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POST-ADOPTION SWITCHING BETWEEN TECHNOLOGY SUBSTITUTES: THE CASE OF WEB BROWSERS

Web-based Information Systems and Applications

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Abstract

In this study, we examine factors that influence users’ post-adoption switching between technology products that are near perfect substitutes. The recent introduction of Mozilla Firefox Web browser provided an ideal empirical setting for this study. Drawing upon literature on post-adoption user behavior, consumer behavior, and online consumer research, we proposed a research model and validated it using cross-sectional field data collected from 306 users on their decisions to switch from Microsoft Internet Explorer to Mozilla Firefox. Findings suggest that user satisfaction and breadth of use of the incumbent product are negatively associated with switching behavior, and perceived ease of use, relative advantage, and perceived security of the substitute product are positively associated with switching behavior. This study contributes to both research and practice by advancing our understanding of users’ post-adoption behavior in general and their switching behavior on Web-related technology products in specific.

Keywords: Post-adoption behavior, user switching, technology substitution, Web browsers.

Introduction

Consumer technologies such as mobile devices and Web browsers are getting increasingly popular. These technologies are characterized by their ease of procurement by consumers, and the simultaneous ease with which users1 can upgrade, abandon, or switch from one product to a substitute. An increasing number of these consumer technologies are Web-enabled. As an open standards-based and ubiquitous technology, the Internet allows products and services to be available to individuals distributed around the globe, using a variety of computing platforms. The Web browser serves as individuals’ doorway to the Internet and plays a crucial role in consumers’ online transaction environment. In this study, we examine consumers’ switching between competing offerings of Web-related and substitutable technology products. Specifically, we examine the factors that lead consumers to switch their Web browser from Microsoft Internet Explorer (IE) to Mozilla Firefox.

1 In this paper, user and consumer are generally interchangeable and we use either of them depending on the context.
Examination of user switching between technology products is critical for several reasons. First, many consumer technology products are increasingly commodity-like. Similar to other types of physical commodities, the cost of acquiring these products is lowering every day, and competing products from different providers are often near perfect substitutes. This poses an interesting problem for technology vendors – how to hold on to their existing customer base and prevent them from switching over to competitive offerings? Understanding the drivers of switching behavior is the first step toward preventing customer attrition. Second, competitive offerings of products have a lot in common and little in the way of differentiations. For example, if we compare IE and Firefox, we would find that the basic features they offer are about the same. To the novice users it will be difficult to make clear cut distinctions between them. This poses an interesting question for researchers – what perceived characteristics of technology products make it more likely for a user to switch? We should note that we are concerned with perceived rather than actual factors because we believe that it is customer perception of particular attributes of particular technology products that influence switching behavior.

User switching between technology products is also interesting to study because it represents a form of post-adoption behavior that is generally unexplored in the IS literature. While there is an abundance of literature on technology adoption (e.g. Davis 1989), only recently have researchers started to examine post-adoption issues (e.g. Jasperson et al. 2005). Among these studies, we believe that we are one of the first to study the switching behavior that is associated with the abandoning of one technology product in favor of a substitute.

The rest of the paper is organized as follows. We first review the relevant literature in IS and marketing. Then we present our theoretical model and research hypotheses. The research methods section starts with a detailed discussion on Web browsers, including the reasons for choosing it as the technology artifact in this study, followed by data collection procedure and the methodology for data analysis. We conclude this paper with discussion of the results, limitations, and implications of our study.

**Literature Review**

Two streams of literature provide key insights regarding technology users’ post-adoption switching behavior: post-adoption user behavior studies in the IS literature; and consumer switching behavior in the marketing literature. Both literature streams are discussed in the following sections.

**Post-Adoption Studies in the IS literature**

How user beliefs and attitudes influence their adoption and acceptance of technologies has been one of the main research areas in the IS literature (e.g. Davis 1989; Venkatesh and Davis 2000). Readers interested in a comprehensive review of previous models in the technology acceptance literature can refer to Venkatesh et al. (2003)’s paper, in which they also formulated the Unified Theory of Acceptance and Use of Technology (UTAUT). Recently, researchers have recognized that successful adoption does not always predict continued use and overall IS success, therefore, the need to study the issue of post-adoption user behavior (e.g. Bhattacharjee 2001; Parthasarathy and Bhattacharjee 1998).

Among the earliest literature that addressed post-adoption user behavior, Karahanna et al. (1999) is especially worth noting. In this study, the authors considered post-adoption behavior as continued use, and applied pre-adoption beliefs from the technology acceptance literature to study intention to continue using a technology post-adoption. Their findings suggested that some of the pre-adoption beliefs such as perceived usefulness continue to influence post-adoption use. However, the relative strength of these factors changed after the users gained experience using the technology.

Similar to the Karahanna et al. (1999) study, most of subsequent post-adoption studies also focused on what drive users’ continued use after initial adoption. Most of these studies also view continuance at least partially as an extension of adoption behaviors and applied the same constructs from adoption research in predicting post-adoption continuance (e.g. Kim and Kim 2003). Most of these studies have also acknowledged the importance of users’ beliefs and attitudes that emerged from their usage experience after initial adoption. Consequently, constructs such as satisfaction/dissatisfaction (Bhattacharjee 2001; Limayem et al. 2003), habit (Jasperson et al. 2005; Limayem et al. 2003), and actual usage (Kim and Malhotra 2005; Parthasarathy and Bhattacharjee 1998) have been integrated into models that predict continued use.
A few most recent studies have also looked beyond innovation adoption literature and applied different theoretical perspectives in understanding post-adoption behavior. Jha et al. (2006) applied attribution and organizational justice theories to explore how users’ perceptions resulted from a technology failure incident and the subsequent complaint management process will affect their intentions to discontinue using the technology. Grounded in the theory of trying, Ahuja and Thatcher (2005) proposed trying to innovate with IT as a dependent variable; and found that perceptions of the work environment such as overload and autonomy influence level of trying to innovate with IT.

While most of past research in post-adoption behavior focused on users’ continued use, it generally does not make distinction between the innovations and the specific technology products that represent them. In reality, for any given technology, there are often multiple products that are similar in functionality, highly substitutable, and direct competition to each other. In this situation, a user’s decision to use a specific technology product is often accompanied by termination or reduction in usage of another product that carries similar functions. Such behavior is a post-adoption behavior that is different from the continuance/discontinuance behavior often considered as equivalent of post-adoption behavior in prior research. As Bhattacharjee (2001, pg 352) pointed out, continuance, or continued use, is “a post-acceptance stage when IS use transcends conscious behavior and becomes part of normal routine activity.” This concept is analogous to what Cooper and Zmud (1990) refer to as “routinization”, or the “confirmation” stage described in innovation diffusion theory (Rogers 2003). Therefore, unlike switching behavior, the discontinuance of usage would entail the complete removal of an innovation from a user’ routine activity.

To illustrate with an example, consider a user who started chatting online using MSN Messenger. After some time, the use of instant messaging has become part of her daily routine in communicating with her friends and family. However, later she decided to pick up Yahoo Messenger as her new primary instant messaging client and reduced or stopped using MSN Messenger. While her initial decision to use MSN Messenger represents adoption of the instant messaging technology; her subsequent decision to terminate or reduce using MSN Messenger in favor of Yahoo Messenger represents a switching behavior. On the other hand, if for any reason she decided to abandon instant messaging as a communication tool and went back to rely on emails or telephone, it would be considered as a discontinuance behavior. The literal term - “switching” may imply the complete change of use of one product to another. However, like some consumer-oriented services such as credit cards or banking, concurrent usage of competing technology options is often possible and sometimes necessary. For example, she might still use MSN Messenger for chatting with some of her friends, because they only use an older version of MSN Messenger that is not interoperable with Yahoo Messenger. Therefore, in this paper, we define user switching as IT users’ termination or significant reduction in usage of one technology product while replacing it completely or substituting it largely with an alternative product that satisfies identical needs.

Despite the significance of technology user switching, there are only a few empirical studies addressing related issues in the IS literature. For example, Chen and Hitt (2002) studied user switching cost of online brokerages, and found user usage pattern and Website characteristics such as ease of use, quality, breadth of offering to be the determinants of user switching behavior. However, they relied on secondary data such as aggregated user rankings provided by third party Web sites for measuring firm characteristics. This limits their unit of analysis to the firm level. Ranganathan et al. (2006) studied the impact of mobile phone users’ relational investments and demographics on their switching behavior. Their reliance on archival data also restricted their ability to evaluate the influence of users’ psychological motivations on switching behavior.

In summary, our review of past research on post-adoption user behavior and user switching in the IS literature reveals that there exists a research gap which requires us to move beyond the continuer vs. discontinuer dichotomy and examine how individual users’ perceptual factors impact their post-adoption switching between technology substitutes.

**Consumer switching behavior in the marketing literature**

Marketing researchers have studied consumers’ switching behavior extensively (e.g. Keaveney 1995; Walters 1991). Traditionally, researchers have focused on consumer switching between frequently purchased consumer products. These studies usually examine the impact of marketing practices such as price promotions or advertisements on product or brand substitution in retail settings (e.g. Kumar and Leone 1988; Walters 1991).

Recently, researchers have also turned their attention to customer switching in service industries such as credit card (Burnham et al. 2003), banking (Ganesh et al. 2000), and Internet Service Providers (Keaveney and Parthasarathy 2001). Studies in this stream focused more on individual beliefs and personalities as determinants of customer
switching behavior. Not surprisingly, most of the antecedents to customer switching studied were directly related to perception or experience of the incumbent product or service. One of the main antecedents to customer switching is customers’ dissatisfaction toward the incumbent (e.g. Ganesh et al. 2000; Keaveney and Parthasarathy 2001). In addition, other product-related factors such as breadth of use (Keaveney and Parthasarathy 2001) and perceived switching costs (Burnham et al. 2003), and individual traits such as consumer risk aversion (Ganesh et al. 2000; Keaveney and Parthasarathy 2001) were also found to influence switching behavior.

Although consumer switching has received unflagging attention in the marketing literature, their findings do not fully explain user switching between technology substitutes for a few reasons. Marketing practices such as price promotions have the most impact on product or brand substitution of goods that are not free, differentiated in price, and most importantly, purchased repeatedly and frequently by the consumers. These conditions do not always hold for technology products. On the other hand, technology products are also different from subscription-based services such as banking or insurance, where customers have to commit to ongoing relationships. More importantly, we cannot ignore the rich set of technology specific characteristics that have been discovered in the IS literature when we try to theorize on a research issue where the IT artifact is clearly present (Orlikowski and Iacono 2001). Therefore, to fully understand technology switching behavior, we also need to take into consideration the factors that are salient and unique to technology products discussed in the IS literature.

Research Model

The main interest of our study is how user perceptions of the attributes and use of technology products influence their switching from an incumbent to a substitute product. Therefore, building on our review of extant literature, with the aim to balance predicting power and parsimony, we identified five factors that affect users’ switching behavior, as illustrated in Figure 1. Our model concentrates on customers’ breadth of use and satisfaction for the incumbent product, and three factors capturing user perceptions of the substitute. Two of them – relative advantage and perceived ease of use – were drawn from the IS literature and represent users’ expectancy on the performance of technologies, and users’ expectancy on the effort in using technologies, respectively (Venkatesh et al. 2003). In addition, perceived security was included because it has lately been identified as a salient factor impacting IS user behavior, especially, user behavior related to Internet-based information system and applications.

As pointed out by Moore and Benbasat (1991, pp. 198): “innovations typically are developed with certain purposes in mind, and they must be perceived to fulfill their intended purposes better than their precursors if they are to be adopted.” Therefore, in the innovation adoption literature, although it is not indicated explicitly in the definitions of perceived characteristics such as usefulness, it is generally assumed that users will evaluate an innovation with implicit comparisons with its precursors. Likewise, users will evaluate the substitute product on the three perceived characteristics with implicit comparisons with the incumbent product, and we do not indicate explicitly the comparative aspect of these factors in our model.

Our model also included three control variables to account for the effects of product-independent factors that may also promote or prohibit user switching. The following sections develop research hypothesis for each factor.
Figure 1: Factors Influencing Users' Switching Behavior of Web Browsers

Breadth of Use

Breadth of use refers to the degree to which a user uses the features offered by a certain product or service. Technology products, especially software products, often come with a variety of features and options enabling the users to tailor the products to better serve their individual needs. These features and options differ in their usefulness and difficulty to master, and users often differ in how much they take advantage of these features and options. Studies have found breadth of use to be an inhibitor of consumer switching in industries such as online brokers (Chen and Hitt 2002) or credit card and long distance phone providers (Burnham et al. 2003). However, the theoretical underpinning for the impact of breadth of use is not clearly discussed in existing literature. We reviewed relevant economics and consumer behavior literature and found the effect of breadth of use can be best explained by the concept of sunk costs and its associated behavioral ramifications.

Sunk costs are costs that have already been incurred and cannot be recovered (Arkes and Ayton 1999). Sunk costs are normally incurred during the start of an activity and represent the investment required to get the effort started. It is important to note that sunk costs represent the portion of investment that cannot be recovered after the termination of an activity, even after the resale of assets. For example, when someone is planning a vacation, the time and effort invested in researching the destination and the non-refundable portion of any reservations made in advance would be sunk costs. Sunk costs influence individuals' decision-making through individuals' loss-aversion, which means that people will prefer to avoid losses than acquire gain (Maxham and Netemeyer 2002). Therefore, if our vacationer learned before the trip that there will be unexpected unpleasant weather at the destination, although a more rational decision would be switching to another destination, he might still take the trip instead because he is reluctant to lose the effort and money he had already invested.

In the context of Web browsers, the time and effort one spent on learning the features and customizing his Web browser can be considered as sunk costs. This can be significant depending on his breadth of use of the browser. Expert users may take it upon themselves to customize the browser, integrate it with other applications, and install various plug-ins to help ease their work. Therefore, higher breadth of use leads to higher sunk costs for a user. The more features a user uses, the more time and effort he would have spent on customizing his browser, the less likely he will be willing to switch to a substitute.

**H1: Greater breadth of use of the incumbent product (IE) is negatively related to switching behavior**

User Satisfaction

Individuals constantly make satisfaction judgments on products and services they have consumed. The expectancy-disconfirmation theory has been used widely to explain how consumer satisfaction decisions are formed (Oliver...
Consumers use pre-consumption expectations on product performance as the standard to compare actual product performance post-consumption. Disconfirmation occurs as a result of such comparison. Consumer satisfaction is a function of expectations and disconfirmation. When product performance exceeds previously held expectations, positive disconfirmation occurs and consumer satisfaction increases, and vice versa.

Consumer satisfaction has been studied extensively by marketing researchers (e.g. Churchill and Surprenant 1982; Oliver 1980), and has been shown to be an important antecedent to repeated purchase intention and brand loyalty (Anderson and Sullivan 1993; Bearden and Teel 1983). Studies in consumer switching behavior have identified satisfaction as a reliable predictor to consumer switching in a variety of industries (e.g. Burnham et al. 2003).

User satisfaction is not a novel construct to IS researchers. However, many IS studies have treated user satisfaction as a dependent variable that represents IS success, rather than an independent variable that influences user behavior (Delone and McLean 1992). Among those using user satisfaction as predictor of post-adoption behavior, it has been found to be a predictor of system use (e.g. Bhattacherjee 2001; Wixom and Todd 2005). We think when users face a substitute technology product; the level of satisfaction on the incumbent product will influence their decision to switch. For Web browsers, the more a user is dissatisfied with her experience with IE, the more likely she is to switch to a substitute when it becomes available.

**H2: User satisfaction with the incumbent product (IE) is negatively related to switching behavior**

**Relative Advantage**

The relative advantage of an innovation is identified in the Diffusion of Innovations theory as one of the perceived characteristics that influences its adoption (Rogers, 2003). Relative advantage can be interpreted as the degree to which a technology is perceived as being more beneficial than its substitute technologies. Benefits can be economic advantages or productivity increases. The more apparent the superiority of a technology, the easier it is for people to distinguish its relative advantage. Relative advantage has been found to be related to user decisions regarding adoption and usage in the IS literature (Moore and Benbasat 1991; Taylor and Todd 1995). Regarding specific technology products, if users perceive more advantages by using one product compared to another, they are likely to want to use that product. Hence, we believe the greater the perceived relative advantage of Firefox compared to IE, the more positively people will be swayed to use Firefox.

**H3: Relative advantage of the alternative product (Firefox) is positively related to switching behavior**

**Perceived Ease of Use**

Perceived ease of use (PEOU) is one of the key variables introduced in the technology acceptance model (TAM), which was developed as an extension of theory of reasoned action (TRA) (Ajzen and Fishbein 1980) to model how users come to accept and use a technology (Davis et al. 1989). There are five variables in TAM: perceived usefulness (PU), PEOU, attitude, behavioral intention, and behavior. PU is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance,” and PEOU is defined as “the degree to which a person believes that using a particular system would be free of effort” (Davis 1989, pg. 320). According to TAM, both PU and PEOU affect behavioral intention to use information technology directly or indirectly though attitude, and behavior is the direct function of behavioral intention. PU is analogous to relative advantage we have discussed previously (Moore and Benbasat 1991; Taylor and Todd 1995). Therefore, our next hypothesis will focus on the PEOU of Firefox. Studies have confirmed that users are more likely to accept and adopt a particular technology if they consider it as being easy to use (e.g. Moore and Benbasat 1991; Pavlou and Fygenson 2006). In the context of browser switching, the more users perceive Firefox as a Web browser that is effortless to use, the more likely they will be to switch from IE.

**H4: Perceived ease of use of the alternative product (Firefox) is positively related to switching behavior**

**Perceived Security**

Information security has received tremendous amount of attention in both popular press and academic literature (e.g. Bank 2005; Straub 1990; Whitman 2003). As computer technologies permeate every aspect of individuals’ daily lives as well as the daily operations of business organizations, the actual damages from security threats such as
computer viruses, network intrusions, and denial of service attacks have also become increasingly severe (Evers 2006; Federal Bureau of Investigation 2006). Studies have documented IT executives’ and end users’ growing concerns with the security of information systems (e.g. Goodhue and Straub 1991; Straub and Welke 1998; Whitman 2003).

The constant expansion of the Internet has not only brought rapid growth in Internet based commerce, but also new breeds of security threats such as spywares and phishing scams that specifically target individual users. Therefore, individual users are especially concerned about the security of on-line electronic transactions and the risk of losing their social security, bank account, or credit card numbers to unscrupulous parties. As a result, end users’ perception of information security has become one of the primary factors when choosing Internet related services (Cyber Security Industry Alliance 2005; Salisbury et al. 2001). Studies have also suggested that the effect of perceived security on individuals’ online behavior is mediated by their trust in the online environment to conduct electronic transactions (Chellappa and Pavlou 2002).

Past literature has investigated consumers’ perception on overall Internet security and security of specific Web based applications. However, perceived security of Web browser – one of the key component of the online environment – has not received much attention in the academic literature. Individual users are more vulnerable to security threats than organizations because many lack sufficient knowledge or resources to deploy and manage hardware or software such as a firewall that is solely dedicated to secure their personal computers. Users therefore try to mitigate this by preferring applications that they perceive as being more secure. Specific to Web browsers, the security vulnerabilities of IE and Firefox’s actual and perceived advantages in browser security has been documented in many industry journals (e.g. Desouza et al. 2006; Goth 2004; Lyman 2005). Thus, we hypothesize that higher perception of the security of Firefox will be positively associated with user switching behavior.

**H5: Perceived security of the substitute product (Firefox) is positively related to switching behavior**

**Control Variables**

Users’ switching behavior may be influenced by their personal characteristics or outside influences perceived by the user, irrespective of the alternative products under consideration. Therefore, the following variables were controlled in our study:

*Computer self-efficacy*, defined as an individual’s perception of his/her capabilities in performing computer related tasks (Compeau and Higgins 1995), has been used by scholars in explaining a range of user behavior in the domain of computing (e.g. Compeau and Higgins 1995; Taylor and Todd 1995). Some of these studies supported the notion that higher computer self-efficacy leads to increased rate of technology adoption and usage (e.g. Thong et al. 2004).

*Risk aversion* is a personality trait used in the marketing literature to measure individuals’ propensity to perform variety seeking behavior (Givan 1984; Raju 1980). Research has shown empirically that consumers with low risk aversion are more likely to try or switch to different products or services (Ganesh et al. 2000; Keaveney and Parthasrathy 2001).

*Social influence* is analogous to the subjective norm construct incorporated in the Theory of Planned Behavior (TPB) (Azjen 1991) and defined as the “perceived social pressure to perform or not to perform the behavior” (Azjen 1991, p.188). In TPB, subjective norm is considered as an antecedent to an individual’s intention to perform certain behavior. In the IS literature, studies have found social influence to be a predictor of users’ intention to use technologies, especially under organizational settings (e.g. Moore and Benbasat 1991; Taylor and Todd 1995).

**Research Methodology**

To test our hypotheses, we conducted a quantitative field study using survey methodology. In this section we describe our technology artifact, data collection, instrument, and analysis strategy.

**Technology Artifact: Web Browsers**

The first Web browser, named World Wide Web, was created by Tim Berners-Lee in 1990. The first widely used Web browser was Mosaic developed in 1993 by Marc Anderson, who later developed the widely popular Netscape
browser. Microsoft Internet Explorer was introduced in 1995 and it has maintained its dominance in the Web browser market since the late 1990s, despite the existence of free alternatives including Opera, Mozilla, and Netscape Navigator (McMillan 2004). However, when the Mozilla Foundation released the 1.0 version of a Web browser called Firefox in November 2004, it posed an immediate challenge for IE. Within five months of its release, Firefox has reached 50 million downloads and achieved a significant market share (Borland 2005). The usage share of Firefox reached 8.6% in October 2005, up from the 2.7% share a year ago, while the usage share of IE has declined from 92.3% to 86.5% in the same time period (Net Applications 2006). More interestingly, the market gain of Firefox came at the expense of IE, which clearly indicates that many individuals have abandoned IE in favor of Firefox.

There are a few reasons why we consider the switch from IE to Firefox as an ideal example for our investigation of why users switch between two highly substitutable technology products. First and foremost reason is the high substitutability between the two browsers. Although Firefox came with improvements over IE such as tabbed browsing and built in popup blocker, the similarities between the two browsers outweigh their differences. After all, they are both applications that provide basic Web browsing features. Compared to other alternative Web browsers, Firefox also has a look and feel that is much similar to IE. For example, six of the seven top menu items in the 1.0 version of Firefox are identical to the six top menu items in the latest version of IE. Moreover, while Firefox is freely downloadable, IE comes at no additional cost with any version of Microsoft Windows operating system. Therefore, we believe that IE and Firefox are near perfect substitutes for the users.

Second, as the main portal to the Web for most computer users, the Web browser is one of the most crucial and commonly used applications in the Internet age. This ensures the availability of respondents and high relevance of our study to both practitioners and end users. Third, individuals’ use of Web browsers is usually volitional; this ensures there is no lock in effects due to contractual obligation or organizational mand ate that could confound or mask the effects from user perceptions. Fourth, the near duopoly of IE and Firefox of the Web browser market means there is little confounding effects from other alternatives. The recent introduction of Firefox and its rapid surge in market share prior to our study also enables us to focus on the user switching from IE to Firefox and makes a perfect timing for conducting this study.

Participants and Procedure

We solicited students from a large public university located in Midwestern US for their voluntary and anonymous participation in our study in November 2005. At the time data was collected, both IE and Firefox were available in all computer labs in this university, and both were officially supported by the academic computing department. Therefore, our result would not be confounded by any mandatory requirements imposed on the respondents. Students from one large undergraduate level and one graduate level course were invited to fill out a paper with pencil questionnaire during the lab sessions of the classes, with the option of taking it home and returning it during the next class. Students were probed for their awareness of different alternative Web browsers; and only those aware of both IE and Firefox were given the questionnaire.

Out of 437 questionnaires distributed, 382 were returned. The pre-screening step described above may have contributed to the relatively large portion of questionnaires returned. After dropping responses from incomplete questionnaire, and those with excessive missing data (for example, more than 1 missing items in any multi-item measurement) or inconsistent information (for example, choosing IE as the primary browser while indicating using Firefox more than 50% of the time), we have 306 usable responses. This yields a net response rate of 70%. Among the respondents, 53% were men, 37% were women, and 10% chose not to provide their gender. 78% of the respondents were undergraduate students, 12% graduate students, and 10% did not provide their school level. In addition, 17% of the respondents were working full-time, 49% were working part-time, 22% were not working but had previous work experience, 2% have never worked, and 10% did not provide work experience information. The high percentage of respondents with work experience is consistent with the general student composition of this public university and indicated our sample should represent the general public more accurately than a sample of students with little work experience.

Instrument

All variables were measured at the individual level. All perceptual measures were adapted from validated scales used in previous studies (Burnham et al. 2003; Compeau and Higgins 1995; Keaveney 2001; Moore and Benbasat
To ensure the face and content validity of the measures, we reviewed the instrument with three faculty members who were experts in scale development and five doctoral students. We conducted a pilot test with the draft of the questionnaire on twenty-six active technology users. Based on the feedbacks from the participants of the pilot test, we further refined some of the measures.

In the final questionnaire, all perceptual questions were scored on a seven point scale (e.g. 1 = “strongly disagree”, 7 = “strongly agree”). For most of the perceptual measures, we use the average score from all items as factor score for subsequent analyses. However, the item and factor score for social influence were calculated differently. Based on Taylor and Todd (1995) and our pilot study, we identified four salient sources of social influences – friends, classmates, professors, and university computer centers. Following Taylor and Todd (1995, pg. 149), each influence factor was measured as “individual’s normative belief concerning a particular referent weighted by the motivation to comply with that referent.” For example, respondents were asked to what extent they agree “My friends share positive information on Firefox,” and “Generally speaking, I would do what my friends think I should do with regard to computer technologies.” The products of the scores to each pair of questions were standardized on a 7 point scale and treated as one item score in subsequent analyses.

To get the most accurate measure of each user’s browser usage behavior, we used multiple questions. We first asked each respondent to give a percentage breakdown of the time she uses different Web browsers. Then we asked each respondent to indicate her primary browser – the browser she does most of her Web browsing. We also asked whether she has switched her primary Web browser within the past year; and her previous browser prior to the switch. In rare occasions (less than 3% of the initial sample), individuals switched to Firefox from a browser other than IE, were using a browser other than IE or Firefox, or provided conflicting information, for example, indicating one browser with highest percent usage and reported another as primary browser. We excluded these responses from our analysis. Although we expected prior to our data collection a small number of respondents may have switched back to IE after using Firefox, we did not find such responses in our sample.

Based on this information, we had two choices to measure the dependent variable in our study – browser switching behavior. Two thirds of the respondents report concurrent usage of both browsers. Therefore, it could be measured either as the percentage a user is using Firefox, or a dichotomous variable classifying a respondent as either a switcher or a non-switcher. We conducted subsequent analyses using both approaches and the results are consistent. Conceptually, percentage usage has the advantage of being a continuous variable that offers a more precise measure of actual usage behavior (a user may have started using Firefox as her primary browser earlier, but the exact percent of time she is actually using Firefox is a better reflection of her current opinion of Firefox). However, due to space limitations, and in accordance with most of the previous studies on consumer switching behavior, in this paper we chose to report our results using the dichotomous outcome variable, because it allows us to assess our model’s ability to accurately predict whether a user will be a switcher or a non-switcher. Such ability is valued in the marketing literature due to its obvious practical significance.

For each construct, the number of items, a sample question, and references of previous studies on which the items were based can be found in Table 1.

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2 Results from using the continuous dependent variable can be obtained from the authors.
Table 1. Construct Reliability, and Sample Items of Scales

<table>
<thead>
<tr>
<th>Construct</th>
<th>Number of Items</th>
<th>α</th>
<th>Sample Item</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switching Behavior</td>
<td>1</td>
<td>N/A</td>
<td>Have you changed your primary Web browser in the past year? *</td>
<td>N/A</td>
</tr>
<tr>
<td>User Satisfaction</td>
<td>4</td>
<td>0.93</td>
<td>“On the whole, I am/was satisfied with my experience with IE.”</td>
<td>Burnham et al. 2003; Keaveney and Parthasarathy 2001</td>
</tr>
<tr>
<td>Risk Aversion</td>
<td>5</td>
<td>0.75</td>
<td>I would rather stick to a brand I usually buy than try something I am not very sure of.</td>
<td>Raju 1980</td>
</tr>
<tr>
<td>Breadth of Use</td>
<td>3</td>
<td>0.80</td>
<td>I have/had used a variety of IE’s features.</td>
<td>Burnham et al. 2003</td>
</tr>
<tr>
<td>Computer Self-Efficacy</td>
<td>5</td>
<td>0.90</td>
<td>I'm confident that I could finish a task with a Web browser if there was no one around to tell me what to do as I go.</td>
<td>Compeau and Higgins 1995</td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>6</td>
<td>0.96</td>
<td>Compared to IE, using Firefox makes it easier to do my job.</td>
<td>Moore and Benbasat 1991</td>
</tr>
<tr>
<td>Perceived Security</td>
<td>4</td>
<td>0.86</td>
<td>Compared to IE, Firefox is a secure Web browser through which to send information.</td>
<td>Salisbury et al. 2001</td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>3</td>
<td>0.86</td>
<td>Compared to IE, it would be easy for me to remember how to perform tasks using Firefox.</td>
<td>Moore and Benbasat 1991</td>
</tr>
<tr>
<td>Social Influence</td>
<td>4</td>
<td>0.87</td>
<td>My friends share positive information on Firefox. / Generally speaking, I would do what my friends think I should do with regard to computer technologies.</td>
<td>Taylor and Todd 1995</td>
</tr>
</tbody>
</table>

* As discussed previously, additional questions were asked to confirm the self-reported switching behavior.

**Statistical Analysis**

Since our research question concerns the predicting powers of a set of explanatory variables on a dichotomous outcome variable, we employed hierarchical binary logistics regression models to test our hypotheses. According to binary logistics model, the probability of a user choosing to switch from IE to Firefox can be modeled as a nonlinear function of the linear combination of main effects as:

\[
\text{Probability of switching} = \frac{e^Y}{1 + e^Y}
\]

where:

\[
Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_kX_k
\]  

(1)

and \(X_1, X_2, \ldots, X_k\) are predictors; and \(b_1, b_2, \ldots, b_k\) are the corresponding coefficients with \(b_0\) as the constant. The predictors are the main effects of the hypothesized variables (SATISF, SECURITY, etc.). This linear regression equation transforms to the logit model:

\[
\log(\text{Probability of switching}) = B_0 + B_1X_1 + B_2X_2 + \ldots + B_kX_k
\]

(2)

Therefore, to test our research hypotheses, we use the following two step hierarchical binary logistics regression model:

Model 1:

\[
\log (\text{SWITCH}) = b_0 + b_1\text{EFFICY} + b_2\text{RISKAV} + b_3\text{INF}
\]

(3)

Model 2:

\[
\log (\text{SWITCH}) = b_0 + b_1\text{EFFICY} + b_2\text{RISKAV} + b_3\text{INF} + b_4\text{BRDU} + b_5\text{SATISF}
\]

\[
+ b_6\text{RELADV} + b_7\text{EOU} + b_8\text{SECUR}
\]

(4)

The main effects of the hypothesized variables are evaluated by testing the significance of the coefficients in model 2, after controlling for the effects of the control variables.

**Results**
**Instrument Validation**

To validate our instrument’s reliability and ensure measurement accuracy, we check the internal consistency of each multi-item perceptual measures by calculating the Cronbach’s alphas. As illustrated in Table 1, all constructs has at least a alpha value of 0.75, higher than the generally agreed upon lower limit of .70 for confirmatory research (Straub et al. 2004), indicating that all constructs are reliable.

To assess the discriminant and convergent validity of our perceptual measures, we conducted a principle component analysis (PCA) with varimax rotation using SPSS. The PCA produced an eight-factor solution as expected. The results from PCA also show satisfactory item loadings for all measures. All except for one of the items loaded on their expected factors with a greater than 0.7 loading. With only one exception, most of the items also had less than 0.4 cross-loadings onto other factors. The eight-factor solution explained 76% total variance in the PCA. Table 2 presents the mean, standard deviation, and factor loading of each measurement items.

To further assess factor validity, we also calculated the Average Variance Extracted (AVE) for each perceptual measure (Fornell and Larcker 1981). Each factor has an AVE above the .50 threshold, and the square root of AVE is higher than the correlation with other factors, demonstrating discriminant and convergent validity (Chin 1998; Straub et al. 2004). Table 3 presents the intercorrelations among the variables and their AVEs.
### Table 2. Item Means, Standard Deviations, and Factor Loadings

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
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<td>1</td>
<td>EFFICAY1</td>
<td>5.543</td>
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<td>7</td>
<td>EOU1</td>
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<td>1.502</td>
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<td>8</td>
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<td>SECUR4</td>
<td>4.858</td>
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</tbody>
</table>

Note: factor loadings below .400 are suppressed.
Table 3. Construct Means, Standard Deviations, Intercorrelations, and Average Variance Extracted

<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>SD</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
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<tbody>
<tr>
<td>1. Switching Behavior (0 = stayed, 1 = switched)</td>
<td>0.44</td>
<td>0.50</td>
<td>N/A</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>2. Computer Self-Efficacy</td>
<td>5.60</td>
<td>1.36</td>
<td>.09</td>
<td>.83</td>
<td></td>
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<td></td>
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<tr>
<td>3. Risk Aversion</td>
<td>3.76</td>
<td>1.18</td>
<td>.18*</td>
<td>.08</td>
<td>.75</td>
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<td></td>
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<tr>
<td>4. Influences</td>
<td>2.67</td>
<td>1.20</td>
<td>.21**</td>
<td>.06</td>
<td>-.09</td>
<td>.82</td>
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<td></td>
</tr>
<tr>
<td>5. Breadth of Use</td>
<td>4.37</td>
<td>1.43</td>
<td>-.20**</td>
<td>.13</td>
<td>.04</td>
<td>-.11</td>
<td>.83</td>
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<tr>
<td>6. User Satisfaction</td>
<td>4.79</td>
<td>1.50</td>
<td>-.51**</td>
<td>.19*</td>
<td>-.17*</td>
<td>.02</td>
<td>.27**</td>
<td>.85</td>
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<td></td>
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</tr>
<tr>
<td>7. Relative Advantage</td>
<td>4.35</td>
<td>1.41</td>
<td>.52**</td>
<td>.17*</td>
<td>.11</td>
<td>.30**</td>
<td>-.11</td>
<td>-.40**</td>
<td>.87</td>
<td></td>
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<tr>
<td>8. Perceived Ease of Use</td>
<td>5.06</td>
<td>1.32</td>
<td>.46**</td>
<td>.35**</td>
<td>.17*</td>
<td>.28**</td>
<td>-.05</td>
<td>-.22**</td>
<td>.56**</td>
<td>.75</td>
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</tr>
<tr>
<td>9. Perceived Security</td>
<td>4.76</td>
<td>1.29</td>
<td>.50**</td>
<td>.19**</td>
<td>.20**</td>
<td>.22**</td>
<td>-.04</td>
<td>-.28**</td>
<td>.51**</td>
<td>.55**</td>
<td>.76</td>
</tr>
</tbody>
</table>

Note: The diagonals are the square root of the AVE of each factor

* Significant at the 0.01 level, one-tailed test

** Significant at the 0.001 level, one-tailed test

Table 3 also lists the mean, standard deviation of all predictor variables and the dependent variable. Correlations ranged from 0.02 to 0.56 (Relative Advantage with Perceived Ease of Use) and all but three correlations between predictor variables were lower than .50. Therefore, the correlations among predictors were generally low. This will help us to achieve better predicting power and clear interpretation of regression results from our subsequent analysis.

Testing of Hypotheses

Table 4 lists the results from hierarchical binary logistic regression analysis using SPSS. After entering the control variables in model 1, our model 2 is significant overall ($\chi^2 = 194.535$, df = 8, $p < 0.001$) and demonstrated significantly better fit than model 1 ($\Delta\chi^2 = 167.407$, df = 5, $p < 0.001$). There is no direct analog to multiple linear regressions’ R$^2$ in logistics regressions; however, Nagelkerke’s R$^2$ is generally accepted as an approximate to it (Nagelkerke 1991). The Nagelkerke’s R$^2$ of our regression model is 0.631, and the $\Delta$R$^2$ between the two models is 0.518. Model 2 yielded a 76.5% accuracy in predicting switchers, 88.2% for non-switchers, and 83.0% overall.

From Table 4, we also observe that the regression coefficients of Breadth of Use, Satisfaction, Relative Advantage, Perceived Ease of Use, and Perceived Security were significant in the predicted directions. All of the five hypotheses were supported.
Table 4. Hierarchical Binary Logistic Regression Results

<table>
<thead>
<tr>
<th>Results of individual predictors</th>
<th>Model 1</th>
<th></th>
<th></th>
<th></th>
<th>Model 2</th>
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<tbody>
<tr>
<td></td>
<td>B</td>
<td>S.E.</td>
<td>Wald</td>
<td>p</td>
<td>B</td>
<td>S.E.</td>
<td>Wald</td>
<td>p</td>
</tr>
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<td>Constant</td>
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<td>.728</td>
<td>19.530</td>
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<td>Social Influence</td>
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<td>.000</td>
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<td>Breadth of Use</td>
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<td>-</td>
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<td>Relative Advantage</td>
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<td>.709</td>
<td>.186</td>
<td>14.598</td>
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</table>

Results of the overall model

<table>
<thead>
<tr>
<th>-2LL $\chi^2$</th>
<th>27.002 (df = 3, $p &lt; .001$)</th>
<th>194.41 (df = 8, $p &lt; .001$)</th>
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<tbody>
<tr>
<td>$R^2$ (Cox &amp; Snell)</td>
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<td>.471</td>
</tr>
<tr>
<td>$R^2$ (Nagelkerke)</td>
<td>.113</td>
<td>.631</td>
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<tr>
<td>$\Delta R^2$ (Nagelkerke)</td>
<td>-</td>
<td>.518</td>
</tr>
<tr>
<td>Classification accuracy rate (Switchers)</td>
<td>46.3%</td>
<td>76.5%</td>
</tr>
<tr>
<td>Classification accuracy rate (Non-switchers)</td>
<td>75.7%</td>
<td>88.2%</td>
</tr>
<tr>
<td>Classification accuracy rate (Overall)</td>
<td>62.6%</td>
<td>83.0%</td>
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</tbody>
</table>

Discussion

Key Findings

The main objective of this study was to understand what may influence users’ decision to switch from one technology product to a highly substitutable alternative. Findings suggest that individuals’ use and perceptions of the technology substitutes play critical role in their switching. As hypothesized, user satisfaction and breadth of use of the incumbent are negatively associated with user switching while perceived easy of use, relative advantage and perceived security of the substitute (as compared to the incumbent) are positively associated with switching behavior.

Among all factors tested, user satisfaction with the incumbent product appeared to be the strongest predictor of switching behavior. This result confirms marketing researchers’ view of satisfaction as the main influencer on consumer switching behaviors. Among the three perceived characteristics of the substitute product, perceived security demonstrated the strongest predicting power on Web browser switching behavior.

One methodological issue we need to consider in interpreting our results is common method bias. As suggested by Straub et al. (2004), the best approach to avoid common method bias is to measure dependent variables using archival data when using perceptual measures for independent variables. In our study, such approach would require tracking each participant’s browser usage overtime without their explicit knowledge, which is obviously impractical. Therefore, we took the next best approach possible. As discussed earlier, we solicited participants’ browser usage by asking them first to give a percentage breakdown of the time they spent on different Web browsers, and indicate their primary browser base on the percentages. These questions were asked at the very beginning of the survey, before they answer any questions on the perceived characteristics of the two browsers. Although we still rely on self-reported data for assessing browser usage, the steps we have taken in our research design should help minimize common method bias that may cause over-estimation of the relationship between independent and dependent variables. Harman’s one-factor test was recommended in the literature to assess the common method bias among the
latent variables quantitatively (Podsakoff and Organ 1986). If the shared variance among the constructs is explained largely by method variance, factor analysis should find a single method factor to be better fit than multifactor solutions. As reported earlier, PCA yields a multifactor solution. Therefore, common method bias was not a significant problem in our data.

limitations

One important limitation of this study is in our ability to make causal inferences from the data analysis. Since we only collected cross-sectional data for all variables, we were only able to establish associative relations between factors and user switching behavior. Longitudinal design is needed in the future to test causal relationships.

The peculiarities of the technology chosen for this study also imposed certain restrictions on our ability to achieve more generalizable results. The two Web browsers are different from many technology products because they are both freely available, they are near perfect substitutes, and users can usually make decision on which one to use on their own. These distinct characteristics helped us in our research design to minimize potential confounding effects. However, it also means further research efforts have to be invested to identify and evaluate the relative strength of other salient factors influencing user switching under different settings, such as paid products. Given the constant product entries in various markets of technology products, there are plenty of opportunities for researchers to extend our work and investigate user switching behavior under different settings.

The timing of our study was set purposely to coincide with the recent introduction of Mozilla Firefox and its rise in market share. This gives us a unique opportunity to investigate user behavior in a market where a single dominating incumbent product is being challenged by a new entrant. Cautions have to be taken applying our discoveries to user behavior in a market where a relatively stable equilibrium has been achieved with more than one established brands. There are plenty of such technology products or services, for example, Web based emails, personal digital assistants (PDA), or Internet service providers, which warrants future studies on user switching behavior in these mature markets.

The limitations we have discussed so far also mean that from the perspective of theoretical contribution, our model is not a comprehensive framework that can explain technology user switching in a general sense. Future research can draw from all past studies and offer a more holistic view of technology user switching by incorporating all relevant factors, such as perceived switching costs, compatibility, and brand image, just to name a few.

In this study we focused on the switching behavior of individual technology users. To understand how the switching decision is made on technology products at the organization level, it would demand a substantially different set of factors. Like individual users, organizations are constantly facing the options to switch between alternative technology products and services. It could be the choice to switch between proprietary and open source server operating systems; or the choice to switch among different brands of network management software; or the choice among different IT outsourcing vendors. The outcome of this type of decision on enterprise IT products and services has profound impact on the business performance of IT using firms as well as the market viability of technology vendors. We urge IS researchers to seek the abundant research opportunities on this topic that is not only interesting but also highly relevant to practitioners.

Both marketing literature and IS literature have noted the inadequacy of using intentions to study consumer or user behavior (e.g. Ahuja and Thatcher 2005; Keaveney 1995). Therefore, our model centers on how various perceptual factors predict user switching behavior. We did not intend to, nor did we analyze the possible antecedent-consequent relationships among these predictors, or how intention mediates the effects of these factors on switching behavior. Researchers interested in these aspects are encouraged to develop intention based models and apply statistical methods such as structural equation modeling to test those models.

implications

Our findings have significant implications for both research and practice. For IS literature, our broader contribution is that we demonstrated the inadequacy in considering a single technology in studying how end users use technologies post-adoption. Our results clearly indicated that users’ experience of an incumbent product greatly influence their decision on whether to use an alternative. Therefore, we think when conducting studies on any IT usage related topics; scholars need to look beyond a single technology and give serious consideration to the more realistic situation of multiple alternative products available for one technology.
This empirical study also demonstrated neither IS nor marketing literature alone is sufficient for explaining user switching behavior between technology products. Our model incorporating factors from both fields has a much stronger explanatory power than it would with constructs from only IS or marketing studies.

Our results also confirmed the importance of users’ perception of a technology product’s security in their use of technologies, especially, Web-related applications. Information security has attracted tremendous amount of attention from popular media, practitioners, and researchers. However, to our knowledge our study is the first one to combine perceived security with other perceived characteristics of information technologies in a single study to understand users’ usage decisions. Our results not only verified perceived security as a factor unique from any other factors under consideration, but also provided empirical evidence for its influence on user behavior.

Our study has considerable implications for practice. As technology vendors constantly vying for users’ support of their products and market share, it is essential to understand what users take into consideration when choosing between alternative products. Our results indicated that the best strategy for a technology vendor still lies in the product itself. Technology vendors should always strive to offer innovative products that are easier to use and has more valuable features. In the mean time, vendors, especially those providing Web-related applications, should also engage in efforts to positively influence users’ perceptions on key dimensions such as the security of the product. Improved user satisfaction, broader usage, better perceptions on dimensions such as ease of use and security are the best defenses against competitors. Going back to the example of Web browsers used in our study, these points are also well illustrated. As indicated by Microsoft chairman Bill Gates at several occasions, the biggest mistakes Microsoft made with IE was its sluggishness in innovating on features and security improvements (Montalbano 2006; Reimer 2006).

In conclusion, this study offers new insights into users’ switching between technology substitutes in general and Web browsers in specific. The finding should provide a more comprehensive understanding of post-adoption technology usage behavior for researchers and practitioners alike.

References


