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Chen Ye

*Department of Management Information Systems, Virginia State University, chenye@gmail.com*

Richard Potter

*Department of Information and Decision Sciences, University of Illinois at Chicago*

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# Communications of the Association for Information Systems

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## The Role of Habit in Post-Adoption Switching of Personal Information Technologies: An Empirical Investigation

Chen Ye

*Department of Management Information Systems, Virginia State University*

*chenye@gmail.com*

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*Department of Information and Decision Sciences, University of Illinois at Chicago*

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### Abstract:

Unlike technology users in business organizations, users of personal information technologies are usually not bound to specific products and have the freedom to switch from one product to a substitute. As a unique and widespread product level post-adoption behavior, IT user switching has not garnered sufficient attention in the current literature. Prior research has suggested that a consumer's decision to switch follows careful reasoning on three distinct groups of factors: push, pull, and mooring. Given the highly routinized nature of post-adoption IT use, we draw from research on habit in social psychology and post-adoption user behavior literatures, and argue that users' habit plays a critical role in post-adoption IT switching. Specifically, we posit that the habit of using the incumbent product both contributes to the mooring effects during the formation of intention to switch, and moderates the relationship between intention and switching. We tested our hypotheses on a sample of 414 users presented with a choice of switching their Web browsers. Our findings confirm the direct influence of potential switchers' habit on switching intention, and the interaction between habit and switching intention on switching. Our overall model explains 55 percent of total variance in users' intention to switch and 23 percent of total variance in user switching. This study advances the theoretical and empirical understanding of post-adoption technology switching, valuable to both researchers and practitioners.

**Keywords:** user switching, habit, push-pull-mooring, post-adoption, use, online survey

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## I. INTRODUCTION

With the markets for many business applications maturing, many technology providers have turned to personal technologies such as video games, mp3 players, smartphones, or Web search engines for their revenue growth and R&D spending [Dornan, 2006; Hertzberg, 2007]. For personal users, these technologies resemble other commonly used personal products such as credit cards, where there is more than one substitutable offering in the market. Consumers are free to switch their usage of a specific product (e.g., Discover Card), either partially or completely, to a substitute (e.g., American Express). Similarly, personal technology users can choose the product they favor and easily substitute part or all of their usage of an incumbent product to an alternative with similar features and functionalities. Such individual usage behavior has profound implications on how organizations position their products in a highly competitive marketplace.

The Web browser is an example. Between October 2004 and December 2010, the worldwide market share of Microsoft Internet Explorer (IE) dropped from 92 percent to 57 percent, while market shares of alternative browsers such as Mozilla Firefox and Google Chrome increased significantly [Net Applications, 2011]. This change indicates that a large number of IE users have switched to the alternatives during this time period. Like browsers, the competitive landscapes of many personal technologies are characterized by products with lowering or zero price, low differentiation, and high substitutability. Thus, it is crucial for providers to understand the drivers of technology user switching.

While the practical implications of user switching between technology products are obvious, as an under-researched form of post-adoption behavior, technology user switching is also important to IS researchers. Departing from viewing post-adoption usage as a one-dimensional phenomenon, scholars have recognized the multifaceted nature of IT usage [e.g., Jaspersen et al., 2005]. While the importance of switching as a unique, product level post-adoption behavior has been noted by some authors [Kim and Son, 2009], to date there have been few studies that focused specifically on technology users' post-adoption switching [Ye et al., 2008]. Marketing researchers, on the other hand, have extensively investigated antecedents to consumer switching. Their findings are summarized in the push-pull-mooring (PPM) switching model [Bansal et al., 2005].

While Bansal et al. successfully used the PPM model to explain a substantial portion of variance in switching intention, they also stressed the need to include additional pull and mooring factors. Consumer habit was highlighted in particular by the authors as a potential mooring factor, echoing many earlier calls to consider habit as a key determinant of consumer switching [e.g., Bitner, 1990; Fornell, 1992]. In addition, prior studies on switching generally assume that a person's behavior faithfully follows intention, formed as a result of conscious reasoning and rationalization, overlooking the unique ability of habit to moderate the relationship between intention and behavior [Limayem et al., 2007]. Despite the repeated calls for attention and the advances in understanding the role of habit in other domains of human behavior, to our knowledge the role of habit on switching has not been addressed either theoretically or empirically. This deficit is particularly detrimental to our understanding of IT user switching. Unlike visits to hairstylists or purchases of flour, post-adoption use of technologies such as Web browsers is often highly ingrained in the daily routines of users. As research in social psychology and post-adoption IT use has revealed, such highly routinized behaviors are often controlled by habits. In addition, a potential switcher's habit of choosing an incumbent product directly counters the intention to use an alternative, giving another reason for habit's particular saliency in the context of switching. Thus, the main goal of this research is to explore the role of users' habit—against the backdrop of the PPM model—in technology switching, with switching between Web browsers as an empirical setting.

## II. THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

### Post-Adoption User Switching

To date, in most of the studies on post-adoption use, users' decision to continue using an innovation and the decision to continue using a specific product is treated as the same. For many personal technologies, however, there are multiple competing products similar in functionality and highly substitutable. A user's decision to discontinue the use of a specific product (e.g., AOL Messenger) does not necessarily imply a decision to discontinue the use of an adopted innovation (e.g., instant messaging), because s/he could easily switch to a substitute (e.g., MSN Messenger). Although researchers have emphasized the theoretical and practical significance of

understanding technology use in a market with multiple competing products [Brynjolfsson and Kemerer, 1996], limited research effort has been invested on the specific issue of user switching [Chen and Hitt, 2002; Kim et al., 2006; Ye et al., 2008].

While consumer switching has drawn ample attention from marketing scholars, the concept of switching has been largely viewed as self-explanatory and not well explicated. What action constitutes a switch? When we give a closer examination to this question, it became clear that the answer depends on the type of products or services under consideration. For services such as car insurance [Carmen et al., 2007], a consumer is not likely to use more than one provider at any given time, and a switch has to be a complete substitution of the incumbent with an alternative. However, for many other products such as credit cards [Burnham et al., 2003], a consumer can own and use multiple vendors' products in parallel. It is more likely for a consumer to substitute the usage of one product with an alternative partially and gradually. Even though switching is only partial for such products, it still impacts the market share of the vendors. Personal technologies often allow parallel use of multiple products by one user, and partial switches, as opposed to all-or-none substitutions, are much more likely to occur [Ye et al., 2008]. Therefore, we define technology user switching as *users' partial reduction or full termination in usage of a specific technology product while substituting it with usage of an alternative product that satisfies identical needs*.

### The Push-Pull-Mooring Migration Model

In marketing research on consumer switching, one stream demonstrated that brand substitution of frequently purchased consumer products [Dodson et al., 1978; Walters, 1991] are motivated extrinsically by price deals and intrinsically by consumers' desire for variety [Mazursky et al., 1987]. Following Keaveney's exploratory study on service switching [1995], another body of literature examined how individuals' perceptions, beliefs, and personal differences influence their switching between different providers for services ranging from banking [Ganesh et al., 2000] and credit cards [Burnham et al., 2003] to Internet service providers [Keaveney and Parthasarathy, 2001] and mobile phones [Kim et al., 2004]. Findings from these studies suggest that consumer switching is motivated or inhibited by a variety of influences, including perceptions and experience of the incumbent product or service, such as satisfaction [Bolton and Bronkhorst, 1995; Ganesh et al., 2000; Burnham et al., 2003] and breadth of use [Keaveney and Parthasarathy, 2001; Lopez et al., 2006]; beliefs and attitudes on the switching itself, such as perceived switching costs [Burnham et al., 2003; Kim et al., 2004]; and individual traits such as risk aversion [Ganesh et al., 2000; Keaveney and Parthasarathy, 2001].

Individuals not only switch between products and services, but also frequently compare two entities and switch from one to another under different circumstances in life. One such behavior is people's migration from one locale to another, a phenomenon well studied in human geography. Comprehensive models such as the push-pull-mooring (PPM) framework have been developed to explain human migration [Moon, 1995]. According to the push-pull-mooring framework, when individuals migrate from one locale to another, they are driven away from the origin by the push factors such as natural disasters, and attracted to the destination by its pull factors such as better employment opportunities. In addition, contextual, personal, and social influences such as moving costs also facilitate or inhibit migration. These factors are referred to as mooring factors [Moon, 1995].

The resemblance between human migration (switching from one locale to another) and consumer switching (from one product or service to another) has been noted by researchers in both human geography and marketing [e.g., Clark and Knapp, 1996; Bansal et al., 2005]. Bansal et al. [2005] drew from the push-pull-mooring framework and built a unified model for explaining consumer service switching behavior. They proposed and tested a push, pull, and mooring (PPM) migration model for service switching. Two second-order latent factors—push effects and pull effects capture the collective force of perceptions and beliefs on the incumbent and alternative provider, respectively. Another latent factor—mooring effects represents the collective effects of situational and contextual constraints such as switching costs or subjective norms, and personal traits such as variety seeking. While push effects, pull effects and mooring effects were hypothesized to directly influence switching intention, mooring effects was also hypothesized to moderate the main effect of the other two second-order factors. The proposed model was able to explain a substantial amount of variance in both switching intention and switching behavior.

### Model Development and Specification

Following the PPM framework as a general guideline, we will first develop a set of baseline hypotheses regarding the prediction of intention to switch before we discuss the role of habit. The push, pull, and mooring effects are in essence aggregates of first order variables influencing different aspects of a switching decision. Bansal et al. [2005] specified each aggregate as a second-order construct reflecting on first order dimensions. A number of authors have discussed the prevalent misspecification of formative constructs as reflective [Jarvis et al. 2003; Petter et al. 2007], and suggested four main criteria for indentifying a formative construct: the causality flows from the measure to the construct; the measures are not interchangeable; the measures do not necessarily covary; the measures may have

independent antecedents and consequences. Applying these criteria, we examined the theoretical relationships between PPM effects and their underlying first order dimensions, and determined that these effects are indeed formative constructs.

We should note that insights from marketing literature, while useful, are not sufficient to explain users' intention to switch between technology substitutes. Consumer information technologies bear little resemblance to common household commodities such as flour [Dodson et al. 1978], which are the main objects of brand switching research, in that the latter are mainly differentiated in price and require repeat and frequent purchases. Unlike services such as mobile phones, many personal technologies such as Web browsers do not require commitment to ongoing relationships through subscriptions and contracts. Thus, we also rely on technology use literature to incorporate the specific dimensions salient to technology products.

### Push and Pull Effects

Lack of satisfaction is the primary reason consumers are pushed away from a particular product [Burnham et al. 2003; Kim et al. 2004]. For IS researchers, user satisfaction has been a key outcome variable that represents IS effectiveness [Delone and McLean, 1992; Seddon, 1997]. However, as Melone [1990, p. 88] pointed out: "user satisfaction alone is not sufficient to adequately capture the full meaning of effectiveness. For one thing, it fails to consider the role user behavior plays in the transformation of inputs to outputs." As an independent variable, user satisfaction was found to be a reliable predictor of post-adoption behaviors including switching [e.g., Bhattacharjee, 2001; Wixom and Todd, 2005; Ye et al., 2008; Kim and Son, 2009]. Therefore:

*H1: The push effects of low satisfaction with the incumbent product are positively related to intention to switch.*

Consumers consider switching also because a substitute offers advantages over the incumbent. This pull effect has been conceptualized as alternative attractiveness [Ping, 1993; Bansal et al., 2005]—an all-encompassing concept which may not capture all salient dimensions individuals would use to compare a substitute with the incumbent for a specific product. We drew on literature in IT user behavior and identified three pull factors that are most likely to affect technology switching: relative advantage, perceived relative ease of use, and perceived relative security. Relative advantage and perceived ease of use (PEOU) are manifestations of the outcome expectancy and effort expectancy constructs, respectively, in the Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al., 2003]. Both expectancies are the main drivers when users adopt new technologies to replace existing tools [Moore and Benbasat, 1991; Taylor and Todd, 1995]. In the context of switching, users would use these dimensions to judge whether the alternative would be better than the incumbent. Specifically, relative advantage captures the degree to which a substitute technology is perceived as being more beneficial, in terms of outcomes such as economic advantages or productivity increases, than its predecessor. In addition, a user would also be more likely to switch to an alternative if she expects it to be easier to use than the incumbent.

In the past two decades, information security has become a key issue for end users, technology managers, and government agencies [Straub, 1990; Federal Bureau of Investigation, 2006]. The growing popularity of the Internet has also exposed individual users to new breeds of threats such as spywares and phishing scams. As a result, users are becoming more proactive in seeking ways to reduce vulnerabilities in their computing environments, secure their online transactions, and mitigate the risk of losing crucial personal information to unscrupulous parties. Both academic and industry literatures have shown that user perception of security is one of the key factors in user selection of personal IT products, especially, Web related products [Salisbury et al., 2001, Ye et al., 2008]. Thus:

*H2: The pull effects of relative advantage, perceived relative ease of use, and perceived relative security of the alternative product are positively related to intention to switch.*

### Mooring Effects

The first mooring factor, subjective norm, is an antecedent to intention to perform social behaviors [Ajzen and Fishbein, 1980; Ajzen, 1985], including the use of technologies [Moore and Benbasat, 1991; Taylor and Todd, 1995]. Consumers' willingness to switch is also a function of their perception of subjective norm toward switching to the alternative [Bansal et al., 2005]. Another prominent mooring factor is perceived switching costs [Jones et al., 2000; Kim et al., 2004], which could come in the form of time and effort, money, or psychological impacts [Burnham et al., 2003]. Switching costs act as a constraint on IT users post-adoption choices [Kim and Son, 2009]. Switching of personal technologies at least involves procedural costs—the time and effort a user has to spend on evaluating, setting up, and learning the substitute technology product if she chooses to switch.

In addition to their direct effects on switching intention, mooring factors have shown moderating effects on push and pull effects in prior studies [Bansal et al., 2005]. The presence of strong mooring effects suppresses the pushing power of the incumbent and the attraction of the alternative. Therefore, we derive the following two hypotheses:

*H3: The mooring effects of low subjective norm toward using the alternative product and higher perceived switching costs are negatively related to intention to switch.*

*H4: Mooring effects moderate the relationships between push/pull effects and intention to switch. The stronger the mooring effects, the weaker are the relationships between push/pull effects and intentions to switch.*

### The Role of Habit

Prior studies on IT user and consumer switching have generally built on the assumption that an individual decision to perform a specific action is solely the result of deliberate reasoning, and subsequent action is solely the result of intention (see Table A-1 for an overview of prior literature on consumer and technology user switching). However, research in social psychology has demonstrated that behaviors are influenced by two competing mechanisms—a controlled or deliberate process and an automatic or spontaneous process [Schneider and Shiffrin, 1977; Fazio, 1990]. As the result of the automatic cognitive process, many routinely performed behaviors are guided partially by habits, as opposed to purely following the sequence of reasoning → intention → behavior [Wood et al., 2002].

The concept of habit was introduced in the early days of psychology [e.g., James, 1890; Hull, 1943]. Currently, habit is defined as “*learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end states*” [Verplanken and Aarts, 1999, p. 104, italics added]. Given this definition, there are two key characteristics of a habit: its automatic performance without any conscious control, and its triggering by a stimulus cue in the environment. A large number of studies in social psychology and other applied fields have assessed the importance of habit through its interactions with intention and behavior, in a variety of social contexts ranging from seat-belt usage [Mittal, 1988] to food consumptions [Mahon et al., 2006; Reinaerts et al., 2007; Kremers et al., 2007]. While some scholars proposed a direct impact of habit on behavior independent of intention [Triandis, 1977; Mittal, 1988; Verplanken and Faes, 1999; Saba et al., 2000; Mahon et al., 2006; Reinaerts et al., 2007], others posit that habit not only competes with intention in determining behavior, but also influence intention directly [Saba et al., 2000; Honkanen et al., 2005; Mahon et al., 2006; De Pelsmacker and Janssens, 2007]. Regardless of how the precise role of habit is theorized, this body of research has provided empirical support for the effect of habit in determining behavior, especially, behavior performed frequently under stable contexts.

We should note that habit influences future behavior only when behavior has been habitualized. The formation of habit requires a certain action to be performed repeatedly and frequently, in a fairly stable environment for a reasonable amount of time. Therefore, habit is most likely to play a role in daily routines. Behaviors performed at longer intervals, such as paying rent or celebrating anniversaries do not usually become habitual despite the repetitive nature.

By definition, post-adoption behavior means continued and repeated use of a specific technology after the initial adoption [Bhattacharjee, 2001]. Like eating, drinking, and traveling to work, the use of personal technologies such as Web browsers has been ingrained into many users' daily routines, providing the ideal ground for habitualization [Ortiz de Guinea and Markus, 2009]. As pointed out by Limayem et al. [2007, p. 709]: “habit has great potential to explain IS related behaviors that may no longer be under total conscious control of the individual.” A number of studies have demonstrated habit as a factor that impacts technology adoption and post-adoption IS use [Bergeron et al., 1995; Gefen, 2003; Limayem and Hirt, 2003; Kim et al., 2005; Liao et al., 2006; Limayem et al., 2007], yielding findings consistent with conclusions from studies in other academic disciplines. Limayem and Hirt [2003], for instance, found habit to be antecedent to affect and actual IS usage. Similarly, Kim et al. [2005] found the effect of past use on future use of IT is better explained by habit. Limayem et al. [2007] also found that stronger habit leads to diminished predictive power of intention on continued IT usage.

In addition, consumers' choice behavior between substitutes of certain technology is also similar to choice selections in other daily routines such as choosing travel modes. As studies in social psychology have demonstrated, under these multi-choice situations, habit toward one mode greatly influences choice of other alternative modes [Verplanken et al., 1994].

### Habit as a Mooring Factor

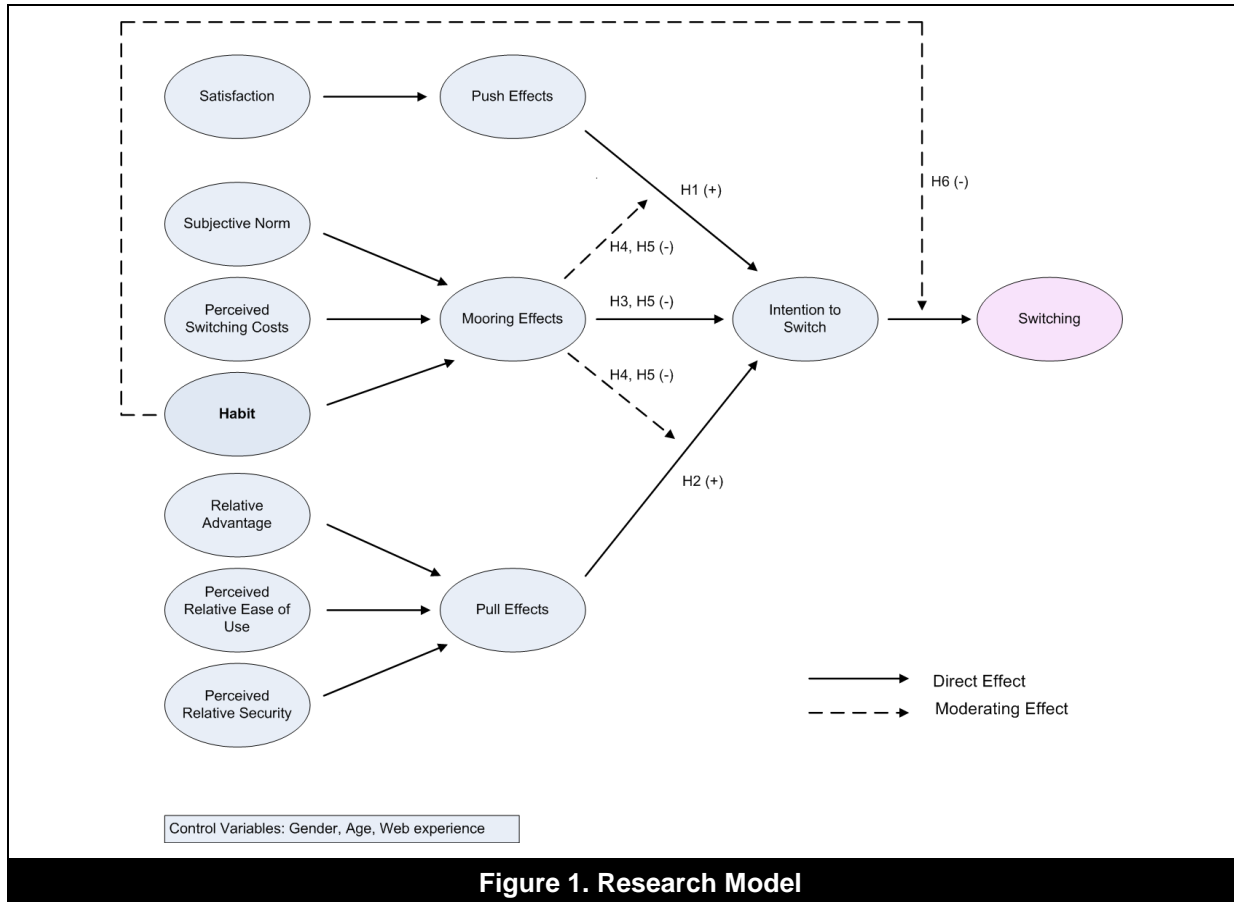
A few authors have contended that habit influences behavior by acting as a direct antecedent to intention [Saba et al., 2000; Honkanen et al., 2005; Mahon et al., 2006; De Pelsmacker and Janssens, 2007]. This effect may be explained by social dissonance theory [Festinger, 1957], which predicts that incompatible beliefs and behavior held

by a person create internal conflicts, and individuals are motivated to avoid or reduce such dissonance by modifying their beliefs, and ignoring information that facilitate the dissonance. For example, if a person who tends to eat unhealthy food and does not exercise heard that one of his friends who shares a similar lifestyle just had a heart attack, a dissonance is created. In this case he might choose to reduce the dissonance by forming an intention to eat healthier and start exercising. However, he might also seek information to convince himself that healthy food and regular exercises do not necessarily reduce the risk of heart attacks, and maintain his intention to continue his current lifestyle. This way, he reduces his dissonance by aligning his beliefs and intention to his existing behavior. Consistent with the basic premise of social dissonance theory, in a study on speeding, De Pelsmacker and Janssens [2007] found that individuals with stronger habit to speed not only are more like to display speeding behavior, but also have stronger intention to speed again. For IT user switching, when a user has habitualized the use of a particular technology product, s/he will be less likely to have the intention to use an alternative, and a strong habit could also suppress the impact of other beliefs s/he has on the two alternatives. In other words, habit effectively acts as an additional mooring factor. Therefore:

*H5: Habit of using the incumbent has mooring effects on user switching.*

### The Moderating Role of Habit on Switching Intention and User Switching

The main reason habit has attracted scholarly interest in social psychology and other academic fields is that it interplays with reasoned influences in determining social behavior. Human actions are the results of not only controlled but also automatic mental processes. As emphasized by Fazio [1990, p. 100]: “Just as deliberate, planned behaviors sometimes may involve a process that includes automatic components, spontaneous behavior that typically follows from an automatic attitude activation occasionally may involve a controlled component.” Conceptually, habit is the embodiment of the automatic side of this dual mode of human cognition [Ronis et al., 1989]. Triandis’s theory of behavior [1977] posits that the probability a person actually performs an act is the sum of the strength of habit and intention, adjusted for their respective weights. When habit and intention are consistent, in other words, when a person’s intended action matches her previous-formed habit, we are not likely to observe any notable difference between the effects of these two antecedents of behavior. However, when habit and intention are not in perfect harmony, for example, when someone intends to drink more water, but has a habit of opening up a can of soda whenever s/he feels thirsty, actual behavior becomes an outcome of the ensuing tug-of-war between habit and intention. So for a given individual, when habit is strong, intention is more likely to be overpowered by habit; when habit is weak, behavior is more likely to follow intention resulting from reasoned deliberation.



**Figure 1. Research Model**

Regardless of how habit is operationalized, the interrelationships among intention, habit, and behavior have received abundant empirical support [Mittal, 1988; Verplanken and Faes, 1999; Saba et al., 2000; Honkanen et al., 2005; Mahon et al., 2006; Reinaerts et al., 2007; De Pelsmacker and Janssens, 2007]. While many authors considered habit as a direct antecedent to behavior, Limayem et al. [2007, pp. 719–720] offered compelling arguments and provided empirical support for modeling habit rather as a moderator of the intention-behavior relationship.

Specific to switching, we also expect habit (of using the incumbent product) to have a suppressor effect on the intention to behavior relationship: when using the incumbent product has become highly habitual for a user, s/he is less likely to actually switch to the substitute product even when s/he has the intention to switch following careful evaluations of the pros and cons of the two alternative products. In comparison, it would be more likely for someone with weak or no habit of using a product to follow a switching intention and actually switch to an alternative. Therefore,

*H6: A stronger habit to use the incumbent will weaken the predictive power of switching intention on switching.*

Although the evidence on demographics' influence on switching has been equivocal [Chen and Hitt, 2002; Ranganathan et al., 2006; Shin and Kim, 2008], we controlled for the possible effects of three demographic variables: age, gender, and length of experience in testing our model. Figure 1 illustrates our full research model. A summary of the key concepts in our research model is provided in Table 1.

**Table 1: Key Concepts, Definitions, and Operationalization**

Concept	Definition	Operationalization in the context of this study
Push effects	Collective influence of perceptions and beliefs on the incumbent product.	A second-order construct with one first-order dimension: satisfaction, measured using a self-reported scale.
Pull effects	Collective influence of perceptions and beliefs on the alternative product.	A second-order construct with three first-order dimensions: relative advantage, perceived relative ease of use, perceived relative security, all of which measured using self-reported scales.
Mooring effects	Collective influence of situational and contextual constraints, and personal traits, independent of the products involved in the switch.	A second-order construct with three first-order dimensions: subjective norm, perceived switching costs, habit, all of which measured using self-reported scales.
Habit	Learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end states [Verplanken and Aarts, 1999].	Measured using a self-reported scale.
Switching	Users' partial reduction or full termination in usage of a specific technology product while substituting it with usage of an alternative product that satisfies identical needs.	Changes in self-reported usage of the alternative versus the incumbent product during the study period.

### III. METHODS

#### Participants and Procedure

We collected data in fall 2008 at a large public university located in the U.S. We invited students enrolled in two undergraduate courses, required for all business majors, to answer a two-wave Web-based survey. A bonus point for the courses was used as a reward to encourage participation. We selected the Web browser as the technology artifact because it is one of the most widely used technologies, with multiple products in the market. Although university students may not be the ideal sample in most organizational studies, they are considered appropriate surrogates for Internet users in the literature [e.g., Limayem et al., 2007; McElroy et al., 2007].

The online survey was developed by the first author in PHP/MySQL. At the beginning of the first wave, respondents were asked to select the browsers they were aware of from a list of browsers. For those aware of at least two browsers, they were asked to indicate their primary browser and the one they were most likely to consider for a



switch. The Web survey customized all subsequent questions, when applicable, with the names of the browsers selected (e.g., “I have used a variety of Internet Explorer’s features”). In addition, the respondents were asked to provide a percentage breakdown of their usage of different browsers.

The first survey also included questions for all perceptual constructs and intention to switch. Six weeks after the first survey was closed, invitations to answer the second survey were sent to all respondents. A reminder was sent one week later, and a final reminder was sent after another week. In the second survey, we collected each respondent’s awareness of different Web browsers and an updated percentage breakdown of their usage of different browsers. To minimize potential methodological artifacts, when applicable the online survey randomized the order of a list of items, for example, the browsers available, or the questions on the same page. Throughout the survey, the respondents were reminded to answer all questions according to their personal use of the Web only.

### Data Sample

To ensure the relevance and integrity of the responses, we applied a few filters to screen the initial data set. First, although the online survey also collects the participants’ responses on applicable constructs when they were aware of only one browser, those responses accounted for less than 8 percent of initial responses, and were excluded from all subsequent analyses. For both waves, the online survey also collected the exact time it took each respondent to complete the entire questionnaire. Using cutoff values determined through the pilot test and the authors’ own experiments, we eliminated 6 percent of the responses with short completion times indicating the respondents probably had rushed through the survey without reading and responding to each question properly. There were also apparent inconsistencies in browser awareness and usage reported in some of the responses, resulting in another 3 percent reduction.

Out of the 637 unique students invited, we received 414 usable responses in our final data set, yielding a net response rate of 65 percent. Before merging the two data sets from the two classes, we performed series of chi-square or T tests and found no significant differences in either demographics or research constructs. To address potential non-response bias, we compared the demographic characteristics of the first and last 10 percent of respondents for each wave and found no significant difference. The respondents finishing both waves did not differ demographically from those who only completed the first wave. Table 2 lists the descriptive statistics of our final sample.

<i>Gender</i>		<i>School Level</i>			
Male:	199 (48.1%)	Freshman:	2 (0.5%)		
Female:	215 (51.9%)	Sophomore:	77 (18.6%)		
<i>Age</i>		Junior:	174 (42.0%)		
		Senior:	149 (36.0%)		
		Graduate:	10 (2.4%)		
		Other:	2 (0.5%)		
		< 20:	69 (16.7%)	<i>Primary Browser (First Wave)</i>	
		20–25:	293 (70.8%)		
25–30:	44 (10.6%)				
30–35:	6 (1.4%)				
35–40:	2 (0.5%)				
> 40:	0	Google Chrome:	11 (2.7%)		
<i>Web Experience (years)</i>		Internet Explorer:	199 (48.1%)		
		Mozilla Firefox:	174 (42.0%)		
		Netscape:	0		
Mean:	9.42	Opera:	1 (0.2%)		
S.D.:	2.33	Safari:	28 (6.8%)		
		Other:	1 (0.2%) <sup>†</sup>		

† The respondent who selected “Other” as primary browser used Konqueror.

### Instrument

For all perceptual constructs, we used validated scales from prior research, adapted for the specific context of this study. We pretested the first draft of the questionnaire with eighteen active technology users and solicited feedback on the measurement items as well as different aspects of the design of the online survey. We refined some items and the survey design according to the feedback. We then conducted a pilot test with 137 students and verified that all scales displayed satisfactory Cronbach’s alpha and factor loadings in a principle component analysis. In the final questionnaire, except for satisfaction and switching intention, all perceptual questions were scored on a seven-point Likert scale (1 = “strongly disagree”, 7 = “strongly agree”). Appendix B lists all measures used in this study.

We measured user switching as the increase in usage percentage of the alternative browser between the two waves. Table 3 demonstrates the calculation of user switching from usage data for two sample respondents. This measure is consistent with our definition of IT user switching, which takes into consideration of partial switches. If we use a simple switcher vs. non-switcher binary measure based on whether a user has changed her primary browser, only twenty respondents in our final sample would be classified as switchers. However, as illustrated in Table 3, respondent 1 would be considered as a non-switcher under such binary classification, despite her significant increase in usage of the alternative browser.

Respondent	Browser Usage	Switching
1	T <sub>0</sub> : IE = 90%; Firefox = 10%	40% – 10% = 30%
	T <sub>1</sub> : IE = 60%; Firefox = 40%	
2	T <sub>0</sub> : IE = 60%; Chrome = 40%	55% – 40% = 15%
	T <sub>1</sub> : IE = 45%; Chrome = 55%	

T<sub>0</sub>: First wave

T<sub>1</sub>: Second wave

#### IV. DATA ANALYSIS AND RESULTS

We applied partial least squares (PLS) using SmartPLS 2.0 [Ringle et al., 2005] in measurement validation and model testing, because it offers several advantages that are pertinent to this study. While PLS enables the verification of a complex model, it also allows testing of individual hypotheses and provides amount of variance explained for each endogenous variable. Compared to covariance-based SEM and regression, it is less susceptible to data nonnormality and small sample size, and more fitting for testing formative models and interaction effects [Chin et al., 2003]. In the first iteration of PLS analysis, one item for perceived switching costs displayed unsatisfactory loading on the intended construct. We excluded this item from all subsequent analyses and results reported henceforth. Prior to the PLS analysis, scores for all measurement items of the push, pull, and mooring factors were reverse coded, when applicable, to the direction of promoting switching.

##### Measurement Validation

As illustrated in Table 4, all measures had composite reliability over .70, demonstrating adequate reliability [Straub et al., 2004]. Table 4 also shows the average variance extracted (AVE), square root of the AVE, and the correlations between the constructs. The AVE of each measure was above .50, indicating convergent validity [Fornell and Larcker, 1981]. For each construct, the square root of AVE was higher than the correlations with other constructs, confirming discriminant validity [Straub et al., 2004]. Table 5 lists the loadings and t-values, and cross-loadings for each item. All items have loadings above .70 with significance at the .01 level, and stronger loadings on intended constructs than cross-loadings, further confirming measurement validity [Straub et al., 2004].

Construct	Mean	SD	CR	AVE	1	2	3	4	5	6	7	8	9
1. Low Satisfaction	2.22	1.01	0.942	0.803	<b>.896</b>								
2. Subjective Norm	5.19	1.35	0.964	0.930	-0.147	<b>.964</b>							
3. Perceived Switching Costs	3.81	1.57	0.931	0.870	-0.123	-0.141	<b>.933</b>						
4. Relative Advantage	3.47	1.22	0.968	0.858	0.309	-0.327	-0.021	<b>.926</b>					
5. Perceived Relative Ease of Use	3.64	1.25	0.944	0.810	0.327	-0.218	-0.169	0.673	<b>.900</b>				
6. Perceived Relative Security	4.93	1.24	0.934	0.781	0.029	-0.102	-0.218	0.245	0.275	<b>.883</b>			
7. Habit	6.34	1.05	0.957	0.880	-0.356	0.231	0.135	-0.275	-0.334	-0.013	<b>.938</b>		
8. Intention to Switch	2.48	1.41	0.965	0.902	0.460	-0.320	-0.186	0.577	0.563	0.258	-0.428	<b>.950</b>	
9. Switching (%)	1.25	11.9	1.000	1.000	0.114	-0.181	-0.071	0.216	0.258	0.133	-0.307	0.357	<b>1.000</b>

The diagonals are the square root of the AVE

Table 5: Item Loadings and T Statistics for Loadings on Intended Constructs										
		1	2	3	4	5	6	7	8	T Statistics
1	SATISFA1	<b>0.842</b>	-0.136	-0.075	0.266	0.298	0.037	-0.351	0.418	17.09*
	SATISFA2	<b>0.904</b>	-0.124	-0.127	0.271	0.306	0.030	-0.283	0.400	29.37*
	SATISFA3	<b>0.928</b>	-0.157	-0.118	0.300	0.320	0.023	-0.317	0.433	61.64*
	SATISFA4	<b>0.909</b>	-0.111	-0.119	0.271	0.250	0.014	-0.327	0.401	55.06*
2	SN1	-0.147	<b>0.963</b>	-0.151	-0.324	-0.212	-0.080	0.215	-0.294	90.17*
	SN2	-0.138	<b>0.966</b>	-0.121	-0.307	-0.209	-0.112	0.229	-0.322	100.01*
3	COSTS2	-0.136	-0.088	<b>0.959</b>	-0.036	-0.178	-0.205	0.138	-0.211	6.59*
	COSTS3	-0.084	-0.198	<b>0.906</b>	0.004	-0.130	-0.203	0.108	-0.119	8.05*
4	RELADV1	0.324	-0.304	-0.049	<b>0.922</b>	0.594	0.194	-0.219	0.543	60.66*
	RELADV2	0.265	-0.321	0.019	<b>0.927</b>	0.585	0.243	-0.253	0.515	63.75*
	RELADV3	0.295	-0.285	-0.021	<b>0.921</b>	0.692	0.244	-0.277	0.543	48.21*
	RELADV4	0.280	-0.308	-0.007	<b>0.930</b>	0.638	0.226	-0.259	0.549	68.11*
	RELADV5	0.270	-0.296	-0.041	<b>0.932</b>	0.603	0.228	-0.266	0.523	60.76*
5	EOU1	0.276	-0.158	-0.113	0.592	<b>0.891</b>	0.270	-0.251	0.448	36.81*
	EOU2	0.330	-0.210	-0.188	0.630	<b>0.916</b>	0.252	-0.343	0.555	50.34*
	EOU3	0.304	-0.249	-0.170	0.654	<b>0.921</b>	0.267	-0.313	0.534	65.57*
	EOU4	0.265	-0.162	-0.136	0.538	<b>0.870</b>	0.199	-0.293	0.486	32.71*
6	SECUR1	0.030	-0.077	-0.194	0.225	0.250	<b>0.927</b>	0.014	0.219	59.46*
	SECUR2	0.033	-0.130	-0.185	0.270	0.278	<b>0.937</b>	-0.025	0.284	70.76*
	SECUR3	0.044	-0.029	-0.211	0.102	0.173	<b>0.721</b>	-0.041	0.167	12.56*
	SECUR4	0.002	-0.096	-0.196	0.234	0.257	<b>0.930</b>	-0.002	0.228	69.79*
7	HABIT1	-0.300	0.228	0.126	-0.260	-0.297	-0.011	<b>0.930</b>	-0.379	38.36*
	HABIT2	-0.362	0.213	0.120	-0.273	-0.324	-0.013	<b>0.946</b>	-0.421	43.56*
	HABIT3	-0.339	0.207	0.133	-0.242	-0.320	-0.012	<b>0.939</b>	-0.404	46.65*
8	INTENT1	0.409	-0.327	-0.173	0.531	0.533	0.259	-0.419	<b>0.944</b>	52.18*
	INTENT2	0.441	-0.306	-0.167	0.564	0.543	0.231	-0.409	<b>0.966</b>	125.73*
	INTENT3	0.462	-0.278	-0.189	0.549	0.527	0.246	-0.391	<b>0.938</b>	69.72*

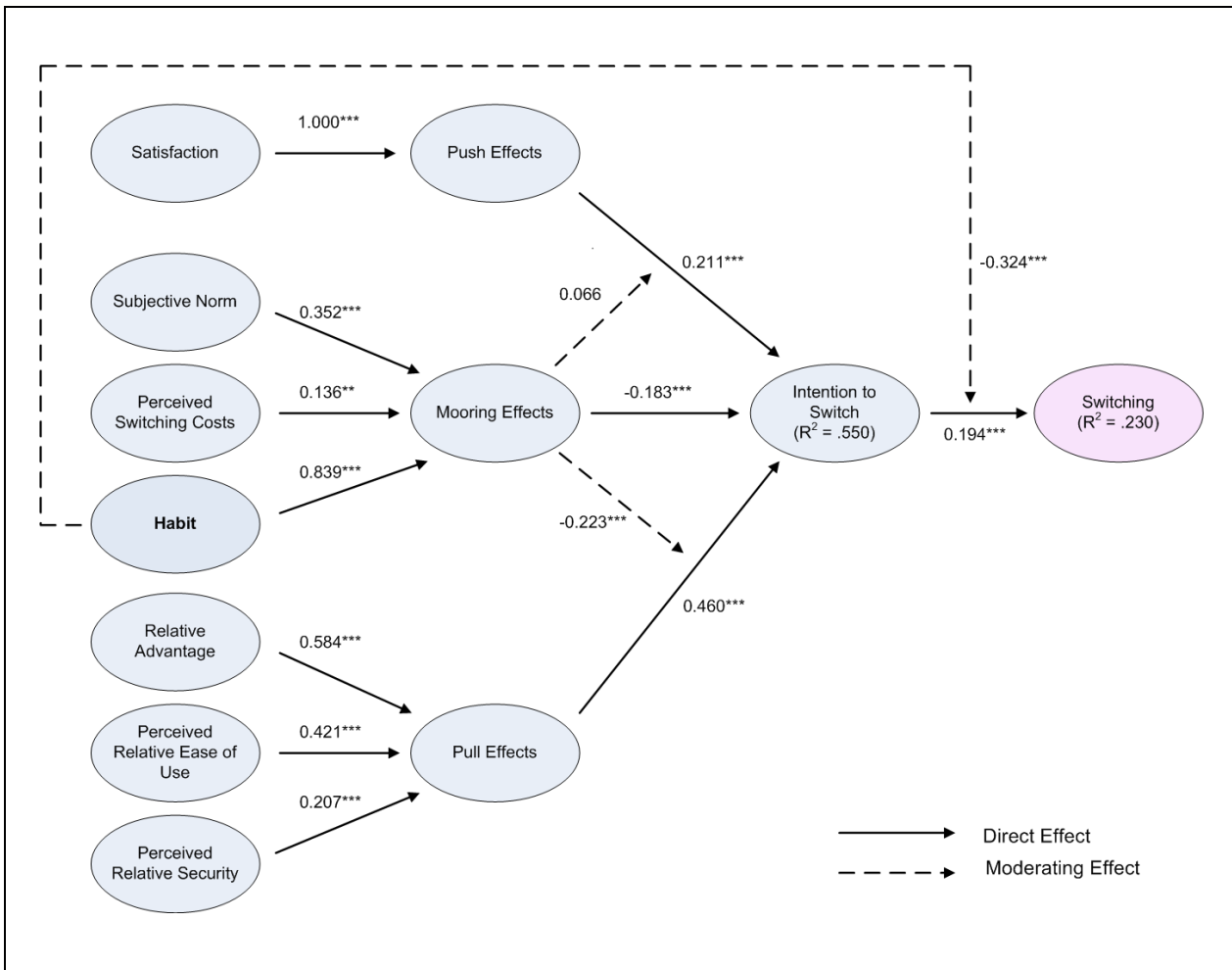
\* Significant at the .01 level

### Testing of Structural Model and Hypotheses

The hypotheses in this study involve second-order formative constructs with both direct and interaction effects. To our knowledge no single source has fully described the procedures for testing such structural model. Therefore, we consulted studies in current literature [e.g., Rai et al., 2006; Chin et al., 2003; Wetzels et al., 2009] that provide recommended procedures and exemplars for different aspects of the empirical testing of our research model. Specifically, we used repeated manifest variables for specifying the second-order constructs [Wetzels et al., 2009]. To test the interactions between mooring and push/pull effects, we followed the two-step score construction procedure described in Chin et al. [2003, Appendix D]. The structural model without these two interactions was estimated with PLS first to obtain composite scores of the formative constructs, and then the interaction terms were created from the composite scores and used in the final PLS run. The interaction term between habit and intention was created following the product indicator approach [Chin et al., 2003].

Figure 2 depicts the results of testing our structural model, with standardized coefficients for each path and R<sup>2</sup> for switching intention and switching. The significance levels of the path coefficients were assessed with a bootstrap resampling. For the prediction of switching intention, the path coefficients for push, pull, and mooring effects were significant with expected signs. Users will have a higher intention to switch when they have low satisfaction toward the incumbent, and when they perceive the alternative has higher relative advantage, relative ease of use, and relative security. Furthermore, perception of low subject norm toward switching, higher switching costs, and stronger habit (of using the incumbent) are associated with lower switching intention. These results support H1-3. The interaction effect between mooring effects and pull effects also received statistical support. However, the interaction between mooring effects and push effects is not significant. Therefore, H4 is only partially supported. With the exception of non-significant mooring by push interaction, the mooring effects of habit predicted in H5 are supported. The push, pull, and mooring effects collectively accounted for 55.0 percent of the variance in switching intention.

For the prediction of switching, the path coefficient of the intention by habit interaction is negative and significant. Our result suggests that the effect of intention on switching is weakened by a strong habit of using the incumbent, lending support to H6. The model explained 23.0 percent of variance of switching. For formative constructs, the relative weight of each underlying dimension indicates its relative importance [Chin and Gopal, 1995]. The weights suggest that habit and relative advantage are the most prominent mooring and pull factor, respectively. Table 6 summarizes the support of our hypotheses from these results.



**Figure 2. PLS Results (Hypothesized Effects)**

\*\*\*:  $p < .01$   
 \*\*:  $p < .05$   
 \*:  $p < .10$

**Table 6: Research Hypotheses and Results**

Research Hypotheses	Result
H1: Push effects → Intention to switch	Supported
H2: Pull effects → Intention to switch	Supported
H3: Mooring effects → Intention to switch	Supported
H4: Mooring effects x Push effects → Intention to switch Mooring effects x Pull effects → Intention to switch	Partially Supported (only mooring by pull effects interaction found)
H5: Habit influences switching as a mooring effect	Supported
H6: Habit x Intention to switch → Switching	Supported

The product indicator approach used to create the habit by intention interaction term may suffer from insufficient statistical power due to capitalization on chance, especially when sample size is small [Goodhue et al., 2007]. We followed the PLS with product of the sums (PLS-PS) approach suggested by Goodhue et al., as an alternative, to calculate the interaction term. The path coefficient for the interaction is -0.321 ( $p < .01$ ), congruent with the result from the product indicator approach.

One of the main premises of this study is that habit is a key construct that can enhance our understanding of user switching. To assess the impact of habit on prediction of switching intention or switching, we calculated the  $R^2$  difference, or  $f^2$  value, between our model and the baseline model without habit. As suggested by Cohen [1988], an  $f^2$  value of 0.02, 0.15, and 0.35 represents small, medium, and large effects. The  $f^2$  value was 0.017 for habit's influence on switching intention, indicating a small effect. The inclusion of habit and its interaction with intention led to an  $f^2$  value of 0.101 for switching, indicating a small to medium effect.

In this study, responses for switching intention and its predictors were collected in a cross-sectional survey, leading to possible common method bias [Straub et al. 2004]. We applied the statistical approach controlling for the effects of a single unmeasured latent method factor, as recommended by Podsakoff et al. [2003], to assess the common method variance among the latent variables. We did not find common method bias to be an issue in interpreting our results.

## V. DISCUSSION

Although Bitner [1990, p. 80, italics added] suggested two decades ago that “Such variables as time or money constraints, lack of alternatives, switching costs, and *habit* all may affect service loyalty”, to date few studies have addressed the specific role of habit in either consumer or IT user switching. Informed by literatures in IS, consumer behavior, and social psychology, we examined the role of user habit in post-adoption switching between personal IT products. Our findings confirm habit as a key mooring factor when users consider a switch to an alternative. Moreover, habit of using the incumbent suppresses the predictive power of intention on switching. Our work advances both marketing and IS literatures by empirically verifying the interrelationship among habit, intention to switch, and switching behavior.

### Implications for Research

Post-adoption IT usage is a complex phenomenon with multiple possible behavioral outcomes [Ahuja and Thatcher, 2005; Kim and Son, 2009]. For many consumer-oriented technologies, there are usually multiple highly substitutable products competing in the marketplace, which leads to users’ proactive and complex decisions regarding how they use these technologies [Lin et al., 2006], including seeking out and trying different alternatives. Our work is among the first that calls attention to the theoretical and practical significance of user switching as a form of post-adoption behavior.

Recognizing the influence of routinized use on post-adoption user switching, we move beyond cognitive reasoning and integrate the habit perspective. Our results confirmed that a user’s habit of choosing an incumbent product will impede his/her intention to switch as well as switching behavior. Studies have shown that at the innovation level, researchers should not ignore the impact of user habit on continued use [Limayem et al., 2007]. Our work further demonstrates the impact of habit in post-adoption technology use at the product level. As habit embodies a person’s automatic response to a specific environmental cue, we expect stronger influence of habit as we move up the ladder of specificity of technology use. Therefore, we contend that the role of habit should not be overlooked as we move our analyses of technology usage into the product or feature level.

As the importance of habit is being demonstrated, it raises a number of interesting questions. For example, under certain situations user switching may be desired by technology vendors or IT managers. As habit of using the incumbent interferes with intended switch, what are the antecedents of habit, and how can the effect of habit be suppressed? Verplanken and Faes [1999] found that implementation intention (a specific plan to carry out intended action) predicts healthy eating behavior independent of intention and counter-intentional habit. Some studies have also suggested that changes in behavioral context can disrupt well-formed habit and allow intention to regain control of behavior [Wood et al., 2005]. Researchers can apply these results in future research of habit and IS usage.

A user’s decision to switch from the incumbent to an alternative involves the evaluations of both products/services. However, prior studies have predominately viewed switching from the perspective of the incumbent product only. Even when the “pull” from the alternative is taken into consideration, it is typically captured by a single construct of alternative attractiveness, as illustrated in Table A-1. Bansal et al. [2005] noted this as one of the main shortcomings in current literature on switching and suggested that “we would benefit from a greater understanding of the specific factors that attract or ‘pull’ customers away” [p. 108]. The near duopoly of the browser market (at the time of data collection) and our research design enabled us to incorporate and test factors capturing the pull of a specific alternative that is competing with the incumbent. By replacing the alternative attractiveness construct with factors representing concrete dimensions users would judge upon an alternative product, we also improved the pull part of the PPM model. Therefore, we call for researchers in both marketing and IS to follow our example and incorporate specific pull factors in future investigations, as it is a promising way to enrich our understanding of both consumer and technology user switching.

### Implications for Practice

For many technology vendors, the fight for market share is intense and it is costly to acquire new users. To excel in the competition, it is crucial for these companies to understand how users choose between alternatives. Our work suggests that users’ habit offers one of the best tools against user defection. Consumer product companies have known the importance of facilitating habitualized consumption for decades. Through meticulously designed marketing campaigns and years of relentless execution, automatic use of certain products was successfully

associated with daily cues for many consumers, e.g., brushing one's teeth after getting up in the morning [Duhigg, 2008]. Consumer technology providers can certainly benefit from applying similar approaches. Moreover, studies [Limayem et al., 2007] have indicated that IS habit can also be promoted by usage comprehensiveness. In addition to habit, our study also suggests that technology vendors should not be complacent with merely keeping existing users satisfied. They need to constantly offer better products with valuable features, and communicate and advertise the benefits of their products to their users. To encourage retention, they can also apply strategies such as loyalty programs to strengthen the perceived switching barrier.

When it comes to winning over users from the competitors, it is also critical to understand how users switch to a new product. As the use of many personal technologies is habitual, a new product needs to be designed to take advantage of rather than working against existing routines. For example, if a new application detects a shortcut to a competitor's product placed on the user's Windows Quick Launch bar, it could offer to place a shortcut right next to it. Our findings also indicate that technology users are convinced to switch by concrete, specific benefits of an alternative, such as relative advantage, ease of use, and security, rather by merely an appeal to their desire to try something new and different. To facilitate switching, it is necessary to reduce switching costs by making the switching process as effortless as possible. For example, although most Web browsers can import simple settings such as bookmarks from a competing browser, the burden is often put on the users to transfer other necessary information such as saved form data, history, stored sessions, cookies, display settings, security configurations, proxies, and plug-ins and associated settings. Even after taking the initiative to install an alternative, a user may still abandon the switch if s/he found it is not worth the effort to set up the new application. Taken together, provider of a new entrant needs to achieve the delicate balance between being innovative and in the meantime being sufficiently similar to an entrenched incumbent.

### Limitations and Future Research

The implications of our results should be viewed with several limitations in mind. For any empirical research, the generalizability of the findings is limited by various aspects of the research design. Our study is not free of these constraints. While our definition of user switching accommodates both partial and complete switches, the present study only addresses the former type of switch empirically. For some personal technologies, an individual cannot use multiple offerings concurrently, and only an all-or-none switch is possible. The predictive power of the push-pull-mooring framework on such type of switches remains to be evaluated.

University students represent the section of Internet users who are well-versed in Internet technology. This sample issue may be mitigated in the present study by the fact that a large portion of the students at the university where we collected our data are nontraditional students, and the fact that switching is an issue more germane to experienced users than to novice and casual users. Nevertheless, a replication with a sample that better represents the general, and global, Internet population can help confirm the robustness of our findings and identify cultural factors that may influence a particular demographic. The cross-sectional research design also limits our ability to empirically verify the causal relationships between the predictors and switching intention.

Similar to most prior research, the present study relied on respondents' self-reported usage to measure switching behavior. Individual bias and inaccuracy in each respondent's interpretation and estimation of usage can lead to measurement error. We encourage the development of objective measures of users' actual usage in future studies of technology switching. Given the 24/7 nature of the usage of many personal products, capturing usage objectively for each respondent poses challenges to the researchers. However, such difficulty is not insurmountable with carefully selected technologies, for example, online services for which login/logoff and clickstream information of specific users can be obtained with assistance from the vendors. In addition, compared to other constructs pertaining to specific browsers, perceived switching costs is more likely to have a measurement error issue, because respondents were not instructed to make the evaluation based on their named alternative browsers.

Technologies such as Web browsers are available to the users at both workplaces and home. Using the Web for personal purpose is not uncommon at workplaces, where corporate standards rather than personal choices determine the Web browser available. Therefore, although the respondents were instructed to answer the survey according to their personal use of the Web only, the predictive power of the research model is nonetheless constrained by the confounding effects of potential workplace usage. Furthermore, transient factors such as network accessibility and Internet speed may also cause fluctuations in a respondent's usage of different browsers.

The primary focus of this study is the role of habit in IT user switching. Therefore, in constructing our research model, besides habit, we include only the key factors that are likely to influence user switching across a wide range of personal IT products or services. We eliminated many variables applicable only in more specific contexts, such as relationship quality or price equity. User switching is certainly a product category dependent phenomenon, and the PPM model can serve as a guideline for researchers who wish to identify salient factors for user switching of any

specific type of technologies. We believe user switching in technology services should be one area of particular interest. From B2C offerings in traditional industries to Web 2.0 services, users face multiple competing alternatives for many technology enabled services. In the service context, there is a set of unique constructs such as trust, commitment, network externality, and price differentiation that could also motivate or moderate user switching. Opportunities for empirical research efforts in this area are abundant—the battle between Netflix and Blockbuster for online video rental subscribers makes a perfect setting, just to name an example.

The selection of Web browsers as the focal technology put into question how much our conclusions apply to other technologies such as mp3 players and video game consoles that are hardware centered and/or with more hedonic utility. In addition, at the time of data collection, the Web browser market was dominated by two major products that are well acquainted to many users. Our model needs to be confirmed under different market settings, for example, when a new entrant is introduced to a monopolized market.

Our model is intended to explain the switching of individual technology users. Business organizations also have to choose between alternative technology products and services frequently, and switch from one product or service to a substitute with similar functionalities. It could be a choice to switch from one brand of network routers to another brand, from one antivirus software to a competitor's offering, or from one cloud service provider to another vendor. The switching of IT products and services at the enterprise level has profound implications, and to date few studies have explored this critical issue [Whitten and Leidner, 2006]. Some of the individual level constructs such as satisfaction and switching costs [Lam et al., 2004] still apply in a business-to-business context. However, organizations have to consider many other factors such as ease of deployment, availability of expertise, standardization and vendor lock-in, compliance, and quality of support in their selection of technology products. Therefore, while our subjects were completely free to switch to a chosen technology, we might expect decision makers in organizations to have less freedom. Ultimately, these circumstances serve to raise more questions and stimulate more scholarly work on the important issue of technology switching in different contexts, at both individual and organizational levels.

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*Editor's Note:* The following reference list contains hyperlinks to World Wide Web pages. Readers who have the ability to access the Web directly from their word processor or are reading the article on the Web, can gain direct access to these linked references. Readers are warned, however, that:

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## APPENDIX A: SUMMARY OF PRIOR STUDIES ON PREDICTING SWITCHING

**Table A-1: Summary of Prior Studies on Predicting Consumer and Technology User Switching (1995–2009)**

Study	Industry	Theory	Data Collection Method/Unit of Analysis	Dependent Variable †	Factors Found to be Direct Antecedents to Switching (Ordered by Effect Size When Applicable)
Bolton and Bronkhorst [1995]	Cellular service	NA	Survey / Individual	B	Customer satisfaction; customer complaint
Keaveney [1995]	Various services	NA	In-person interviews / Individual	B	Pricing; inconvenience; core service failures; service encounter failures; employee responses to service failures; attraction by competitors; ethical problems; involuntary switching
Zeithaml et al. [1996]	Computer manufacturing; retail; automobile insurance; life insurance	NA	Mail survey / Individual and business customer	I	Service quality
Mittal and Lassar [1998]	Health care and care repair	NA	Survey / Individual	I	Customer satisfaction; service quality
Mittal et al. [1998]	Primary care physician	N/A	Telephone interview / Individual	I	Satisfaction; performance
Bansal and Taylor [1999]	Mortgage	Service Provider Switching Model	Mail and phone survey / Individual	I and B	Satisfaction; attitude; switching costs; service quality; perceived relevance; subjective norms
Athanassopoulos [2000]	Banking	N/A	Survey / Individual and business	B	Satisfaction; age
McDougall and Levesque [2000]	Dentist; auto service; restaurant; haircut	N/A	Survey / Individual	I	Satisfaction
Colgate and Hedge [2001]	Banking	N/A	Mail survey / Individual	B	Pricing problems; services failures; denied services
Keaveney and Parthasarathy [2001]	ISP	NA	Mail survey / Individual	B	Source of information; service usage; propensity for risk-taking behavior; income; education; satisfaction; involvement
Lee and Cunningham [2001]	Banking and travel agency	N/A	Survey / Individual	I ‡	Switching costs; transaction cost; service quality
Liu et al. [2001]	Banking	Culture theories	Survey / Individual	I	Uncertainty avoidance; individualism; masculinity
Bansal and Taylor [2002]	Mortgage	Theory of Planned Behavior	Mail survey and phone interview / Individual	I and B	Attitude; perceived behavioral control



**Table A-1: Summary of Prior Studies on Predicting Consumer and Technology User Switching (1995–2009) – Continued**

Chen and Hitt [2002]	Online brokerage	NA	Archival data (clickstream and Gomez ratings) / Individual and brokerage firm	B	Individual: website usage; change in usage; use of multiple brokers; Firm: website quality, product line breath
Burnham et al. [2003]	Long distance telephone; credit card	NA	Survey / Individual	I ‡	Satisfaction; switching costs
Capraro et al. [2003]	Health insurance	N/A	Mail survey / Individual	B	Knowledge about alternatives; switching risk; satisfaction
Patterson and Smith [2003]	Travel agency; medical service; hairdresser	N/A	Survey / Individual	I ‡	Switching barriers; satisfaction
Ranaweera and Prabhu [2003]	Fixed line telephone	N/A	Mail survey / Individual	I	Satisfaction; trust; switching barrier
Verhoef [2003]	Insurance	NA	Longitudinal survey and archival data / Individual	B	Affective commitment; loyalty program
Bansal et al. [2004]	Auto repair	N/A	Mail survey / Individual	I	Alternative attractiveness; normative commitment; continuance commitment
Chakravarty et al. [2004]	Banking	N/A	Mail survey / Individual	I	Service quality; age; duration of relationship; past problems; past switching
Gerrard and Cunningham [2004]	Banking	N/A	In person survey / Individual	B	Pricing; service failures; inconvenience
Kim et al. [2004]	Mobile phone	NA	In person survey / Individual	I ‡	Satisfaction (determined by service quality); switching barrier (determined by switching cost and interpersonal relationship)
Bansal et al. [2005]	Auto repair; hair styling	PPM frame-work	Mail and telephone survey / Individual	I and B	<i>Push factors:</i> Low quality; low satisfaction; low value; low trust; low commitment; high price perception <i>Pull factor:</i> Alternative attractiveness <i>Mooring factors:</i> Unfavorable attitude towards switching; unfavorable subjective norms; high switching costs; infrequent prior switching behavior; low variety seeking

**Table A-1: Summary of Prior Studies on Predicting Consumer and Technology User Switching (1995–2009) – Continued**

Fullerton [2005]	Financial services; retail-grocery services; tele-communications services	N/A	Personal interview and paper survey / Individual	I	Affective commitment; continuance commitment; affective commitment X continuance commitment; service quality
Gounaris [2005]	Middle and senior management training and recruitment services	N/A	Mail survey / Company	I ‡	Affective commitment
Gustafsson et al. [2005]	Phone and Internet services	N/A	Survey and archival data / Individual	B ‡	Satisfaction; calculative commitment; prior switching; satisfaction X prior switching
Lui [2005]	Mobile data service; ISP	PPM frame-work	Online survey / Individual	I	<i>Push factors:</i> Satisfaction; perceived price equity. <i>Pull factor:</i> Attractiveness of alternative <i>Mooring factors:</i> perceived switching cost; perceived service value ambiguity
Walsh et al. [2005]	Energy supplier	NA	Survey / Individual	I	Satisfaction; monetary-motivated curiosity
Kim et al. [2006]	Email service	NA	Online survey/Individual	I	User satisfaction; switching costs; attractive alternatives
Lopez et al. [2006]	Fixed line telephone	N/A	Survey/Individual	B	Attitude toward the service; breadth of usage; marital status; family structure; length of usage; depth of usage; age
Ranganathan et al. [2006]	Mobile phone	Theories of relationship Marketing and switching costs	Archival data / Individual	B	Relational investments (service usage, relationship duration, service bundling) demographics (age and gender)
Carmen et al. [2007]	Car insurance	N/A	Survey / Individual	I	Price unfairness; satisfaction; anger incident
Eshghi et al. [2007]	Wireless phone	N/A	Phone survey / Individual	I	Satisfaction; wireless orientation
Li et al. [2007]	E-commerce websites	N/A	Survey / Individual	I	Satisfaction; trust; commitment; comparison level of alternatives; non-retrievable investment
Wieringa and Verhoef [2007]	Energy supplier	NA	Survey and archival data / Individual	I	Relationship quality; switching costs; attractiveness of switching; usage



**Table A-1: Summary of Prior Studies on Predicting Consumer and Technology User Switching (1995–2009) – Continued**

Shin and Kim [2008]	Mobile phone	NA	Telephone survey / Individual	I	Customer satisfaction; perceived switching barriers; demographics (age and education)
Ye et al. [2008]	Web browser	NA	Survey / Individual	B	Breadth of use; satisfaction; relative advantage; perceived ease of use; perceived security
Zhang et al. [2008]	Blog service	PPM frame-work	Online survey/Individual	I	<i>Push factor:</i> Satisfaction. <i>Pull factor:</i> attractive alternatives. <i>Mooring factor:</i> switching costs
Hou et al. [2009]	Online games	PPM frame-work	Online survey / Individual	I	<i>Pull factor:</i> alternative attractiveness <i>Mooring factors:</i> switching costs; social relationships; prior switching experience

\* Studies prior to 1995 generally focused on brand switching of frequently purchased consumer products, with price deals and variety seeking as the main explanatory variables. These studies are not listed in the table.

† I: intention to switch; B: switching behavior

‡ The dependent variable in these studies is intention to stay with an incumbent or the staying behavior. Given the types of services studied, we can reasonably assume that consumers will switch to an alternative if they chose not to stay. Therefore, we consider these studies as related to prediction of switching intention/behavior also.

## APPENDIX B: MEASURES

### Web Experience

First, how long have you been using the Internet? \_\_\_\_\_ years.

### Browser Awareness

Please select all the browsers you are *aware of*, regardless of whether you have ever used it yourself.

\_\_\_\_\_ Chrome \_\_\_\_\_ IE \_\_\_\_\_ Firefox \_\_\_\_\_ Netscape \_\_\_\_\_ Opera \_\_\_\_\_ Safari \_\_\_\_\_ (Other)

Please tell us the name of the browser if you selected “Other” above. \_\_\_\_\_

### Browser Usage

Please select the browser you consider as your primary Web browser—the browser that you use the most for all your Internet related activities.

[A list of Web browsers the respondent is aware of.]

Please give us a percentage breakdown of your non-workplace usage of different Web browsers, based on your browser usage *in the past week*. Your best estimate is fine. Please make sure the total adds up to 100%.

[A list of Web browsers the respondent is aware of.]

### Alternative Browser

Now, imagine that you want to switch to a different browser, which one of the following would you most likely to consider?

[A list of Web browsers the respondent is aware of, minus the primary browser.]

### Habit [Limayem et al., 2007]

Choosing [name of primary browser] to browse the Web has become automatic to me.

Using [name of primary browser] to browse the Internet is natural to me.

When I need to browse the Web, using [name of primary browser] is an obvious choice for me.



*Satisfaction* [Bhattacharjee, 2001]

On a scale from 1 to 7, please select a score for each pair of words that describe your overall experience of using [name of primary browser]:  
Very dissatisfied ... Very satisfied.  
Very displeased ... Very pleased.  
Very frustrated ... Very contented.  
Absolutely terrible ... Absolutely delighted.

*Subjective Norm* [Taylor and Todd, 1995]

People who influence my behavior would think that I should switch my Web browser to [name of alternative browser].  
People who are important to me would think that I should use [name of alternative browser] as my browser.

*Perceived Switching Costs* [Bansal et al., 2005]

On the whole, I would spend a lot of time and effort to switch my browser from [name of primary browser] to another browser. (*Item dropped due to unsatisfactory loadings*)  
Generally speaking, the costs in time, effort, and grief to switch from [name of primary browser] to a different browser would be high.  
Considering everything, the costs to stop using [name of primary browser] and start up with another Web browser would be high.

*Perceived Relative Ease of Use* [Moore and Benbasat, 1991]

Compared with [name of primary browser]:  
My interaction with [name of alternative browser] would be more clear and understandable.  
I believe that it would be easier to get [name of alternative browser] to do what I want it to do.  
Overall, I believe that [name of alternative browser] would be easier to use.  
Learning to use [name of alternative browser] would be easy for me.

*Relative Advantage* [Venkatesh et al., 2003]

Compared with [name of primary browser]:  
Using [name of alternative browser] enables me to accomplish tasks on the Web more quickly.  
Using [name of alternative browser] improves the quality of work I do on the Web.  
Using [name of alternative browser] makes it easier to browse the Web.  
Using [name of alternative browser] enhances my effectiveness using the Web.  
Using [name of alternative browser] increases my productivity when I browse the Web.

*Perceived Relative Security* [Salisbury et al., 2001]

Compared with [name of primary browser]:  
I would feel secure sending sensitive information using [name of alternative browser].  
[name of alternative browser] is a secure Web browser through which to send information.  
I would not give out sensitive information using [name of alternative browser]. (Reverse item)  
Overall, [name of alternative browser] is a safe Web browser to transmit sensitive information with.

*Intention to Switch* [Bansal et al. 2005]

Please rate the probability that you would switch from [name of primary browser] to [name of alternative browser] within the next 2 months. (All questions anchor on a 1 to 7 scale.)  
Very Unlikely ... Very Likely  
Improbable ... Probable  
No chance ... Certain

*Demographics*

Your Gender: \_\_\_\_\_ (M) \_\_\_\_\_ (F)  
Your Year in School: \_\_\_\_\_ (freshman) \_\_\_\_\_ (sophomore) \_\_\_\_\_ (junior) \_\_\_\_\_ (senior) \_\_\_\_\_ (graduate) \_\_\_\_\_ (Other)

Note:

1. Except satisfaction and switching intention, all perceptual measures use a 7-point Likert scale with Strongly disagree = 1 and Strongly agree = 7.
2. The same questions for browser awareness and browser usage were used for both waves of the survey.
3. Throughout the survey, the respondents were reminded to answer all questions according to their personal use of the Web only.

## ABOUT THE AUTHORS

**Chen Ye** is an assistant professor of Management Information Systems at the Reginald F. Lewis School of Business, Virginia State University. He received his M.S. and Ph.D. in MIS from University of Illinois at Chicago. His primary research interest is information technology usage at the individual level. He has published his research in *Communications of the ACM*, *Journal of the American Society for Information Science and Technology*, and *International Journal of Product Development*.

**Richard Potter** is an associate professor of Information and Decision Sciences at the College of Business Administration of the University of Illinois at Chicago. He received his MS and Ph.D. from the University of Arizona. His primary research interests include cognition and behavior in computer-supported environments, virtual team interaction, performance, and collaboration, and executive management of information systems and resources. He has published his research in *MIS Quarterly*, *Database*, *International Journal of Human Computer Interaction*, *Communications of the ACM*, and other leading journals.



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