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Research Note

Online Users' Switching Costs: Their Nature and Formation

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The highly competitive and rapidly changing market for online services is becoming increasingly effective at locking users in through the coercive effects of switching costs. Although the information systems field increasingly recognizes that switching costs plays a big part in enforcing loyalty, little is known about what factors users regard as switching costs or why they perceive these costs. Consequently, it is hard for online services to know what lock-in strategies to use and when to apply them. We address this problem by first developing a theory-driven structure of online users' perceived switching costs that distinguishes between vendor-related and user-related factors. We then propose that important antecedent influences on switching costs from economic value, technical self-efficacy, and past investments are more complex and intertwined than previously thought. We empirically validated the proposed model using data collected from home users of Internet service providers. Our findings demonstrate that an online service's economic value more heavily influences users' perceptions of vendor-related switching costs than does technical self-efficacy. However, users' technical abilities outweigh economic value in influencing user-related switching costs. Furthermore, although we confirmed the commonly held notion that deeply invested users are generally more vulnerable to lock-in, we also found that this relationship is contingent on users' technical abilities. Finally, we found that our multidimensional measure of switching costs is a valid predictor of user loyalty and is more powerful than previous global measures. Overall, this study uncovered a finer network of switching-cost production than had been previously established and suggests a new approach to modeling and exploiting online users' perceived switching costs.

Key words: switching costs; online consumer behavior; survey data; partial least squares; structural equation modeling
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1. Introduction

Much of the information systems (IS) research on the stickiness of online services shows that users continue to use a service because they are, to some extent, attracted to its attributes, such as perceived usefulness (Devaraj et al. 2002), usability (Venkatesh and Agarwal 2006), and service quality (Gefen 2002). Nevertheless, awareness is growing in IS that the repeated use of an online service also is enforced by constraints that make it costly to switch to another service (Chen and Hitt 2002, Whitten and Green 2005). These constraints on switching include the time and effort that consumers must expend to find and evaluate suitable alternatives (Farrell and Shapiro 1988) and the financial penalties that consumers would incur if they left a service before expiration of a contract (Jones et al. 2002, Burnham et al. 2003). These constraints are widely referred to as switching costs, which are defined as the time, money, and psychological and physical effort required to ensure compatibility between a new purchase and earlier investments (Klemperer 1995). Considering how many Web features are developed to "lock in" customers (e.g., registered user accounts and personalized product recommendations at online stores), a thorough understanding of switching costs is more critical than ever for researchers and practitioners who seek to understand online consumer behavior (Kim and Son 2009).

Compared with the wealth of research on the attractive factors promoting the long-term use of information technology (IT), little research has been done in the IS area on coercive switching-cost factors. The switching-cost studies that have been undertaken in IS (Gefen 2002, Chen and Hitt 2002, Whitten and Green 2005, Kim and Son 2009, Kim and Kankanhalli 2009) demonstrate that switching costs deserve greater attention in the IS literature. Yet, our understanding of switching costs suffers from critical gaps that hinder the further development of switching-cost research and strategy. First, although perceived switching costs are believed to be multifaceted (Jones et al. 2002, Burnham et al. 2003), no generalizable collection of switching-cost factors has been identified that is customized for IS research or that can be applied across IT settings. Instead, the gamut of IT users' perceived switching costs has been measured mostly either by a single construct (Gefen 2002, Kim and Kankanhalli 2009) or by a multidimensional construct adopted from another discipline without modification (Whitten and Green 2005). Second, we have limited knowledge of the antecedents of switching costs and their relative influences and interactions on the various types of switching costs. For example, users' service-specific investments and self-efficacy are identified as significant sources of switching costs (Kim and Son 2009, Kim and Kankanhalli 2009), even though we do not know whether they are unequivocally influential for all types of switching costs and under all conditions.

To further our understanding of switching costs in information systems, we developed a model of the composition and antecedents of online consumers' perceived switching costs. Drawing on economic and marketing literature (Klemperer 1987, Jones et al. 2002, Burnham et al. 2003), we first proposed a multidimensional structure of perceived switching costs that is applicable to online services ranging from e-mail and news sites, which are often free and intangible, to online retail sites and Internet service provision, which can entail fees and product delivery. Specifically, we identified two major groups of switching costs that emerge in online services, namely, vendor-related switching costs and user-related switching costs, each of which consists of more specific subfactors. We then identified three key antecedents that give rise to switching costs: the economic value of services, the past investments of users, and the technical self-efficacy of users. We contend that the formation of vendor-related switching costs differs from that of user-related switching costs because of the technologically intensive nature of online services. In particular, we argue that whereas economic value drives vendor-related switching costs, technical self-efficacy primarily affects user-related switching costs. We also suggest that past investments influence both vendor- and user-related switching costs, but technical efficacy moderates their impact on user-related switching costs. Past research has identified many components and antecedents of switching costs but paid little attention to how those antecedents might have different effects on the various components of switching costs. We aim to clarify and emphasize that the high-tech nature of online services gives rise to a sophisticated network of relationships between the antecedents and components of online switching costs.

2. The Structure of Online Users' Perceived Switching Costs

Our investigation of online switching costs follows in the tradition of business research that has examined why consumers and organizations resist changing products, partners, and practices, despite having strong incentives to do so (Oliver 1999, Weiss and Anderson 1992). For example, organizational theorists have proposed that structural changes are rarely implemented and that structural inertia is more likely to be the norm (Hannan and Freeman 1984). The notion of *switching costs* is an emerging explanation for this inertia, and it has found particular traction in explaining why consumers are averse to switching from their current products and services (Weiss and Anderson 1992). Switching costs consist of the time, money, and effort that consumers expect will be required of them to ensure compatibility between new purchases and earlier investments (Klemperer 1995). Online users' perceived switching costs, then, capture the expected costs of switching from a current online service to an alternative one.

At the foundation of switching-cost theory laid down in economics are two major categories of switching-cost factors: artificial costs that we refer to as *vendor-related costs* and real social costs that we refer to as *user-related costs* (Klemperer 1987, Guiltinan 1989). Examples of vendor-related costs are the loss of benefits, such as favored pricing and customized features that are specific to an incumbent service and that cannot be readily transferred to a new service. On the other hand, a user-related cost would be the actual time and effort the user expends in looking for alternative providers and evaluating them. Various subfactors were thought to exist for both categories of switching costs (Klemperer 1987), and much of the subsequent empirical research in marketing has focused on identifying the existence of these specific subfactors (Jones et al. 2002, Burnham et al. 2003). These empirical works, however, seem to have ignored the ramifications of the vendor-related versus user-related grouping of switching costs in favor of identifying their many specific subfactors. Our study aimed to reconcile the parsimonious two-way categorization of switching costs found in the

Table 1 ePSC Factors versus Past Empirical Typologies

	Corresponding switching-cost factors in past empirical research empirical research	
ePSC factors	Jones et al. (2002)	Burnham et al. (2003)
Vendor-related switching costs		
Benefit-loss costs	• Lost performance costs	• Benefit-loss costs
Service-uncertainty costs	• Uncertainty costs	• Economic risk costs
Brand relationship costs		• Brand relationship costs
User-related switching costs		
Search and evaluation costs	• Preswitching search and evaluation costs	• Evaluation costs
Transfer costs	• Setup costs	• Setup costs • Monetary loss costs
Learning costs	• Postswitching behavioral and cognitive costs	• Learning costs
n/a—included in our study as an antecedent to switching costs (past investments)	• Sunk costs	
n/a—personal interaction not expected in most online services		• Personal relationship costs

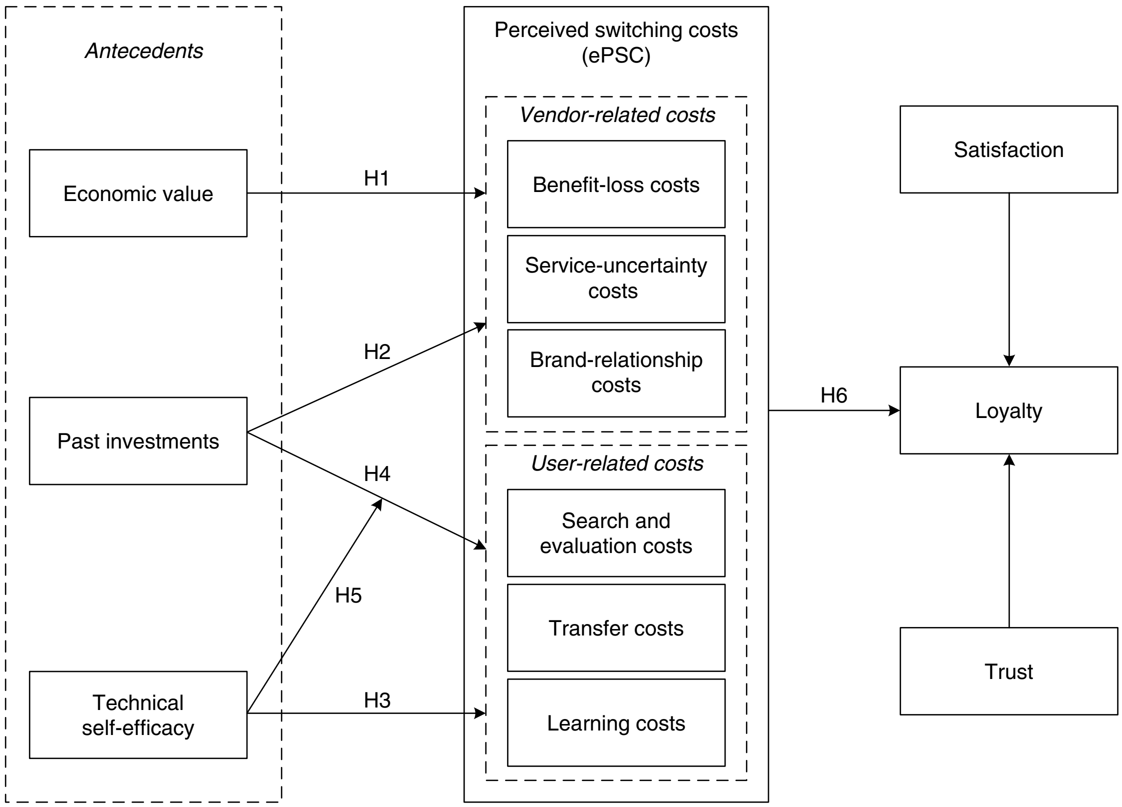
economic literature with the many specific subfactors found in the marketing literature. After reviewing the major theoretical and empirical works on switching-cost typology (detailed in our supplementary online appendix),[1] we found that the gamut of switching cost factors found in the literature can be generally summarized by three vendor-related switching-cost factors and three user-related factors. Table 1 shows how these six online perceived switching-cost subfactors, which we refer to as ePSC, relate to factors discussed in more general empirical investigations of switching-cost typology.

Vendor-related switching costs reflect the value of nonreproducible assets that will be lost in switching from an online vendor. Our study found in the literature three vendor-related costs that arise from losing benefits, performance, and relationships with online services. *Benefit-loss costs* come from loyalty programs, rewards, and benefits that a consumer will lose upon switching and also include contractual obligations that impose penalties for switching (Klemperer 1987, Chen and Hitt 2002, Burnham et al. 2003). For example, ISPs bundle-in nontransferable benefits, such as a customized e-mail address or can provide a discounted rate for those who sign multi-year contracts. *Service-uncertainty costs* arise when the actual value of a new vendor's service is less than expected, resulting in lost performance, money, and convenience (Beggs and Klemperer 1992, Jones et al. 2002, Burnham et al. 2003). Users could be uncertain about the actual service they could receive from a new provider if they suspect that the service provider is either falsely claiming to provide a higher-than-actual quality of service or is inflating prices to falsely signal higher quality (Beggs and Klemperer 1992, Dodds et al. 1991). *Brand relationship costs* are psychological costs that come from the affective loss of severing ties with a brand that one has bonded with (Burnham et al. 2003). The loss of a brand relationship results in a loss of the cultural meanings that the affiliation brought and the sense of community and identity drawn from the brand relationship (Muniz and O'Guinn 2001, Burnham et al. 2003).

User-related switching costs arise from the resources that users must expend to ensure a satisfactory switch of service and to recreate or transfer features. From prior literature, we found three user-related costs that arise from the unavoidable costs of time, effort, and money required to accomplish various tasks before, during, and after switching online services. *Search and evaluation costs* are the time and effort required to find and compare providers before switching (Jones et al. 2002, Burnham et al. 2003). Searching for suitable alternatives can be complicated by the dispersion of information and by the limited regional availability of alternatives (Jones et al. 2002, Zeithaml 1981). Evaluating alternatives also takes time and effort because all available information must be restructured and analyzed (Burnham et al. 2003, Shugan 1980). *Transfer costs* include the time, effort, and money required to end a service with one online provider and start a new service with another (Klemperer 1987). The installation and configuration of a new service requires an investment of time, effort, and other assets by the consumer (Guiltinan 1989), and ending an old service also can involve procedural tasks. Finally, *learning costs*

[1] An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

Figure 1 Hypothesized Model of ePSC Antecedents



are the time and effort needed to adapt to a new provider (Klemperer 1987, Jones et al. 2002). The inadequate standardization of services makes it difficult to transfer all the learning associated with one service to another one, even when the services are functionally equivalent (Farrell and Shapiro 1988, Klemperer 1987).

We refer to these six aforementioned perceived switching-cost factors as ePSC to distinguish them from more general perceived switching-cost typologies found in marketing. Our conceptualization of ePSC is distinct from earlier empirical typologies because it explicitly distinguishes between vendor-related and user-related factors, is tailored to online services, and consistently reflects users' expectations of future costs and losses. The distinction between vendor-related and user-related switching costs is the most important difference between our study and past studies because it leads us to look carefully at how the two groups of switching costs arise. Differences in antecedent effects can provide major insight into how switching costs can be managed and when certain strategies might fail.

3. The Antecedents of Online Users' Perceived Switching Costs

To understand how the switching costs in ePSC arise, our study looked at three important antecedent factors that influence users' perceived switching costs at online services: the value characteristics of services and providers, the technical expertise of users, and the past investments of users at online services. These three antecedents have been shown to strongly affect switching costs in the brick-and-mortar markets in which switching costs have traditionally been studied (Burnham et al. 2003). We continue to use these three antecedents to study online settings because they broadly represent the institutional, personal, and relational forces that demotivate consumers from switching to other options (Sheth and Parvatiyar 1995). Figure 1 summarizes the hypothesized theoretical model we developed to explain how these antecedent forces influence the components of ePSC.

In contrast to the findings of switching-cost studies in traditional settings, we do not believe that the three antecedents of value, expertise, and investments all have equivalent effects on the various switching-cost factors in an online setting. The high-tech area of online services is characterized by rapid changes that quickly make experiential knowledge obsolete (Heide and Weiss 1995). Our study proposes that the cognitive difficulty of staying up to date and making technical decisions about online services means that users' technical expertise plays an important role in forming switching costs and even moderates the impact of perceived value and past investments on certain costs.

Specifically, we propose three distinct differences in how switching costs arise for online users: (1) the value proposition of online services should influence primarily vendor-related switching costs instead of user-related switching costs; (2) users' technical expertise should predominantly influence perceptions of user-related switching costs instead of vendor-related switching costs; and (3) although past investments can significantly influence all online switching costs, their effect on user-related switching costs hinges on the level of users' technical expertise. We arrived at these propositions by looking in detail at how these antecedent factors influence users' vendor-related and user-related switching costs.

3.1. Antecedents of Vendor-Related Switching Costs

3.1.1. Perceived Economic Value. To influence users' perceptions of switching costs, service providers can limit the attractiveness of alternative services by adjusting the price of their own service and the quality and breadth of their features (Chen and Hitt 2002, Burnham et al. 2003, Sheth and Parvatiyar 1995). These manipulations by vendors affect an online service's *economic value*, which is the perceived fairness of the service's price for the level of quality and complexity of features offered (Verhoef 2003, Dodds et al. 1991). Implicit in users' calculation of economic value is the relative price and quality of competitors (Verhoef 2003). This setting-independent information about a provider's combination of price, quality, and features relative to its competitor's makes perceived economic value a parsimonious and generalizable measure of service characteristics that influence switching costs.

We expect that high economic value, be it from low pricing or good benefits, increases users' perceptions of ePSC's three vendor-related switching costs. An online service provider can increase users' potential benefit-loss costs by offering a price and quality that is unparalleled by its competitors or by offering features that cannot be transferred to another service (Klemperer 1987, Burnham et al. 2003). The threat of losing these service-specific assets increases consumers' dependence and the degree to which they are locked in (Heide and John 1988, Williamson 1985). Providers also can raise economic value to increase service-uncertainty costs, either by claiming to provide higher value than their competitors or by adjusting their prices to increase value or signal higher quality (Beggs and Klemperer 1992, Dodds et al. 1991). Finally, economic value also can increase brand-relationship costs because users who stay for the good value will tend to affectively identify with the brand and its customer base and subsequently bond with their provider because of expectations of long-term reciprocity (Burnham et al. 2003). Altogether, we hypothesize that economic value will increase the three vendor-related switching costs relating to benefit loss, service uncertainty, and brand relationships.

Hypothesis H1A. *Perceived economic value positively influences benefit-loss costs.*

Hypothesis H1B. *Perceived economic value positively influences service-uncertainty costs.*

Hypothesis H1C. *Perceived economic value positively influences brand-relationship costs.*

3.1.2. Past Investments. *Past investments* of time, effort, and money that consumers sink into their relationships with service providers are a major antecedent to switching costs because these past investments have the power to lock consumers into services for relational, economic, and normative reasons (Burnham et al. 2003, Rokkan et al. 2003, Arkes and Blumer 1985). Users invest time and effort at online services to create benefits, foster certainty, and establish brand relationships, all of which could be lost when switching to new services. First, users switching between services will lose benefits that they have created to improve their old service. For example, users of an online store might have created user profiles, category preferences, or wish lists that cannot be reused at another store. Furthermore, long-time users of an online service who have grown very familiar with their incumbent service will likely face service unpredictability and uncertainty about features provided by a new provider. This uncertainty stems from competing services often not being standardized, even when they are functionally similar (Farrell and Shapiro 1988). Finally, long-time users also incur relational losses when switching providers. Long-time users of a provider's service often develop affective ties with the brand (Rokkan et al. 2003) that must be severed if they leave the provider (Burnham et al. 2003). Altogether, we predict that users who have invested a significant amount of time at a provider's service will face higher vendor-related switching costs in terms of benefit-loss, uncertainty, and brand-relationship loss.

Hypothesis H2A. *Past investments positively influence benefit-loss costs.*

Hypothesis H2B. *Past investments positively influence service-uncertainty costs.*

Hypothesis H2C. *Past investments positively influence brand-relationship costs.*

3.2. Antecedents of User-Related Switching Costs

3.2.1. Technical Self-Efficacy. Consumers' technical expertise is an important influence on switching costs in general markets (Burnham et al. 2003) and encompasses many of the personal and psychological reasons that influence users to stay with their vendors even when better options exist (for a greater discussion on these personal motivations, see Sheth and Parvatiyar 1995). In IS research, *technical self-efficacy* is a powerful measure that captures users' beliefs in their proficiency with an IT-related task and accounts for factors, such as the encouragement of peers and the availability of technical support (Compeau and Higgins 1995, Webster and Martocchio 1992).

The task of finding, switching, and adapting to a new provider requires users to expend time, energy, and possibly money. To find information on alternative providers, users can get functional information from the Web, and they can get experiential information from peers or by using other services for a trial period (Hui and Chau 2002, Ratchford et al. 2001). Switching to a new service requires closing down service with the old provider, abandoning features and accounts associated with that service, and starting and setting up features at the new service. Even after switching, users must adapt not only to a new interface but also to new processes and routines (Whitten and Green 2005).

These switching-related tasks, which correspond to the three user-related factors of ePSC, are especially difficult when dealing with online services because experiential knowledge, such as prior knowledge about alternative services and current technologies, is quickly rendered obsolete in dynamic, high-tech contexts like the Internet (Heide and Weiss 1995, Alba and Hutchinson 1987, Zeithaml 1981). Based on the literature on technical self-efficacy, we expect IT users with higher technical self-efficacy to be less encumbered by these technical tasks because they possess key advantages: They can process technical information more efficiently; they can exploit the Internet as a source of information more effectively; they require less time and effort to conduct technical tasks; and they anticipate better outcomes and face technical tasks with less anxiety (Compeau and Higgins 1995, Ratchford et al. 2001). Consequently, we expect users with higher technical self-efficacy to perceive lower user-related switching costs related to search and evaluation, transfer, and learning.

Hypothesis H3A. *Technical self-efficacy negatively influences search and evaluation costs.*

Hypothesis H3B. *Technical self-efficacy negatively influences transfer costs.*

Hypothesis H3C. *Technical self-efficacy negatively influences learning costs.*

3.2.2. Past Investments. Earlier, we considered how nontransferable benefits automatically gained from past investments increase vendor-related switching costs. However, past investments also can increase user-related switching costs because users who have manually modified or customized their services must expend time and effort to recreate settings and preferences at a new service. For example, users trying to switch from an ISP's e-mail service must re-enter their contact information into a new service's address book and customize new settings according to past preferences. Before satisfactorily re-creating past settings and preferences, users must first find an online service with comparable features and a similar level of customization. Furthermore, manually transferring information or re-creating settings takes time and effort. Finally, users must adapt to any differences between their new service and the customizations of their old service. Therefore, we believe that users' past investments also will increase the three user-related switching costs relating to search and evaluation, transfer, and learning.

Hypothesis H4A. *Past investments positively influence search and evaluation costs.*

Hypothesis H4B. *Past investments positively influence transfer costs.*

Hypothesis H4C. *Past investments positively influence learning costs.*

3.2.3. The Interaction Between Technical Self-Efficacy and Past Investments. Although past investments should increase user-related switching costs, we believe that this relationship is contingent on users' level of technical self-efficacy. Users with low technical abilities are likely to be so swamped with the technical issues relating to switching and adapting to a new service that the additional burden of past investments might be inconsequential. For example, users trying to use a new e-mail service might be dissuaded even by the technical issues of comparing e-mail services, changing settings in their e-mail client application, applying spam filters, and so on. Such users might perceive high switching costs related to finding, transferring to, and learning a new service even when they have not invested much time creating custom contacts, folders, or other features. On the other hand, users with higher technical abilities do not face any major user-related switching barriers when past investments are low, but research shows that even they are often locked in by very large past investments (Vatanasombut et al. 2004). In our earlier example of e-mail services, users with high technical self-efficacy would not have any major technical difficulties when switching to a new e-mail account, unless they had customized contacts lists, folders, and settings. Therefore, users with low technical self-efficacy perceive high switching costs at all times, regardless of past investments, but users with high technical self-efficacy face very low switching costs without past investments and very high costs when they have invested much. Our reasoning suggests that there should be a positive interaction between past investments and technical self-efficacy on user-related switching costs, because users with greater technical self-efficacy will react more sharply to past investments than less capable users, who always perceive high switching costs.

Hypothesis H5A. *When technical self-efficacy increases* (*decreases*), *the influence of past investments on search and evaluation costs increases* (*decreases*).

Hypothesis H5B. *When technical self-efficacy increases* (*decreases*), *the influence of past investments on transfer costs increases* (*decreases*).

Hypothesis H5C. *When technical self-efficacy increases* (*decreases*), *the influence of past investments on learning costs increases* (*decreases*).

3.2.4. Potential Crossover Effects. Prior research on the antecedents of switching-cost factors has modeled major antecedents as having comparable influences on all switching-cost factors (Burnham et al. 2003). In contrast, we do not hypothesize cross-effects from economic value to user-related switching-costs, or from technical self-efficacy to vendor-related switching-costs. Instead, our model shows that vendor-related switching-costs are largely determined by economic value and past investments, but user-related switching costs are largely determined by users' technical self-efficacy and past investments. Some evidence suggests that the cross-effects omitted from our model could be significant (Burnham et al. 2003). However, we assert that the hypothesized main effects of economic value and technical self-efficacy yield a sounder theoretical view of the antecedent forces on online users' switching costs and should be considerably stronger than any cross-effects.

First, economic value relates to the features, quality, and pricing of an online vendor's service, relative to the services of other vendors. Because economic value captures vendor-related attributes, differences in perceived economic value should relate directly to vendor-related switching costs that reflect losses resulting from an abrupt change of vendors. On the other hand, the relationship between economic value and user-related costs is more tenuous because changes in vendors' attributes do not clearly necessitate extra effort on the part of users. Therefore, although we cannot completely rule out cross-effects from economic value to user-related switching costs, we posit that such effects will be significantly smaller than the more direct relationship between economic value and vendor-related switching costs.

Technical self-efficacy relates to the confidence users have in their ability to complete technical tasks. Therefore, users' technical self-efficacy directly relate to user-related switching costs because users' abilities clearly relate to how much time and effort they think they must expend on the technical tasks of switching. In this case, the relationship between technical self-efficacy and vendor-related costs are tenuous because users' attributes do not clearly relate to the loss of benefits, certainty of service quality, or brand affiliations attributed to vendors. Therefore, although we cannot rule out cross-effects from technical self-efficacy to vendor-related switching costs, we posit that such effects will be significantly smaller than in the more direct relationship we hypothesized between technical self-efficacy and user-related switching costs.

Both sets of cross-effects, then, are hard to defend because one set relates vendor attributes to user efforts while the other set relates user attributes to vendor-created losses. The main hypothesized effects, however, consistently relate vendor attributes to vendor-created losses and user attributes to user efforts. Lacking a strong theoretical rationale for strong cross-effects, we expect the cross-effects to be small or insignificant compared with our hypothesized effects. To validate our reasoning, we will later use our structural model to empirically test the proposed differences between the hypothesized effects and nonhypothesized cross-effects of economic value and technical self-efficacy.

3.3. Nomological Implications of ePSC

The consequence of switching costs that is of major interest to IS research is how switching costs can enforce loyalty (Gefen 2002, Whitten and Green 2005). Although past research agrees that switching costs also should increase IT users' loyalty beyond what is explained by satisfaction and trust (Kim and Son 2009, Gefen 2002), only a one-dimensional measure of switching costs has been generally examined. The six factors of ePSC capture the global lock-in phenomenon more broadly than the one-dimensional views of online switching costs employed thus far. Therefore, we hypothesize that the collective variance of the six ePSC factors, represented by a second-order ePSC construct, also should increase the continued loyalty of users.

Hypothesis 6. *Users' overall, or second-order, perceived switching costs positively influence loyalty.*

Past studies of switching costs in information systems also have considered the effect on loyalty from the positive attributes of online services (Kim and Son 2009, Whitten and Green 2005) and the positive attributes of the providers of these services (Gefen 2002). For example, satisfaction with a service is a key means of initially gaining consumer loyalty in online and offline settings (Kim and Son 2009, Oliver 1999). However, as the consumer-provider relationship matures, the bond between the two parties becomes an increasingly important contributor to loyalty (Oliver 1999). In particular, trust plays an increasingly larger role in determining loyalty in long-term relationships between users and providers (Bhattacherjee 2002, Gefen 2002). Therefore, our model controls for both satisfaction and trust as dedication-based antecedents of loyalty.

4. Methodology and Data Analysis

4.1. Survey Development and Deployment

4.1.1. The ISP Setting. We tested our model with data collected from a survey of ISP users. By ISP, we refer specifically to providers of home Internet connectivity, such as AOL, SBC/Yahoo!, and NetZero. Our study targeted the population of adult North American home users of ISPs. The ISP setting has several major benefits of interest to our study. The ISP setting offers a very clear understanding of what is entailed in "switching" because customers of ISPs must usually sever their association with their incumbent provider when they choose a new, alternate provider. The home use of ISPs also entails a richer relationship than many other online services in that ISP use involves technical interaction, financial exchange, and contractual obligation, and it has the potential for a long-term relational commitment (Greenstein 2001). Despite the variety of switching costs present in the ISP market, it remains highly competitive and characterized by higher churn rates than other telecommunication markets, such as mobile telephony (Keaveney and Parthasarathy 2001, Madden et al. 1999).

For the purposes of the survey, respondents were asked to consider only the current, primary ISP used at home. These ISPs might offer dial-up Internet access, high-speed broadband service, or other value-added and premium services (Keaveney and Parthasarathy 2001). Customers might even have free home Internet access provided by an employer. We considered users of both commercial and free providers because home consumers of both types of service have the option of switching.

4.1.2. Selection of Measures. The measurement items in our survey, listed in the appendix, were largely derived from validated scales in the literature. Some items were reworded to be specific to the use of Internet service and also revised for easier comprehension. Measures for the dimensions of ePSC were derived from Jones et al. (2002) and Burnham et al. (2003), and a few new items were introduced (see the supplementary online appendix for details on the development of ePSC subfactor scales). Measures for the antecedent factors were derived from the relevant literature. The perceived economic value of a service was derived from Sweeney and Soutar's (2001) price construct and measures the affordability of the service and value for the money. Using items derived from Taylor and Todd (1995), we also developed a global measure of technical self-efficacy with ISPs. Our adaptation of global terms of self-efficacy measured users' beliefs regarding their capability to accomplish broad future tasks (Compeau and Higgins 1995). One item of technical self-efficacy was reworded to measure belief in proficiency instead of confidence or comfort of use (Webster and Martocchio 1992). Past investments were measured using items derived from Rokkan et al. (2003) measures of specific investments in interfirm relationships. Finally, single-item control variables were included for age, gender, household income, length of experience with the current ISP, breadth of service features offered by the ISP, and the bundling of Internet service with other telecommunication services.

4.1.3. Survey Deployment and Data Collection. A pilot survey was conducted to get feedback on the usability of our instrument. Invitations were sent to individuals chosen randomly from a panel maintained by a marketing research firm. We invited only a small number of panelists to participate in the pilot survey because most of the measures and scales in our survey had already been tested in other studies. The 48 respondents who completed the survey received a small cash reward deposited to PayPal or similar online accounts. Upon completion, respondents were asked to give open feedback on the comprehensibility of the measures, the overall time required, and any other issues they faced in completing the instrument. Cronbach alpha values were used to help attain acceptable reliability levels. Based on users' feedback on item clarity and on internal consistency checks, hard-to-understand measures that contributed unique meaning to our constructs were modified without losing construct meaning.

The final instrument was sent to 2,000 individuals chosen randomly from the survey panel used earlier, excluding those invited to participate in the pilot survey. The rewards for respondents were the same as those in the pilot survey. The survey was left open for 14 days, with a single reminder sent to nonrespondents on the seventh day after the first wave of responses had slowed. In all, 478 responses were collected.

The data were screened to eliminate incomplete or rushed responses. The Web survey application automatically recorded the time taken by respondents to complete the survey. Respondents who either had unusually low completion times or had not satisfactorily completed the survey were dropped from further analysis. Eventually, 472 responses were deemed usable, giving a 23.6% effective response rate. The average age of respondents was 51.6 years, and 55% were female.

Because we could not obtain demographic information on nonrespondents, we compared the demographics of early respondents with those of late respondents, who often are similar to nonrespondents (Miller and Smith 1983). We found, from a sampling of those who responded early and those who responded after a reminder was sent out, that the demographics of the two groups did not differ significantly. We concluded that nonrespondents were not likely to differ significantly from our sample set and that their absence would not affect our findings.

4.2. Model Analysis

A partial least squares (PLS) model of the antecedent network was created using SmartPLS v2.0M3 (Ringle et al. 2005) to evaluate the overall measurement properties and proposed hypotheses of our model. Using PLS in this study allowed for a formative second-order ePSC construct that was defined by its subfactors (Chin and Gopal 1995). PLS also helped us examine the antecedent influences on switching costs because this modeling technique is well suited to study associations between latent variables when new theoretical ground is being explored (Fornell and Bookstein 1982).

Our PLS model included the six ePSC subfactors, the three antecedent factors, as well as satisfaction, trust, and loyalty as first-order, reflective constructs. The interaction between technical self-efficacy and the six first-order ePSC factors was modeled using standardized product items (Chin et al. 2003). To create the formative, second-order ePSC construct, we used the hierarchical components approach that replicates a principal components measurement model (Lohmöller 1989).

4.2.1. Measurement Quality. Measurement properties of the first-order reflective constructs were estimated along with structural relationships in PLS model estimation. The measurement items of these constructs loaded above the threshold value of 0.70 (Barclay et al. 1995); most loaded above 0.80. For reflective constructs to be considered reliable, they must have a composite reliability greater than 0.70, and the average variances extracted by the constructs should exceed 0.50 (Bagozzi and Yi 1988, Fornell and Larcker 1981). The major reflective constructs demonstrated high internal consistency: composite reliability values exceeded 0.90, and average variance extracted values were more than 0.70. Table 2 summarizes the measurement quality statistics.

Discriminant validity between constructs was confirmed by two methods. We first examined all item cross-loadings to ensure no construct loaded better upon any construct than it did on its own. We then also determined that no construct shared more variance with any other construct than it did with its own measures; this determination was made by ensuring that the square root of the average variance extracted for all constructs was larger than the correlations between constructs.

Finally, single-survey studies should ensure that common method variance is not a significant contributor to correlations between constructs. We first investigated the potential for common method variance with a Harman one-factor test that used a principal components analysis to confirm that neither did only one factor emerge nor did a single factor account for a majority of the variance (Podsakoff et al. 2003). We found that nine factors emerged with eigenvalues larger than 1.0 that explained 77% of the total variance, and the largest principal component accounted for 33.1% of the variance. As a further check of common method variance, we also conducted a marker-variable analysis (Lindell and Whitney 2001, Malhotra et al. 2006) in which we examined factor correlations and used the second-smallest correlation as a proxy for common method variance. An inspection of the correlation table reveals that the second-smallest correlation is 0.03, which is not statistically significant given the sample size ($n = 472$). To be more conservative, we also examined the third-smallest correlation (i.e., 0.05), but it was not significant either. Taken together with other results, it seems safe to argue that common method variance is not a significant concern in this particular study.[2]

4.2.2. Structural Model. We verified the structural hypotheses of our model by analyzing the structural estimates produced by PLS. We conducted a bootstrap procedure with 300 subsamples to determine the significance of path estimates and to compare path estimates statistically. Table 3 contains an overview of these structural results. Only minor associations between our demographic controls and our main constructs were found.

[2] A more sensitive test of common method variance often used in covariance-based structural equation models is the common method factor approach (Podsakoff et al. 2003). We reconstructed our PLS model as a covariance-based LISREL model and inserted a common method factor. We also created a parallel PLS model that approximated the common method factor. Both sets of results suggested that the use of a common method was a very small contributor to variance.

Table 2 Measurement Quality and Factor Correlations

	Mean	SD	AVE	$\sqrt{AVE}$	CR	BLC	SUC	BRC	EVC	TSC	LSC	ePSC	VAL	INV	EFF	SAT	TST	LOY
BLC	3.72	1.67	0.76	0.87	0.93	1.00												
SUC	4.74	1.52	0.79	0.89	0.94	0.43^{**}	1.00											
BRC	4.78	1.37	0.89	0.94	0.94	0.41^{**}	0.38^{**}	1.00										
EVC	3.85	1.64	0.74	0.86	0.90	0.44^{**}	0.58^{**}	0.24^{**}	1.00									
TSC	4.63	1.54	0.82	0.91	0.95	0.43^{**}	0.52^{**}	0.18^{**}	0.52^{**}	1.00								
LSC	4.23	1.60	0.83	0.91	0.95	0.56^{**}	0.59^{**}	0.28^{**}	0.59^{**}	0.67^{**}	1.00							
ePSC	4.32	1.07	0.46	0.68	0.95	0.74^{**}	0.80^{**}	0.49^{**}	0.74^{**}	0.78^{**}	0.86^{**}	1.00						
VAL	4.89	1.58	0.87	0.93	0.96	0.36^{**}	0.29^{**}	0.60^{**}	0.16^{**}	0.17^{**}	0.26^{**}	0.38^{**}	1.00					
INV	4.05	1.54	0.70	0.84	0.90	0.51^{**}	0.38^{**}	0.35^{**}	0.32^{**}	0.40^{**}	0.40^{**}	0.53^{**}	0.16^{**}	1.00				
EFF	5.03	1.44	0.73	0.86	0.89	-0.23^{**}	-0.22^{**}	0.04	-0.35^{**}	-0.29^{**}	-0.42^{**}	-0.35^{**}	0.05	−0.06	1.00			
SAT	5.68	1.21	0.90	0.95	0.96	0.17^{**}	0.22^{**}	0.55^{**}	0.03	0.02	0.13^{**}	0.21^{**}	0.49^{**}	0.05	0.10^{*}	1.00		
TST	5.50	1.25	0.81	0.90	0.96	0.24^{**}	0.22^{**}	0.70^{**}	0.06	0.08	0.19^{**}	0.29^{**}	0.58^{**}	0.12^{**}	0.10^{*}	0.74^{**}	1.00	
LOY	4.79	1.58	0.89	0.94	0.97	0.43^{**}	0.35^{**}	0.74^{**}	0.19^{**}	0.16^{**}	0.28^{**}	0.44^{**}	0.57^{**}	0.33^{**}	0.03	0.67^{**}	0.71^{**}	1.00

Notes. SD: standard deviations; AVE: average variance extracted of reflexive factors; CR: composite reliability of reflexive factors; BLC: benefit-loss costs; SUC: service-uncertainty costs; BRC: brand relationship cost; TSC: transaction costs; EVC: search and evaluation costs; LSC: learning costs; ePSC: second-order online users' perceived switching costs; VAL: perceived economic value; EFF: technical self-efficacy; INV: users' past investments; TST: trust in provider; LOY: loyalty to provider.

$^{*}p < 0.05$, $^{**}p < 0.01$, not significant otherwise (two-tailed).

We first looked at the main effects upon ePSC from their antecedents. All three antecedents had significant effects upon the subfactors of ePSC that they were hypothesized to influence (see bold values in Table 3), thus fully supporting Hypotheses 1, 2, 3, and 4. The hypothesized moderating role of self-efficacy upon the relationships between past investments and the three user-related switching costs was upheld. The interaction term had significant effects upon all three user-related factors, supporting Hypothesis 5.

Prior literature has found that antecedent factors similar to economic value and technical self-efficacy could influence all factors of switching costs, not just the ones suggested by Hypotheses 1 and 3. Our study found that four of the six nonhypothesized cross-effects were indeed significant. However, we

Table 3 Structural Results of PLS Model

	BLC	SUC	BRC	EVC	TSC	LSC	LOY
R^2	0.43	0.27	0.45	0.27	0.29	0.40	0.63
Independent							
VAL	$\mathbf{0.32}^{***}$	$\mathbf{0.26}^{***}$	$\mathbf{0.54}^{***}$	0.14^{**}	0.13^{**}	0.23^{***}	
INV	$\mathbf{0.42}^{***}$	$\mathbf{0.31}^{***}$	$\mathbf{0.25}^{***}$	$\mathbf{0.27}^{***}$	$\mathbf{0.35}^{***}$	$\mathbf{0.31}^{***}$	
EFF	-0.23^{***}	-0.21^{***}	0.03	$\mathbf{-0.33}^{***}$	$\mathbf{-0.26}^{***}$	$\mathbf{-0.42}^{***}$	
INV × EFF	0.17^{***}	0.10	−0.08	$\mathbf{0.16}^{***}$	$\mathbf{0.19}^{***}$	$\mathbf{0.15}^{***}$	
ePSC							$\mathbf{0.24}$s***
SAT							0.31^{***}
TRUST							0.40^{***}
Covariates							
Age	0.04	−0.02	0.03	0.03	−0.06	−0.02	0.05^{**}
Gender	-0.09^{*}	0.01	0.03	0.04	0.07	−0.03	−0.02
HHInc	−0.03	0.08	0.00	0.09	0.06	0.07	−0.03
Features	0.04	−0.01	0.09^{**}	−0.07	−0.02	0.04	0.07^{*}
Bundling	0.07^{*}	0.06	0.10^{**}	−0.03	−0.04	−0.03	0.05
ISP experience	0.03	0.03	0.04	0.03	0.01	0.05	0.08^{*}

Notes. Table shows standardized path coefficients for hypothesized relationships (***shown in bold***) and control paths (not in bold).

R^2: total variance explained; BLC: benefit-loss costs; SUC: service-uncertainty costs; BRC: brand relationship cost; EVC: search and evaluation costs; TSC: transaction costs; LSC: learning costs; VAL: perceived economic value; INV: users' past investments; EFF: technical self-efficacy; SAT: satisfaction with provider; TST: users' trust in provider; LOY: loyalty to provider; HHInc: household income; Features: whether respondent uses features of ISP other than connectivity; ISP experience: time spent with current ISP; bundling: If ISP package is bundled with other media.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, not significant otherwise (two-tailed).

Table 4 Comparison of Antecedent Effects on Switching Cost Factors

Comparisons	Mean path (of left)	Mean path (of right)	Absolute difference	*T*-value	*p*-level (one-tailed)
$\|VAL \rightarrow BLC\| > \|Val \rightarrow EVC\|$	0.318	0.140	0.178	3.021	<0.01
$\|VAL \rightarrow BLC\| > \|Val \rightarrow TSC\|$	0.318	0.124	0.194	3.416	<0.001
$\|VAL \rightarrow BLC\| > \|Val \rightarrow LSC\|$	0.318	0.233	0.085	1.626	n.s.
$\|VAL \rightarrow SUC\| > \|Val \rightarrow EVC\|$	0.259	0.140	0.119	1.867	<0.05
$\|VAL \rightarrow SUC\| > \|Val \rightarrow TSC\|$	0.259	0.124	0.135	2.184	<0.05
$\|VAL \rightarrow SUC\| > \|Val \rightarrow LSC\|$	0.259	0.233	0.026	0.449	n.s.
$\|VAL \rightarrow BRC\| > \|Val \rightarrow EVC\|$	0.534	0.140	0.395	6.817	<0.001
$\|VAL \rightarrow BRC\| > \|Val \rightarrow TSC\|$	0.534	0.124	0.410	7.379	<0.001
$\|VAL \rightarrow BRC\| > \|Val \rightarrow LSC\|$	0.534	0.233	0.301	5.901	<0.001
$\|EFF \rightarrow EVC\| > \|EFF \rightarrow BLC\|$	−0.334	−0.232	0.101	1.798	<0.05
$\|EFF \rightarrow EVC\| > \|EFF \rightarrow SUC\|$	−0.334	−0.208	0.126	2.091	<0.05
$\|EFF \rightarrow EVC\| > \|EFF \rightarrow BRC\|$	−0.334	0.030	0.363	6.106	<0.001
$\|EFF \rightarrow TSC\| > \|EFF \rightarrow BLC\|$	−0.259	−0.232	0.027	0.527	n.s.
$\|EFF \rightarrow TSC\| > \|EFF \rightarrow SUC\|$	−0.259	−0.208	0.051	0.933	n.s.
$\|EFF \rightarrow TSC\| > \|EFF \rightarrow BRC\|$	−0.259	0.030	0.289	5.332	<0.001
$\|EFF \rightarrow LSC\| > \|EFF \rightarrow BLC\|$	−0.412	−0.232	0.180	3.668	<0.001
$\|EFF \rightarrow LSC\| > \|EFF \rightarrow SUC\|$	−0.412	−0.208	0.204	3.827	<0.001
$\|EFF \rightarrow LSC\| > \|EFF \rightarrow BRC\|$	−0.412	0.030	0.442	8.403	<0.001

Notes. BLC: benefit-loss costs; SUC: service-uncertainty costs; BRC: brand relationship cost; EVC: search and evaluation costs; TSC: transaction costs; LSC: learning costs; VAL: perceived economic value; INV: users' past investments; EFF: technical self-efficacy; SAT: satisfaction with provider; TST: users' trust in provider; LOY: loyalty to provider. Path means computed from 300 bootstrapped PLS runs. *T*-statistic of difference is calculated as:

$$t = \frac{(\bar{\beta}_1 - \bar{\beta}_2)}{\sqrt{\sigma^2_{\beta_1} + \sigma^2_{\beta_2} - 2\sigma^2_{\beta_{1,2}}}},$$

$\bar{\beta}_i$ is mean of path coefficient; $\sigma^2_{\beta_i}$ is variance of path coefficient; $\sigma^2_{\beta_{1,2}}$ is covariance of two path coefficients.

argued that the two sets of hypothesized paths are significantly more important than the cross-effects we did not hypothesize. We tested this proposition by comparing economic value and technical self-efficacy's hypothesized effects on ePSC subfactors to their nonhypothesized effects on ePSC subfactors. To make this comparison, we used the bootstrap estimates of path coefficients to conduct a t-test of the difference between the hypothesized paths posited to be larger and the nonhypothesized control paths believed to be smaller (see results in Table 4). These differences required 18 tests comparing the effects of past investments and technical self-efficacy upon the three vendor-produced switching costs versus the effects upon the three user-induced switching costs. Our proposed differences were largely supported; only 4 of 18 difference tests failed to pass.

Finally, we determined that the second-order ePSC construct had a significant effect on loyalty (0.22), even with satisfaction and trust accounted for, as put forth by Hypothesis 6. Second-order ePSC was found to increase the total explained variance (R^2) of loyalty to 63% from 57%, a difference of 6%. To further demonstrate the advantage of using ePSC, we compared the above model with an alternate model in which the second-order ePSC was replaced with a global, one-dimensional switching-cost factor (GPSC) similar to that found in earlier IS literature (Gefen 2002, Kim and Son 2009). The GPSC factor had a considerably smaller effect on loyalty (0.13) than ePSC. Furthermore, the GPSC factor increased the total explained variance of loyalty only to 58% from 57%, an addition of 1%.

5. Discussion

The objective of this study was to develop and test a theoretical framework that identifies the composition and antecedents of online consumers' perceived switching costs, or ePSC. This study proposed that ePSC consists of two groups of switching costs: vendor-related factors and user-related factors. Furthermore, we proposed that each group of switching-cost factors is affected differently by economic value, past investments, and technical self-efficacy. We also suggested that technical self-efficacy moderates the effect of past investments on user-related switching-cost factors. The proposed model was tested based on data collected from 472 ISP home users. As expected, our findings indicate that economic value and past investments increase vendor-related switching costs. We also found that technical self-efficacy decreases user-related switching costs. More important, technical self-efficacy moderates the impact of past investments on all three user-related switching costs. In general, this study uncovers a more complex network of switching-cost formation than previously established and suggests a new approach to modeling and exploiting online users' perceptions of switching costs.

5.1. Theoretical Contributions

One of the major efforts of this study was to advance a typology of switching costs that is specific to the perceptions of IT users, that takes advantage of the extensive prior work on switching-cost typology, and that suggests strategic ways of managing users' perceptions of switching costs. Borrowing a general typology of switching costs can pose problems, as demonstrated by a study of the switching costs of cell phone users (Whitten and Green 2005) that used a six-factor switching-cost scale from the marketing literature (Jones et al. 2002). The cell phone study showed that four of its six switching-cost factors were either uncorrelated or positively correlated with switching intentions (and thus negatively correlated with loyalty). These problematic correlations indicate that the switching-cost factors in prior typologies might not accurately capture the switching barriers faced by IT users. To avoid the problems highlighted by Whitten and Green (2005), we reexamined our choice of switching-cost factors and refined the chosen factors to capture the range of tasks confronting IT users (see the supplementary online appendix for details). We found that all six factors of ePSC are positively correlated with loyalty, suggesting that our choice and conceptualization of switching-cost factors makes ePSC a more appropriate measure of online users' switching costs than earlier marketing typologies.

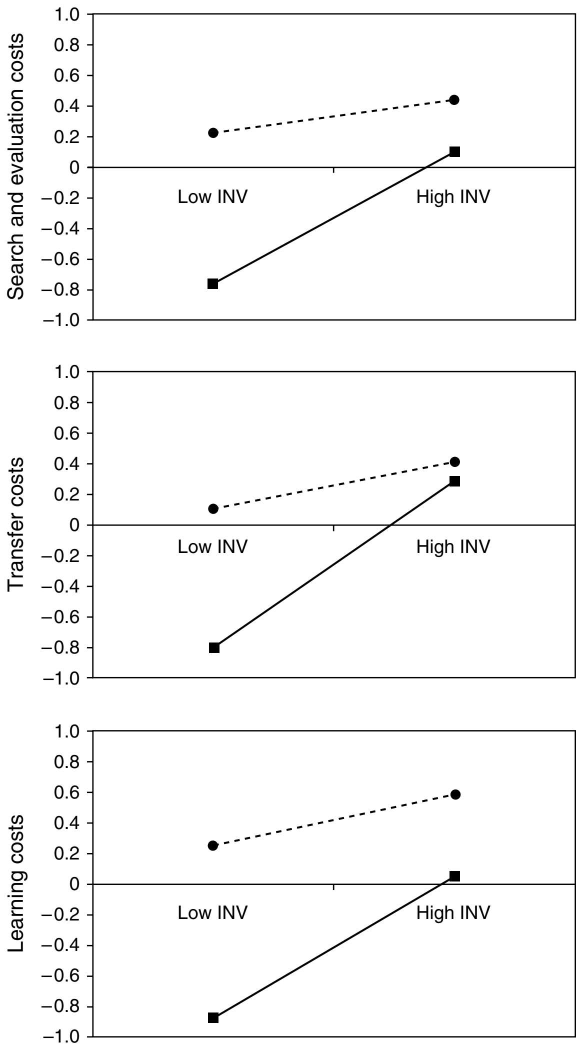
However, the main contribution of ePSC is that it conceptually distinguishes between two groups of switching-cost factors: vendor-related versus user-related switching costs. Typically, past research has considered only the formation of overall switching costs and assumed a similarity in the formation mechanisms of different switching cost factors (Burnham et al. 2003, Kim and Kankanhalli 2009, Kim and Son 2009). As a result, little attention has been paid to potential differential effects of antecedents on distinct components of switching costs. Our study is an early attempt to highlight that the antecedent factors of switching costs do not have equivalent effects on the various switching-cost factors in online service settings. Instead, we started by studying a unique characteristic of online services, namely, that individuals face significant cognitive challenges when making decisions about high-tech environments. This critical difference helped us uncover the different formative mechanisms of vendor- and user-related switching costs in the specific context of online services. Our results demonstrate that this two-way distinction between online switching costs reflects more than just conceptual differences between switching-cost factors. This distinction arises because the three major antecedents of switching costs, namely, economic value, past investments, and technical self-efficacy, have different relationships with each of the two groups of switching costs.

First, we looked at how vendor-related switching costs arise primarily from the influences of perceived economic value and past investments. Whereas prior research believed that elements of economic value, such as price or quality, affect overall perceptions of switching costs (Burnham et al. 2003, Chen and Hitt 2002), this study shows that changes in economic value have a significantly larger effect on vendor-related switching costs than on user-related switching costs. Therefore, when examining online service settings in which vendor-related switching costs are uniformly high but user-related costs are low or moderate, economic value might not always have as much of an effect on overall switching costs as prior research might suggest.

Second, this study examined how user-related switching costs are largely the result of technical self-efficacy and past investments. Although prior research on switching costs in IT services shows that self-efficacy reduces perceptions of switching costs (Kim and Kankanhalli 2009), our study cautions that technical self-efficacy primarily influences user-related switching costs rather than vendor-related switching costs. Therefore, researchers studying online service settings with little variance in user-related switching costs might find that the effect of self-efficacy on overall switching costs might be muted or nonexistent.

Exploring the underlying assumption in prior research that IT artifacts can increase users' overall switching costs by taking advantage of users' past investments (Riemer and Totz 2003), we demonstrated an interaction between past investments and technical self-efficacy that changes this story. We showed that the effect of past investments on user-related switching costs is marginal for online customers with low self-efficacy. Figure 2 shows how the technical self-efficacy of users changes the relationship between past investments and the three user-related switching costs. This figure shows that even when small investments are involved, the low self-efficacy group already perceives high user-related switching costs, and the perceived level of these switching costs does not increase dramatically with the increase in past investments. This finding suggests that online customers with low self-efficacy are overwhelmed by the technical challenges associated with switching to a new online service, and thus

Figure 2 **Self-Efficacy × Past Investments Interaction on User-Related Switching Costs**



the issue of past investments might be secondary to seemingly more pressing technical difficulties (e.g., usability, ease of use, etc.). Furthermore, users with low technical self-efficacy might not make enough use of personalized features to be locked in by past investments. As also seen in Figure 2, the high self-efficacy group perceives switching to a new service to be easy when small investments are committed to the incumbent service; however, when past investments accumulate, this technically proficient group finally feels the pressure of being locked in. This finding implies that the amount of resources that technically proficient people have committed is crucially important to them when they evaluate switching costs.

The interaction between past investments and technical self-efficacy is a departure from prior switching-cost studies that have treated users' past investments and technical self-efficacy simply as antecedents of switching costs (Burnham et al. 2003, Kim and Son 2009, Kim and Kankanhalli 2004). Our study offers a more nuanced view of the relationship between past investments, technical self-efficacy, and switching costs. The interaction of past investments and technical self-efficacy suggests that IT artifacts that take advantage of users' past investments, such as personalization tools, are especially effective at locking in sophisticated users. To the best of our knowledge, the present study is the first to demonstrate this important interaction effect. We hope that researchers who study the role of IT tools designed to exploit prior commitments take into account that the effectiveness of such tools varies with individuals' technical abilities.

Finally, this study reconfirms the growing belief in the IS area that switching costs have a large and significant bearing on user loyalty beyond what is explained by traditional factors of technology acceptance (Gefen 2002). Our results show that ePSC is a nomologically valid, multidimensional conceptualization of IT users' switching costs. Furthermore, our second-order ePSC is considerably more powerful in predicting loyalty than a global, one-dimensional measure of switching costs. Combining the importance of a multidimensional view of switching costs with the our finding that antecedent factors have different influences on switching costs, this study serves to warn against a generalized examination of the formation of switching costs that does not consider the idiosyncrasy of the IS context under scrutiny. The multifaceted ePSC construct gives us the opportunity to make more balanced assessments of the major factors that increase user loyalty while also raising new questions regarding the role of well-established factors like technical self-efficacy.

5.2. Managerial Implications

Apart from the theoretical value of our study, our results offer new perspectives for practitioners seeking to manage users' perceptions of switching costs. First, differentiating between vendor-related and user-related costs means that ePSC also is useful for those IT practitioners who want to make base measurements of their users' switching-cost perceptions. Measuring vendor-related switching-cost factors allows managers to gauge the power of their policies and practices to retain users, and measuring perceptions of user-related switching costs can reveal how market and user characteristics might contribute to user retention or attrition.

Our antecedent model also suggests that vendors must deploy resources strategically to influence specific switching costs. We see that although vendors have great influence over vendor-related costs, they have significantly less influence on user-related costs. As such, vendors who wish to increase perceptions of user-related switching costs cannot rely primarily on value perceptions to achieve this objective.

Instead, they should take advantage of past investments, which also have a strong influence on user-related switching costs. Therefore, one of the key contributions of this study has been to demonstrate that the multidimensional switching-cost representation of ePSC has practical implications in the measurement and management of online users' switching-cost perceptions.

The moderating effect of technical self-efficacy adds another strategic qualification for managers to consider. Firms providing online services need first to gauge the technical abilities of their user base to fully understand which mechanisms might significantly lower user attrition. For example, our findings imply that people with low self-efficacy find it challenging to switch to a competing vendor, probably because they are afraid of a new technical environment. Thus, vendors who operate in segments of the market with technically less capable users need to ensure that potential customers are given the needed information and assistance to use their new online service. Meanwhile, vendors who wish to influence the future patronage decisions of more proficient users will find better returns from tools and features that increase and exploit users' investments. Unlike users with low self-efficacy, those with high self-efficacy can explore and move more freely to an alternative online service. To retain those technically proficient customers, vendors should increase lock-in by using users' committed resources, such as customized settings, e-mails, personal content in social networking websites, pictures, videos, etc. Our findings indicate that even highly skillful users hardly escape from the power of lock-in; practitioners need to devise a way to increase committed resources among those sophisticated customers.

5.3. Limitations and Further Research

Although our proposed antecedent model was largely supported in the empirical analysis, we must remember that this study is limited by its choice of setting, study design, and choice of variables. Until corroborated by further evidence, our findings must be interpreted with caution. First, the choice of ISP use as our study setting poses several constraints. Although the use of ISPs provides a rich setting in which to study user-vendor relationships that involve financial and contractual interactions, this setting does not generally entail the extensive technical interactions that other online services could offer. Furthermore, by focusing on home users of ISPs, our survey very likely got the response of older homeowners (average respondent age was 51.6 years), who have greater influence over the selection of household utilities, and missed much of the response variance of teenagers and college students.

Another limitation relates to our exclusive reliance on the data collected in a single survey. Although this potential problem could be critical to the study in which IT users' behavior is a primary question, it would be less so to the present study in which the primary focus is on the relationships between perceived switching costs and their antecedents. Given the specific focus of this research note, the methodology employed in this study is believed to be acceptable, if not desirable.

We also note the omission of research variables that could be important in the context of switching behavior. For example, the attractiveness or availability of alternatives has been shown in prior research to be significant in determining continuance intention (Ping 1994, Keil et al. 1995, Whitten and Green 2005). Similarly, we expect switching behavior to be influenced by a variety of other variables that are not investigated in the present study. Future research also should focus on the measurement of technical self-efficacy. For the purposes of our study, we limited ourselves to a simple, global self-efficacy scale (e.g., Taylor and Todd 1995). However, recent research has emphasized that self-efficacy, like switching costs, is itself multidimensional in nature (Marakas et al. 1998). Having seen how important a role self-efficacy can play in raising certain switching-cost concerns, a logical next step would be to investigate whether the dimensions of self-efficacy have different effects in the context of switching costs.

Finally, we observe that the study of online consumer switching costs is at a nascent, exploratory stage. Although ePSC gives us a working proposition, even the basic dynamics of switching costs in complex environments remain a mystery. For example, future studies should differentiate between the coercive, constraint-based outcomes of switching costs, and the long-term bonding that also arises from being locked in (Rokkan et al. 2003). Longitudinal studies of how relationships between users and service providers evolve under switching-cost constraints could yield a deeper understanding of the psychology of users under lock-in.

5.4. Conclusions

This study shows the advantages of studying the antecedents of online switching costs and of taking a multidimensional view of switching costs in IS research. Taken together, the multiple facets of ePSC have a greater power to predict users' loyalty than the one-dimensional switching-cost factors seen thus far in much of the IS research. Separating ePSC into multiple factors reveals the different ways in which antecedent factors influence lock-in. Meanwhile, the interaction between antecedents informs us that there are situations in which the nature of lock-in is complex and unusual. These findings lay the groundwork for a more nuanced approach to modeling and exploiting online switching costs. Nevertheless, we have only begun investigating this important topic, and a number of issues are still to be addressed regarding switching costs in IT settings. It is our hope that the conceptual framework presented here provides a helpful basis for further clarifying the composition, formation, and outcome of IT users' switching costs.

Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://isr.journal.informs.org/.

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Appendix

Benefit-Loss Costs (BLC)—based on Burnham et al. (2003), Jones et al. (2002):

BLC1: I will lose benefits of being a long-term customer if I leave my service provider.
BLC2: By continuing to use the same ISP, I receive certain benefits that I would not receive if I switched to a new one.
BLC3: There are certain benefits I would not retain if I were to switch ISPs.
BLC4: I would lose preferential treatment if I changed ISPs.

Service-Uncertainty Costs (SUC)—based on Burnham et al. (2003), Jones et al. (2002):

SUC1: I worry that the service offered by other service providers won't work as well as expected.
SUC2: I am not sure what the level of service would be if I switched to a new ISP.
SUC3: If I were to change ISP, the service I receive at the new place could be worse than the service I now receive.
SUC4: The service from another ISP could be worse than the service I now receive.

Brand Relationship Loss Costs (BRC)—based on Burnham et al. (2003):

BRC1: I like the public image my service provider has.
BRC2: I support my service provider as a firm.

Search and Evaluation Costs (EVC)—based on Burnham et al. (2003), Jones et al. (2002):

EVC1: It is hard to compare the other service providers.
EVC2: Even when I have the information, comparing my service provider with other service providers is difficult.
EVC3: If I stopped using my current ISP, I would have to search a lot for a new one.

Transfer Costs (TSC)—based on Burnham et al. (2003):

TSC1: Switching to a new ISP involves a lot of steps.
TSC2: The process of starting up with a new service is not easy.
TSC3: The process of switching ISP service is unpleasant.
TSC4: There are a lot of formalities involved in switching to a new service provider.

Learning Costs (LSC)—based on Burnham et al. (2003):

LSC1: Understanding a new service provider well is difficult. (new)
LSC2: It would take time to learn to be as good at using the features of a new service provider, as I am at using my current service.
LSC3: Even after switching, it would take effort to "get up to speed" with a new service.
LSC4: Getting used to how another service provider works would be hard.

Economic Value (VAL)—based on Sweeney and Soutar (2001):

VAL1: My current ISP is reasonably priced.
VAL2: My current ISP offers value for money.
VAL3: My current ISP is a good service for the price.
VAL4: My current ISP is economical.

Past Investments (INV)–based on Rokkan et al. (2003):

INV1: I have made significant investments dedicated to my relationship with this service provider.
INV2: A lot of energy, time, and effort have gone into getting my current service working.
INV3: A lot of time, money and effort have gone into building and maintaining the relationship with this service provider.
INV4: I have made changes during the setup of my service, that are specific to my current ISP.

Technical Self-Efficacy (EFF)—based on Taylor and Todd (1995):

EFF1: If I wanted, I could easily switch to a new ISP on my own.
EFF2: I would be able to use the features of a new ISP's Internet service even if there is no one around to show me how to use it.
EFF3: I would be capable of proficiently using the features of a new ISP's Internet service.

Satisfaction with Internet Service (SAT)—based on Lam et al. (2004):

SAT1: In general, I am satisfied with the services of the ISP I currently use.
SAT2: Overall, the service of this current ISP comes up to my expectation.
SAT3: Overall, I am very satisfied with my relationship with this ISP.

Trust in Vendor (TRUST)—derived from Gefen et al. (2003) and Bhattacherjee (2002):

TRUST1: This current ISP cares about its customers.
TRUST2: This current ISP makes good-faith efforts to address most customer concerns.
TRUST3: This current ISP is honest.
TRUST4: This current ISP is fair in its conduct.
TRUST5: This current ISP is a competent service provider.

TRUST6: This current ISP has the ability to meet most customer needs.

Loyalty (LOY)—based on Kim and Son (2009):
LOY1: I consider myself to be highly loyal to this ISP.
LOY2: I am willing "to go to the extra mile" to remain a customer of this ISP.
LOY3: I feel loyal towards this ISP.
LOY4: It means a lot to me to continue to use this ISP.

Control Variables:
ISPExp: How many years have you been using your current ISP? (Enter number of years—if less than 1 year, enter 0.)
BNDL: Does your Internet provider also currently provide you with another service (such as TV cable, phone connection, etc.)?
FEAT: Do you use features provided by your ISP other than just the basic Internet connection (for example, an e-mail account, a start page for your browser, and so on)?
GEN: Respondent gender (Male/Female)
AGE: Age of respondent
HHInc: Gross household income (in US$)

References

Alba, J. W., J. W. Hutchinson. 1987. Dimensions of consumer expertise. *J. Consumer Res.* **13**(4) 411–454.

Arkes, H., C. Blumer. 1985. The psychology of sunk cost. *Organ. Behav. Human Decision Processes* **35** 124–140.

Bagozzi, R. P., Y. Yi. 1988. On the evaluation of structural equation models. *J. Acad. Marketing Sci.* **16**(1) 74–94.

Barclay, D., C. Higgins, R. Thompson. 1995. The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Tech. Stud.* **2**(2) 285–309.

Beggs, A., P. Klemperer. 1992. Multi-period competition with switching costs. *Econometrica* **60**(3) 651–666.

Bhattacherjee, A. 2002. Individual trust in online firms: Scale development and initial test. *J. Management Inform. Systems* **19**(1) 211–241.

Burnham, T. A., J. K. Frels, V. Mahajan. 2003. Consumer switching costs: A typology, antecedents, and consequences. *J. Acad. Marketing Sci.* **31**(2) 109–126.

Chen, P. Y., C. Forman. 2006. Can vendors influence switching costs and compatibility in an environment with open standards? *MIS Quart.* **30**(Special issue) 541–562.

Chen, P. Y., L. M. Hitt. 2002. Measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. *Inform. Systems Res.* **13**(3) 255–274.

Chin, W. W., A. Gopal. 1995. Adoption intention in GSS—Relative importance of beliefs. *Database Adv. Inform. Systems* **26**(2/3) 42–64.

Chin, W. W., B. L. Marcolin, P. R. Newsted. 2003. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Inform. Systems Res.* **14**(2) 189–217.

Compeau, D. R., C. A. Higgins. 1995. Computer self-efficacy: Development of a measure and initial test. *MIS Quart.* **19**(2) 189–211.

Devaraj, S., M. Fan, R. Kohli. 2002. Antecedents of B2C channel satisfaction and preference: Validating e-commerce metrics. *Inform. Systems Res.* **13**(3) 316–333.

Dodds, W. B., K. B. Monroe, D. Grewal. 1991. Effects of price, brand, and store information on buyers' product evaluations. *J. Marketing Res.* **28**(3) 307–319.

Farrell, J., C. Shapiro. 1988. Dynamic competition with switching costs. *RAND J. Econom.* **19**(1) 123–137.

Fornell, C., F. L. Bookstein. 1982. Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *J. Marketing Res.* **19**(4) 440–452.

Fornell, C., D. F. Larcker. 1981. Evaluating structural equation models with unobservable variables and measurement error. *J. Marketing Res.* **18**(1) 39–50.

Gefen, D. 2002. Customer loyalty in e-commerce. *J. Assoc. Inform. Systems* **3** 27–51.

Gefen, D., E. Karahanna, D. W. Straub. 2003. Trust and TAM in online shopping: An integrated model. *MIS Quart.* **27**(1) 51–90.

Guiltinan, J. P. 1989. A classification of switching costs with implications for relationship marketing. T. L. Childers et al. eds. *1989 AMA Winter Educators' Conf.: Marketing Theory and Practice*, AMA, Chicago, 216–220.

Greenstein, S. 2001. Technological mediation and commercial development in the early Internet access market. *California Management Rev.* **43**(2) 75–94.

Hannan, M., J. Freeman. 1984. Structural inertia and organizational change. *Amer. Sociol. Rev.* **49**(2) 149–164.

Heide, J. B., G. John. 1988. The role of dependence balancing in safeguarding transaction-specific assets in conventional channels. *J. Marketing* **52**(1) 20–35.

Heide, J. B., A. M. Weiss. 1995. Vendor consideration and switching behavior for buyers in high-technology markets. *J. Marketing* **59**(3) 30–43.

Hui, K. L., P. Y. K. Chau. 2002. Classifying digital products. *Comm. ACM* **45**(6) 73–79.

Jarvis, C. B., S. B. MacKenzie, P. M. Podsakoff. 2003. A critical review of construct indicators and measurement model misspecifications in marketing and consumer research. *J. Consumer Res.* **30**(2) 199–218.

Jones, M. A., D. L. Mothersbaugh, S. E. Beatty. 2002. Why customers stay: measuring the underlying dimensions of services switching costs and managing their differential strategic outcomes. *J. Bus. Res.* **55**(6) 441–450.

Keaveney, S. M., M. Parthasarathy. 2001. Customer switching behavior in online services: An exploratory study of the role of selected attitudinal, behavioral, and demographic factors. *J. Acad. Marketing Sci.* **29**(4) 374–390.

Keil, M., D. P. Truex, R. Mixon. 1995. The effects of sunk cost and project completion on information technology project escalation. *IEEE Trans. Engrg. Management* **42**(4) 372–381.

Kim, H., A. Kankanhalli. 2009. Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quart.* **33**(3) 567–582.

Kim, S. S., J. Son. 2009. Out of dedication or constraint? A dual model of post-adoption phenomena and its empirical test in the context of online services. *MIS Quart.* **33**(1) 49–70.

Klemperer, P. 1995. Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. *Rev. Econom. Stud.* **62**(4) 515–539.

Klemperer, P. 1987. Markets with consumer switching costs. *Quart. J. Econom.* **102**(2) 375–394.

Lam, S. Y., V. Shankar, M. K. E. B. Murthy. 2004. Customer value, satisfaction, loyalty, and switching costs: An illustration from a business-to-business service context. *J. Acad. Marketing Sci.* **32**(3) 293–311.

Lindell, M., D. Whitney, 2001. Accounting for common method variance in cross-sectional research designs. *J. Appl. Psych.* **86**(1) 114–121.

Lohmöller, J. 1989. *Latent Variable Path Modeling with Partial Least Squares*. Physica-Verlag, Heidelberg.

Madden, G., S. J. Savage, G. Coble-Neal. 1999. Subscriber churn in the Australian ISP market. *Inform. Econom. Policy* **11**(2) 195–207.

Malhotra, N. K., S. S. Kim, A. Patil. 2006. Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management Sci.* **52**(2) 1865–1883.

Marakas, G., M. Yi, R. Johnson. 1998. The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Inform. Systems Res.* **9**(2) 126–163.

Miller, L. E., K. L. Smith. 1983. Handling nonresponse issues. *J. Extension* **21**(5) 45–50.

Muniz, A. M., T. C. O'Guinn. 2001. Brand community. *J. Consumer Res.* **27**(4) 412–432.

Oliver, R. L. 1999. Whence customer loyalty. *J. Marketing* **63**(Special Issue) 33–44.

Ping, R. A. 1994. Does satisfaction moderate the association between alternative attractiveness and exit intention in a marketing channel? *J. Acad. Marketing Sci.* **22**(4) 364–371.

Podsakoff, P., S. Mackenzie, J. Lee, N. Podsakoff. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psych.* **88**(5) 879–903.

Ratchford, B. T., D. Talukdar, M. S. Lee. 2001. A model of consumer choice of the Internet as an information source. *Internat. J. Electronic Commerce* **5**(3) 7–21.

Riemer, K., C. Totz. 2003. The many faces of personalization—An integrated economic overview of mass customization. M. Tseng, F. T. Piller, eds. *The Customer Centric Enterprise: Advances in Mass Customization and Personalization*. Springer, Berlin, 35–50.

Ringle, C. M., S. Wende, A. Will. 2005. SmartPLS 2.0 (beta), Hamburg, Germany, http://www.smartpls.de.

Rokkan, A. I., J. B. Heide, K. H. Wathne. 2003. Specific investments in marketing relationships: Expropriation and bonding effects. *J. Marketing Res.* **40**(2) 210–224.

Sheth, J., A. Parvatiyar. 1995. Relationship marketing in consumer markets: Antecedents and consequences. *J. Acad. Marketing Sci.* **23**(4) 255–271.

Shugan, S. M. 1980. The costs of thinking. *J. Consumer Res.* **7**(September) 99–111.

Sweeney, J. C., G. N. Soutar. 2001. Consumer perceived value: The development of a multiple item scale. *J. Retailing* **77**(2) 203–220.

Taylor, S., P. A. Todd. 1995. Understanding information technology usage: A test of competing models. *Inform. Systems Res.* **6**(2) 144–176.

Vatanasombut, B., A. C. Stylianou, M. Igbaria. 2004. How to retain online customers. *Comm. ACM* **46**(6) 65–69.

Venkatesh, V., R. Agarwal. 2006. Turning visitors into customers: A usability-centric perspective on purchase behavior in electronic channels. *Management Sci.* **52**(3) 367–382.

Venkatesh, V., F. D. Davis. 1996. A model of the antecedents of perceived ease of use: Development and test. *Decision Sci.* **27**(3) 451–481.

Verhoef, P. C. 2003. Understanding the effect of customer relationship management efforts on customer retention and customer share development. *J. Marketing* **67**(4) 30–45.

Webster, J., J. J. Martocchio. 1992. Microcomputer playfulness: Development of a measure with workplace implications. *MIS Quart.* **16**(2) 201–226.

Weiss, A. M., E. Anderson. 1992. Converting from independent to employee salesforces: The role of perceived switching costs. *J. Marketing Res.* **29**(1) 101–115.

Whitten, D., K. Green, Jr. 2005. The effect of switching costs on intent to switch: An application in IS service provision markets. *Internat. J. Mobile Comm.* **3**(4) 428–444.

Williamson, O. E. 1985. *The Economic Institutions of Capitalism*. Free Press, New York.

Zeithaml, V. A. 1981. How consumer evaluation processes differ between goods and services. *Marketing of Services*. American Marketing Association, Chicago, 186–190.