (Model 2), indicating that past usage does not mean habituation. Habit is a complex mental construct that has a number of facets, of which subjectively perceived frequency of past behavior is only one part. The study by Verplanken (2006) shows that habit has predictive power over and above past frequency and the effect of habit cannot be attributed to any of the variables theorized by the theory of planned behavior. Likewise, our research findings reveal that habit dominates over past usage in explaining system continuance intention and habit overshadows the effects of evaluations on intention.

Furthermore, prior measures of system usage are insufficient from a conceptual viewpoint. Burton-Jones and Straub (2006) have proposed a two-stage method for researchers to develop valid and contextualized usage measures by specifying which elements (i.e., system, user, task) and which measures of usage are most relevant for a given theoretical context. Their results show how an inappropriate choice of usage measures can lead researchers to draw opposite conclusions in an empirical study. Therefore, it will be interesting to compare different measures of system usage (e.g., breadth of use, cognitive absorption, and deep structure) in terms of their numerous features.

Finally, with the advances in Information Technology, most web-based services are implemented with hedonic elements for the purpose of prolonged system usage. Under such conditions, PEOU is a basic requirement for system design. Prior studies (Trevino & Webster, 1992; Venkatesh, 1999) have indicated that cognitive absorption may serve as intrinsic motivation. It is also evidenced that cognitive absorption outweighed PEOU as a more viable variable for predicting system usage intention (Agarwal & Karahanna, 2000) and exerting a significant influence on system performance (Burton-Jones & Straub, 2006). Future research is needed to shed light on how cognitive absorption is strengthened through habit and how the predicting power of PEOU and cognitive absorption may vary over time.

Implications for practice

An insight from our study is that habit strength is an important criterion to include in the segmentation of target groups when planning interventions, given that as habit strengthens, users becomes less evaluative and less deliberate. This improved understanding can help managers to develop intervention strategies such as implementation intentions (Gollwitzer, 1993; Verplanken & Faes, 1999), changes of the environment (Wood et al., 2005), and interruption of the employees' routines (Tyre & Orlikowski, 1994), which can be designed to trigger non-deliberate behavior change and encourage the development of the desired new usage habits (Jasperson et al., 2005). The SRHI may be a useful instrument for this purpose.

Note that habit is a double-edged sword concerning the cyber-world for managers. For instance, habitual users often adhere to a particular information system and reject changes (Bamberg et al., 2003). Managers should carefully examine the effects of changes on the behavioral patterns of their users to keep a firm's long-term profitability (Kim et al., 2005). In addition, past usage is not a good and safe index for website managers to assess if their customers have been habituated toward using their website. Before a frequently performed behavior becomes habituated, the customers may change their attitudes and intention to return to use the website again.

Limitations

The current study has certain limitations. Beliefs, attitudes and decisions are dynamic and not static. As a result, cross-sectional studies such as this may not fully capture the complexity or periodicity of the continuance usage processes. Therefore, the results of this study should be viewed as only preliminary evidence with respect to the self-perception process that dominates evaluations under the post-adoption environment. Longitudinal studies that examine how evaluations and attitudes of the same users evolve temporally would provide a rigorous test of how the determinants of behavioral intention are modified over time and to what extent self-perceptions might explain the residual variance.

In addition, we have relied on a self-reported behavioral measure for the construct of past usage. As pointed out by Straub et al. (1995), this could be supplemented with other objective, computer-recorded measures, which, in addition to providing greater opportunities to assess the user and impacts of information technologies, may avoid response bias and the demand characteristics of the subjects (Orne, 1979). Computer-recorded longitudinal data may permit researchers to go beyond cross-sectional research into the dynamics of various psychological mechanisms underlying IT usage.

Finally, we have investigated only one web-based service (i.e., Google search). Considering the variety of information technologies, types of users, and usage contexts that exist currently, the proposed models should be tested further in diverse empirical settings to determine the external validity and the generalizability of these findings.

Conclusion

Our study provides the theoretical conceptualization and empirical validation to the distinction between habitual usage and past usage in post-adoption context. Clarifying the influences of different types of past experience contributes to both the foundation for theory development and practical strategy for management. In addition, through the lens of self-perception theory, our study demonstrates that overt behavior not only influences how IS users evaluate their inner attitudes and continuance intention but also impacts their decision process by diluting the analytical processing of evaluative information. Finally, based on the current research findings, we expect that future research on IS continuance usage can gain a deeper understanding of how users make decisions.

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Appendix A. Item Loadings and Cross Loadings

Model 1 (TAM + Past Usage)					Model 2 (TAM + Habitual Usage)				
	PEOU	PU	BI	USE		PEOU	PU	BI	HA
PEOU1	0.891	0.440	0.556	0.378	PEOU1	0.891	0.440	0.556	0.504
PEOU2	0.930	0.486	0.485	0.351	PEOU2	0.930	0.486	0.485	0.474
PEOU3	0.917	0.492	0.542	0.356	PEOU3	0.918	0.492	0.542	0.502
PEOU4	0.925	0.528	0.552	0.385	PEOU4	0.925	0.528	0.552	0.530
PU1	0.480	0.847	0.432	0.224	PU1	0.481	0.846	0.432	0.473
PU2	0.469	0.912	0.501	0.279	PU2	0.469	0.912	0.501	0.508
PU3	0.465	0.859	0.424	0.238	PU3	0.465	0.860	0.424	0.487
PU4	0.442	0.873	0.410	0.268	PU4	0.442	0.872	0.410	0.444
BI1	0.581	0.505	0.973	0.533	BI1	0.581	0.505	0.973	0.678
BI2	0.555	0.483	0.973	0.570	BI2	0.555	0.483	0.973	0.697
USE1	0.407	0.308	0.594	0.978	HA1	0.581	0.521	0.740	0.886
USE2	0.147	0.041	0.125	0.511	HA10	0.441	0.477	0.591	0.918
					HA2	0.557	0.526	0.698	0.951
					HA3	0.530	0.515	0.698	0.949
					HA4	0.406	0.445	0.498	0.838
					HA5	0.519	0.515	0.645	0.950
					HA6	0.263	0.365	0.362	0.613
					HA7	0.532	0.522	0.693	0.957
					HA8	0.557	0.524	0.692	0.965
					HA9	0.441	0.479	0.605	0.878

PEOU: Perceived ease of use; PU: Perceived usefulness; BI: Behavioral Intention;
USE: Past usage; HA: Habitual Usage

Appendix B. Common Method Bias Analysis (Model 1)

Construct	Item	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Perceived Ease of Use (PEOU)	PEOU1	0.901**	0.812	-0.012	0.000
	PEOU2	0.913**	0.834	-0.091	0.008
	PEOU3	0.907**	0.823	0.011	0.000
	PEOU4	0.844**	0.712	0.090	0.008
Perceived Usefulness (PU)	PU1	0.806**	0.650	0.046	0.002
	PU2	0.899**	0.808	0.014	0.000
	PU3	0.862**	0.743	-0.002	0.000
	PU4	0.925**	0.856	-0.058	0.003
Behavioral Intention (BI)	BI1	0.955**	0.912	0.023	0.001
	BI2	0.991**	0.982	-0.023	0.001
Past Usage (USE)	USE1	0.794**	0.630	0.173**	0.030
	USE2	0.856**	0.733	-0.248**	0.062
Average		**0.888**	**0.791**	**0.006**	**0.010**
**: $p < 0.01$					

Appendix B. Common Method Bias Analysis (Model 2)

Construct	Item	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Perceived Ease of Use (PEOU)	PEOU1	0.878**	0.771	0.018	0.000
	PEOU2	0.986**	0.972	-0.073	0.005
	PEOU3	0.915**	0.837	0.003	0.000
	PEOU4	0.886**	0.785	0.051	0.003
Perceived Usefulness (PU)	PU1	0.822**	0.676	0.030	0.001
	PU2	0.897**	0.805	0.018	0.000
	PU3	0.845**	0.714	0.021	0.000
	PU4	0.927**	0.859	-0.069	0.005
Behavioral Intention (BI)	BI1	0.976**	0.953	-0.004	0.000
	BI2	0.970**	0.941	0.004	0.000
Habitual Usage (HA)	HA1	0.442**	0.195	0.461**	0.213
	HA2	0.807**	0.651	0.148*	0.022
	HA3	0.883**	0.780	0.068	0.005
	HA4	0.984**	0.968	-0.284**	0.081
	HA5	0.984**	0.968	-0.036	0.001
	HA6	0.835**	0.697	-0.225	0.051
	HA7	0.909**	0.826	0.049	0.002
	HA8	0.891**	0.794	0.078	0.006
	HA9	0.983**	0.966	-0.109	0.012
	HA10	0.987**	0.974	-0.259**	0.067
Average		**0.890**	**0.807**	**0.006**	**0.024**
*: $p < 0.05$; **: $p < 0.01$					