Inf Syst Front (2017) 19:625–644
DOI 10.1007/s10796-015-9618-6

Integrating switching costs to information systems adoption: An empirical study on learning management systems

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Published online: 10 December 2015

Abstract When evaluating a new information system, users' experiences with the prior system, as well as characteristics of the new system, may influence their adoption behavior. However, most existing research either focuses solely on assessment of the new system using information systems adoption theories, or focuses only on the extent and types of switching costs associated with the transition from the prior system to the new one. In addition, little research has examined system switching and adoption of new learning management systems. To address these gaps, this study develops a research model that integrates the theoretical perspectives of switching costs and information systems adoption. The model is developed and tested in the context of the adoption of learning management systems. The results indicate that emotional costs and reduced performance costs can significantly influence perceived switching value. Perceived switching value, performance expectancy, effort expectancy, and social influence have significant impacts on users' intention to use the new learning management system.

Keywords Switching costs · Information systems adoption · Leaning management systems

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1 Introduction

Successfully adopting an information system can help an organization gain competitive advantage, as the system improves the effectiveness and efficiency of performance across the organization (Ferneley and Sobreperez 2006; Applegate and Elam 1992; Matook 2013). Almost all modern organizations use information systems of some type to automate their business processes and improve the organizational efficiency. In general, new information systems can offer more and potentially better functions compared with old systems. For example, Linux and Microsoft Windows operating systems are more functional and user friendly than the old Microsoft DOS. Over time, their replacement of Microsoft DOS has led to an increased popularity and interest in computer usage among general users.

However, it is not always true that people will choose new, appealing, and possibly more effective systems. Instead, they may prefer to retain the existing system, even when the new alternative offers more features with better functionality and improved usability. This may be due to people's propensity to avoid change. Pogue (2006) reported that 85 % of Internet users continued using Microsoft Internet Explorer although other Internet browser software such as Firefox and Opera provided additional useful features free of charge. Facebook and Google + provide another example. Facebook (facebook.com) was founded in 2004 and is one of the most popular social networking sites. Compared with Facebook, Google + (plus.google.com) is much more recent, it was launched in 2011. Although computing experts have suggested switching from Facebook to Google + since the latter has more advanced features such as better friend management, better mobile apps, better photo tagging, and safer content sharing (Sullivan 2011), recent market share reports (as of June 2013) indicate that Facebook still has a much larger share than Google + (Kallas 2013). One reason for this may be that users are already familiar with Facebook and they are hesitant to switch to another similar site.

Several theories and models have been developed to assess the success of information systems adoption, including the technology acceptance model (TAM) (Davis 1989), TAM2 (Venkatesh and Davis 2000), TAM 3 (Venkatesh and Bala 2008), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003), UTAUT2 (Venkatesh et al. 2012), and the DeLone and McLean IS Success Model (DeLone and McLean 1992, 2003). However, those theories focus only on the system being adopted, ignoring any potential impact of prior system utilization (i.e., the system to be replaced) by users. Most existing research on information systems adoption focuses solely on the current, new system. Further, few studies have examined the system transition process for learning management systems.

To address the gaps, this study integrates the switching costs theoretical perspective into an information systems adoption model. Specifically, a research model is developed and tested in the context of a transition between two learning management systems. The model examines the relationships among different types of switching costs and information systems adoption constructs from the UTAUT model. An empirical study is conducted to test the model. The results indicate that emotional costs and reduced performance costs can significantly influence users' perceived value associated with the transition between learning management systems. Further, perceived switching value, performance expectancy, effort expectancy, and social influence have significant impacts on users' intentions to use the new learning management system. In addition, participants' comments about the two learning management systems are also analyzed.

The remainder of this paper is organized as follows. First, we describe our theoretical foundations and related literature, and highlight the research gaps. Then the research model and hypotheses are presented. After that, the research methods are discussed in detail, followed by data analyses and discussion of results. Finally, the contributions and limitations of the study, as well as, suggested future directions for related research are presented, concluding with a brief summary of the paper.

2 Theoretical foundations and related literature

2.1 Switching costs

Switching costs are defined as the overall cost or difficulty associated with moving from one option to an alternative (Whitten and Wakefield 2006). Switching costs have been well studied in Marketing literature, where they are typically referred to as the costs (such as the time, money, and effort) incurred when a customer changes from one service provider or supplier to another (Wang et al. 2011). Although some studies have treated switching costs as one conceptual variable and used a global measure to assess them, others have identified multiple dimensions of switching costs. Based on previous research, switching costs can be categorized into two major groups: economic expenditures and intangible costs (Whitten and Wakefield 2006). Economic expenditures refer to the monetary costs of setting up and adapting to the new alternative, and intangible costs are concerned with the user' psychological or relational costs associated with the transition (Whitten and Wakefield 2006). Other studies have identified more detailed types of switching costs, such as emotional costs, learning costs, implementation costs, reduced performance costs, and sunk costs (Kim and Perera 2008; Kim 2011). Emotional costs refer to the psychological or emotional discomfort associated with the switch from one option to an alternative, which can be attributed to the individual's loyalty to the prior option (Guiltinan 1989). Learning costs are the costs associated with learning how to adapt to the new alternative (Klemperer 1987; Jones et al. 2002; Burnham et al. 2003). Implementation costs involve the direct monetary expenses in acquiring, setting up, and fine-tuning a new system, and can be measured by time, effort, and money (Spekman and Strauss 1986; Burnham et al. 2003; Jones et al. 2002; Whitten and Wakefield 2006). Reduced performance costs refer to the loss of tangible or intangible benefits when switching to an alternative (Gwinner et al. 1998; Jones et al. 2002). Sunk costs involve the non-recoverable expenditures of time, effort, and/or money that were already invested in establishing and maintaining the prior option (Guiltinan 1989; Jones et al. 2002).

Previous research in Marketing has found switching costs to be a crucial factor in determining customer loyalty (Wang et al. 2011; Blut et al. 2014; Matos et al. 2013). In general, customers tended to remain loyal to the original product or service provider if they perceived the costs associated with changing from the original provider were higher than the perceived benefits of building a new relationship with another provider (Wang et al. 2011), Wang et al. (2011) investigated e-tailing service failure and found that perceived switching costs could significantly influence customers' loyalty to e-tailers. Matos et al. (2013) found that switching costs were a direct antecedent of customer loyalty in the banking industry. They also found a significant moderating effect of switching costs on the customer satisfaction-loyalty relationship. Blut et al. (2014) further examined the relationship between switching costs and customer loyalty by separating switching costs into two constructs, internal and external switching costs. They found that external switching costs (which are the costs created by the product or service provider aiming at attracting the customer) had a stronger effect on customer loyalty than internal switching costs (which are the costs rooted in the customer's lack of ability to switch) did. They also found that certain service characteristics could moderate the switching costs-customer loyalty relationship. Previous research on customer retention (a concept that shares similarity with loyalty) found switching costs to be an important determining factor (Edward and Sahadev 2011; Nagengast et al. 2014; Lee et al. 2011). For example, Edward and Sahadev (2011) found that switching costs had a significant positive effect on customer retention, and customer satisfaction could significantly influence both switching costs and customer retention. Lee et al. (2011) studied users' repurchase intention in brick-and-click bookstores, and found that the user's personal schema (frame of reference based on past experience and training) could significantly influence switching costs, and both of them were significantly associated with repurchase intention.

The switching scenarios occur not only in the Marketing related industries but also in the IS field. For examples, many companies may change or upgrade their software or hardware systems periodically. When adopting a new information system, it is important to assess its usability in order to ensure the success of the adoption. However, even when the new system can provide substantial advantages aimed at improving users' task performance compared with the prior system, it is not always true that users will be willing to switch to the new system (Hsu 2014; Agrawala et al. 2005; Ha and Yang 2012). Sometimes substantial resistance to acceptance of the new system can be seen (Ye et al. 2008; Janssen et al. 2015). This phenomenon is not new to business information systems. Even in the early days of computing, such resistance existed, ranging from passive non-use (Schmitt and Kozar 1978) to physical sabotages (Dickson et al. 1974). Users' resistance to change may attributed to their deep belief in the status quo due to their comfort with and loyalty to the prior system (Nov and Ye 2009). Thus, the prior system becomes the anchor of their perceptions of future systems. Changes from the anchor could make them feel uncomfortable or even nervous about the new system. Such impact cannot be ignored when an organization wants to make sure of a successful adoption of a new information system. Thus, the switching costs theoretical perspective can be leveraged to study the system transition process.

Research in the IS field has examined system switching scenarios in various contexts such as Web browsers (Kim and Perera 2008; Ye et al. 2008), enterprise systems (Kim 2011; Kim and Kankanhalli 2009), email systems (Kim et al. 2006), and IT outsourcing (Whitten et al. 2010). For example, Kim and Kankanhalli (2009) investigated the switchover to a new enterprise system, and found that both switching costs and switching benefits could significantly influence the perceived value which, in turn, influenced user resistance to change. Chen and Forman (2006) investigated whether vendors could influence switching costs in an environment with open standards. Specifically, they studied the market for routers and switches (two networking related hardware components) and found that vendors were able to maintain high switching costs in such markets despite the presence of open standards in the industry. In another study, Techatassanasoontorn and Suo (2011) examined factors influencing standards adoption using the economic theory of networks, and found that switching costs significantly influenced de facto standardization adoption in static small-world networks and scale-free networks.

In addition, different types of switching costs related to information systems have been identified and investigated in previous IS research (Kim and Perera 2008; Kim 2011; Zhang et al. 2009; Whitten et al. 2010). For example, Kim and Perera (2008) studied the relationships between different types of switching costs and user resistance to change in the context of Web browsers, and found that reduced performance costs and emotional costs had significant impacts on user resistance to change. In another study, Zhang et al. (2009) found that sunk costs were significantly associated with bloggers' intention to switch their blog services. Whitten et al. (2010) investigated the impact of different switching costs on IT outsourcing strategy, and found that both sunk costs and reduced performance costs were positively associated with outsourcing continuance and negatively associated with vendor switching and backsoucing.

2.2 TAM and UTAUT

Information systems play an increasingly important role in the modern era (Beck et al. 2008; Brown 2008; Rana et al. 2015). Using the capabilities of mass data storage and access, analytical and decision making support, and effective information visualization, an information system can provide integrated access for information retrieval, analysis, and presentation in an effective and efficient manner (Adeoti-Adekeye 1997; Khodakarami and Chan 2014; Hota et al. 2015). To help evaluate the performance and success of an information system, various adoption theories and models have been developed The most widely used ones include the technology acceptance model (TAM) (Davis 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003).

Developed based on the theory of reasoned action (TRA) (Fishbein and Ajzen 1975). TAM (Davis 1989) is one of the most influential theories of user acceptance and usage of information systems. It states that ease of use and usefulness influence behavioral intention, which ultimately determines system use (Davis 1989). Later research has further validated and extended TAM. Venkatesh and Davis (2000) developed TAM2 to examine antecedents of perceived usefulness and intention to use. TAM2 includes two groups of determining factors based on social influence processes and cognitive instrumental processes. Tested on four different data sets, it was consistently found that subjective norm, image, job relevance, output quality, and result demonstrability significantly influenced perceived usefulness, while subjective norm, perceived usefulness and perceived ease of use were significant influential factors on intention to use. In addition, experience and voluntariness had significant moderating effects on the subjective norm-intention relationship. A later extension on TAM is TAM3 (Venkatesh and Bala 2008) which further explored the antecedents of both perceived usefulness and ease of use. This model includes a set of factors which impact perceived usefulness, including subjective norm, image, job relevance, output quality, and result demonstrability. It also specifies determining factors of perceived ease of use, which include computer self-efficacy, perceptions of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability.

A great body of research has applied TAM and its extensions to study information systems adoption in different settings. For example, Lederer et al. (2000) validated TAM in the context of job-related Web site usage. They also identified significant antecedents of both perceived usefulness and ease of use. Specifically, they found that when using Web sites to conduct job-related tasks, ease of understanding and ease of finding were significant predictors of ease of use, and that information quality predicted usefulness. Wu and Wang (2005) leveraged TAM to examine user acceptance of mobile commerce. In their model, in addition to perceived usefulness and ease of use, they also included factors of perceived risk, cost, and compatibility. They found that all factors, except perceived ease of use, could significantly influence users' intentions to use mobile commerce, which in turn impacted the actual usage behavior. Using TAM as the theoretical foundation, Rau and Haerem (2010) looked at technological gatekeepers' decisions about exploring or exploiting features of new information systems. They elaborated factors that could influence such decision making, and suggested future research to conduct more micro-level studies on new technology deployment. In a study of user acceptance of mobile government applications, Shareef et al. (2015) found that both perceived usefulness and ease of use were significant determinants of intention to use. In another study, Chen et al. (2008) found that both perceived usefulness and ease of use significantly influenced public health nurses' intentions on Web-based learning.

Developed through a review and consolidation of constructs from eight prior models (which included TRA and TAM) that had been used to explain information system usage behavior, the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) has been widely acknowledged and adopted in current IS research. The theory states that four key constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of usage intention and behavior. Similar to the cencepts of perceived usefullness and ease of use in the original TAM model, performance expectancy and effort expectancy aim to measure users' beliefs. Performance expectancy is defied as "the degree.

to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447), and effort expectancy is defined as "the degree of ease associated with the use of the system" (p. 450) (Venkatesh et al. 2003). UTAUT also includes two new constructs as the determinants of usage intention and behavior: social influence and facilitating conditions. Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451), while facilitating conditions refer to "the degree to which an Individual believes that an organizational and technical infrastructure exists to support use of the system" (p. 453) (Venkatesh et al. 2003). In their study, Venkatesh and his colleagues (2003) also empirically tested UTAUT and developed a set of validated measurement items for constructs in the model. Because of its popularity and validity in IS adoption research, this study leverages UTAUT as its second theoretical foundation.

As one of the most widely accepted adoption theories, UTAUT has been used to assess information systems in various contexts. For example, Shibl et al. (2013) applied UTAUT to examine the acceptance of clinical DSS among general practitioners. They found that the four factors of performance expectancy, effort expectancy, facilitating conditions, and trust in the knowledge base significantly influenced clinical DSS acceptance and use. Miltgen et al. (2013) leveraged the theories of UTAUT, TAM, and diffusion of innovations (DOI) to examine end-user acceptance of biometrics. The results indicated that perceived usefulness, facilitating conditions, compatibility, and perceived risks significantly influenced users' behavioral intention to accept the biometrics technology, which was then significantly associated with behavioral intention to recommend using biometrics. Hung et al. (2014) investigated the factors that influenced nurses' use of primary health information systems, and found that compatibility had a significant impact on perceived usefulness and perceived trust in the system which, in turn, influenced users' attitudes and intention to use. Brown et al. (2010) extended UTAUT in the context of collaboration technology use, and found that collaboration technology characteristics, individual and group characteristics, task characteristics, and situational characteristics were important antecedents of UTAUT constructs. Venkatesh et al. (2012) recently presented an expanded UTAUT model which they call UTAUT2. This model incorporated consumer good factors of hedonic motivation (enjoyment of use) and the direct price paid for the product or service. They posited that these factors would impact adoption of new technologies that were directly purchased by their users and viewed, in whole or part, as consumer goods.

2.3 Learning management systems

Learning management systems are designed to support students' learning activities (Schoonenboom 2014; Zhang and Nunamaker 2003). They have been widely used in higher education to support both face-to-face teaching and distance education (Schoonenboom 2014; Lu et al. 2003; Campbell 2000; Baloian and Zurita 2015). Learning management systems typically provide a varied group of tools to effectively support students' learning activities (Schoonenboom 2014; Sun et al. 2009; Lu et al. 2003; Tyran and Shepherd 2001). For example, the course materials sharing tool enables students' to view and download documents posted by instructors. The grade center tool can help provide feedback on students' performance in a timely manner. The message and email tool enables focused communication between the instructor and students, as well as among students themselves. Critical functions of Web-based learning management systems have been found to include instruction presentation and student learning management (Sun et al. 2009).

Previous studies have examined the adoption of learning management systems. For example, Schoonenboom (2014) utilized TAM (Davis 1989) to investigate instructors' intentions to use learning management systems in higher education, and found that task performance, usefulness of learning management systems, and ease of use associated with learning management systems significantly influenced instructors' intentions to use the systems. Based on TAM2 (Venkatesh and Davis 2000), Smet et al. (2012) examined the adoption of learning management systems by secondary school teachers. They found that perceived usefulness, perceived ease of use, subjective norm, personal innovativeness, and internal technology support influenced users' usage intention and behavior. Oztekin et al. (2013) emphasized the usability and quality of Web-based learning management systems. They proposed a machine-learning based evaluation method to select the most important items from a large item pool based on their contribution to the overall system usability. Xu et al. (2014) studied and compared learning management systems designed for virtual learning environments. They found that the system with personalized learning functions could significantly enhance students' learning effectiveness in terms of examination, satisfaction, and self-efficacy compared with the system that did not provide personalized learning functions. Campbell (2000) discussed and demonstrated how a Web-based learning management system could support flexible learning in which students could interact with their instructors, classmates, and learning resources in a flexible manner.

2.4 Research gap

Successful adoption of information systems is essential to organizations, as more and more companies start to use advanced information systems to support part or all of their daily businesses and functions. When adopting an information system, most modern companies are not doing it from scratch; rather, in most cases, there is already an existing system to be replaced by the new one. Therefore, when studying the adoption of a new system, it is not enough to assess it based solely on factors related to the use of the new system (such as factors stated in UTAUT). Instead, users' perceptions of the overall system switching process should also be taken into account. However, most of the existing systems adoption research focuses only on characteristics of the new system. To address this gap, in this study, we combine both the switching costs and UTAUT theories to examine how users' perceptions toward the system transition process, as well as factors about the new system, influence their adoption behavior.

In the existing literature, there are two parallel groups of research on systems adoption and switching costs respectively, which have little overlap with each other. On one hand, the set of studies works with leading, related theories (such as TAM and UTAUT) to examine the performance and success of information systems (focusing only on the new system being adopted). As discussed in Section 2.2, these studies rarely consider potential influences introduced by the usage experience of the prior system (i.e., the system to be replaced by the new one). On the other hand, there is a second set of studies which focuses only on the system switching process itself, and typically measures and compares different types of costs related to switch in order to understand whether (and to what extent) the user resists system change and other related switching behavior. As discussed in Section 2.1, these studies rarely consider detailed systems adoption factors. One major contribution made in this study is the bringing together of features of these two sets of studies into an integrated model.

Although there are a few studies that have examined factors related to information systems adoption and switching costs, very few of them have incorporated either a diverse set of systems adoption factors or various specific types of switching costs, or both. Instead, they only examined a limited set of factors from the two theoretical perspectives. For example, Chen and Hitt (2003) developed a research model to study customer retention in the online brokerage industry. The model measured a set of attributes related to the customer and the firm, and examined their impacts on switching and attrition. However, the model had just one system adoption factor (ease of use), and it treated switching cost as a single construct. Zhang et al. (2009) developed a research model to examine bloggers' switching behavior. The model included three independent variables - sunk costs, satisfaction, and attractive alternative, all of which were found to significantly influence users' intention to switch. However, the model only considered one type of switching costs (sunk costs), and only incorporated satisfaction and intention from the adoption perspective. Ye et al. (2008) studied the switching scenario from Microsoft Internet Explorer (IE) to Mozilla Firefox, and found that breadth of use, satisfaction, relative advantage, perceived ease of use, and perceived security were direct antecedents of switching behavior. Although their model included various adoption related constructs, it examined switching behavior as a whole, instead of specifying different types of switching or its costs. Hsu (2014) developed a research model to study the switching intentions of smart phone users. The model stated that both switching costs and switching benefits could influence perceived switching value, and all three of them could further influence switching intention. Significant relationships were found among those constructs except for the one from switching costs to switching intention. In this model, switching costs were treated as a multi-dimensional construct with uncertainty costs, sunk costs, transition costs, and loss costs being its first dimensions. Although the model was complex and considered different types of switching costs, it did not examine specific adoption related factors. In addition, the dependent variable about intention (i.e., the construct Switching Intention) focused on users' intention towards the switching process, instead of their intention to use the new system.

Compared with the above listed studies, we believe our proposed research model (as shown in Section 3) is more advanced and more balanced in its treatment of the two theoretical lenses, since we incorporate various detailed types of switching costs and a diverse set of adoption factors (based on UTAUT).

Furthermore, learning management systems are an important type of system widely used in educational institutions as well as the training departments of other types of organizations. However, relatively few studies have been done on the adoption of learning management systems. In addition, no study has specifically investigated the system switching process of this type of system. The present study addresses this gap by examining the impacts of both switching cost factors and adoption factors on the behavioral intention of using the new learning management system. The research model and analysis results should provide educators and system developers with insights about the acceptance and development of learning management systems, and help them better understand learners' information systems usage behavior.

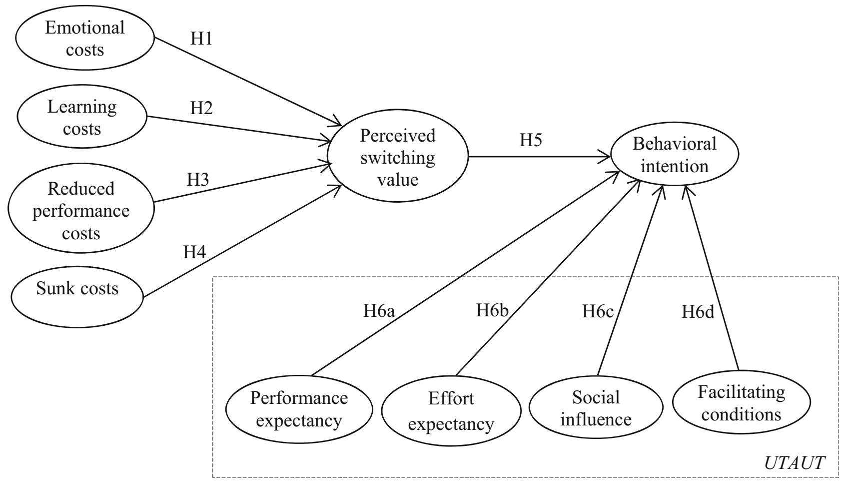
3 Research model and hypotheses

In this section, we present our research model and hypotheses. As shown in Fig. 1, the proposed research model incorporates various types of switching costs (including emotional costs, learning costs, reduced performance costs, and sunk costs), perceived switching value, and UTAUT constructs.

Emotional costs (EMC) refer to the psychological or emotional discomfort associated with the switch from the prior system to an alternative (Guiltinan 1989; Kim and Perera 2008). Previous IS research has found that emotional costs significantly influenced user resistance to change in the context of Web browsers (Kim and Perera 2008). In Marketing literature, emotional costs are sometimes referred to as relational switching costs which are defined as the psychological or emotional discomfort associated with the breaking of bonds with the existing product or service provider (Meng and Elliott 2009; Vasudevan et al. 2006). It was found that relational switching costs had a significant impact on customers' commitment in business relationships with product or service providers (Vasudevan et al. 2006). Relational switching costs were also found to have a negative impact on the use of e-book readers (Huang and Hsieh 2012). Perceived switching value (PSV) (referred to as perceived value in some studies) means the benefits gained from switching to the new system from the prior system (i.e., the system to be replaced) (Kim and Kankanhalli 2009; Kim 2011; Hsu 2014). It has been used to examine the success of system transition in different contexts, such as smartphones (Hsu 2014) and enterprise systems (Kim and Kankanhalli 2009; Kim 2011). A negative relationship has been found between switching costs and perceived switching value (Kim and Kankanhalli 2009; Kim 2011; Hsu 2014). During system transition, if a user has had a very positive experience in using the prior system, he/she could become loyal to that system. When required to stop using it and move on to a new system, a significant amount of emotional costs may be imposed on the user. Because of the negative feeling associated with those emotional costs, the user is likely to overlook the value brought by the new system even when the value outweighs any possible loss caused by discontinuance of the prior system. This could be even more true for the transition of learning management systems, since users of this type of systems typically utilize the system regularly and intensively to perform their learning related tasks and activities, and thus a strong emotional tie to the current system might be expected. Changing to a new system as mandated by the university could possibly lead to users' negative feelings toward the value brought by the change to the new system. Therefore, we hypothesize:

H1: Emotional costs will negatively influence perceived switching value when adopting a new learning management system.

Fig. 1 Research model



Learning costs (LRN) are the costs associated with learning how to use a new system (Klemperer 1987; Jones et al. 2002; Burnham et al. 2003; Kim and Perera 2008). Previous research on switches of service providers mentioned that learning costs could include costs associated with finding out and evaluating alternatives, as well as costs of adjusting to the new service provider once it's selected (Jones et al. 2002). In our context, learning costs mean the time and effort that students need to take in getting familiar with and becoming proficient in using the new learning management system to perform their learning tasks. Previous research has found that learning costs (as a dimension of procedural costs) could significantly influence consumer intentions to stay with an incumbent provider (Burnham et al. 2015). When studying factors that could influence a company's decisions to continue outsourcing, switch vendors, or back source, it was found that in-house learning costs were positively associated with both outsourcing continuation and vendor switching, but negatively associated with back sourcing (Whitten et al. 2010). Previous research also found learning costs to be an important factor to consider when adopting information-intensive systems (Chen and Hitt 2006). Lower learning costs were typically associated with a smoother adoption of those systems (Chen and Hitt 2006). In our context, the new learning management system provides a set of functions similar to the prior system and provides additional and advanced features, but uses a somewhat modified interface design. Thus the user may need to spend a considerable amount of time and effort to learn how to effectively use those new features and to get familiar with the system interface. If a higher level of costs is perceived by the user during the learning process, a negative feeling toward the system may be formed, thus leading to a decreased degree of perceived value associated with the system transition. Therefore, we hypothesize:

H2: Learning costs will negatively influence perceived switching value when adopting a new learning management system.

Reduced performance costs (RPF) refer to the loss of tangible or intangible benefits when switching to a new system (Gwinner et al. 1998; Jones et al. 2002). Previous research on outsourcing continuance found that when reduced performance costs were high, companies tended to choose outsourcing continuance without vendor switching or back sourcing (Whitten et al. 2010). The reasons included the comfort and trust with the current vendor and the concern of time and monetary loss in searching for another vendor (Whitten et al. 2010). Previous research also examined the relationship between reduced performance costs and user resistance to change in the transition of Web browsers, and found that reduced performance costs had a significant positive impact on user resistance to change. When studying the impact of reduced performance costs on users' perceived switching value, Kim (2011) found that loss costs (which is a concept similar to reduced performance costs) had a significant negative effect on perceived switching value in the context of enterprise systems, and Hsu (2014) found a significant negative relationship between lost costs (as a dimension of the switching costs construct) and perceived switching value in the smartphone industry. Similarly, in our context of learning management systems, we also expect reduced performance costs to play a significant negative role on perceived switching value. During the transition to a new learning management system, the user will face new system features and an interface design that differ from those in the prior system. During this time, users may feel a decrease of efficiency in managing their learning related tasks by using the new system. As such costs increase, the net benefits brought by the system transition decrease. Therefore, we hypothesize:

H3: Reduced performance costs will negatively influence perceived switching value when adopting a new learning management system.

Sunk costs (SNK) involve the non-recoverable expenditures of time, effort, and/or money invested in establishing and maintaining the prior system (Guiltinan 1989; Jones et al. 2002; Kim and Perera 2008). Consideration of this investment may make users more reluctant to switch to a new system. Previous studies have examined the impact of sunk costs on users' system switching behavior. For example, Zhang et al. (2009) found that sunk costs had a significant impact on users' intention to switch. Kim (2011) found that sunk costs had a significant positive impact on user resistance to change to new enterprise systems. Zhang et al. (2012) found that sunk costs played a significant negative role in users' intention to switch blog service providers. When examining the adoption of Computer Aided Design (CAD) and Computer.

Numerically Controlled (CNC) machine tools, Åstebro (2004) found that sunk costs were negatively correlated with both the depth and probability of CAD and CNC adoption. In addition, when investigating the relationship between switching costs and perceived switching value, Hsu (2014) treated sunk costs as a formative dimension of switching costs, and found a significant negative impact of switching costs on perceived switching value. In our context of learning management systems, sunk costs are about the time and effort that users have already invested to become effective and efficient in using the current system to help manage and complete their learning related tasks and activities. The more sunk costs associated with using the current system, the less likely the user would be to believe the benefits (as perceived by them) outweigh the losses brought by the system transition. Thus, we hypothesize:

> H4: Sunk costs will negatively influence perceived switching value when adopting a new learning management system.

As originally described in the Marketing literature, perceived value is a measure of the net benefits a customer perceives from a product or service after evaluating both the benefits and losses it brings (Kuo et al. 2009; Turel et al. 2007). Previous literature has found a significant relationship between perceived value and behavior intention (Kuo et al. 2009; Turel et al. 2007). For example, Turel et al. (2007) studied the adoption of wireless short messaging services (SMS) and found that perceived value could significantly influence users' intention to use SMS. Kuo et al. (2009) found that perceived value had a significant positive impact on users' post-purchase intention to use mobile value-added services such as games, icons, ringtones, messages, web browsing, and electronic transactions. In the context of system switching, the perceived value of the switching process (i.e., perceived switching value) refers to the net benefits obtained by switching from the prior system (i.e., the system to be replaced) to the new system (Kim and Kankanhalli 2009; Kim 2011; Hsu 2014). When making decisions, it is believed that people always seek to maximize value (net benefits) (Sirdeshmukh et al. 2002). This is also true when people decide their reactions about the switch to a new system. If the user perceives a higher level of value associated with the system transition process, it is more likely that he/she will be willing to use the new system. Previous research found that perceived switching value had a significant negative impact on user resistance to change (Kim and Kankanhalli 2009; Kim 2011). When studying the impact of perceived switching value on intention, most previous literature focused on switching intention, and found perceived switching value as a significant determinant on switching intention in different contexts (Hsu 2014). For example, Hsu (2014) found that perceived switching value could significantly influence users' switching intention to new smartphone platforms. Lin et al. (2013) found that perceived switching value had a significant positive impact on switching intention among online auction sellers. The behavioral intention examined in this study is the intention to use the new system, and perceived switching value is expected to significantly influence this type of intention. If the user perceives greater value associated with the switch from the prior learning management system to the new one, he/she is more likely to intend to use the new system with a higher level of system acceptance. Therefore, we hypothesize:

> H5: Perceived switching value will be positively associated with users' behavioral intention to use a new learning management system.

To gain a comprehensive view of the nomological network, we also include in our research model factors based on the theoretical foundation of UTAUT (Venkatesh et al. 2003) that have been found to affect intent to use the new system. In addition to perceived switching value, four other factors are also expected to be the direct antecedents of intention to use the new learning management system: performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI). In this context, if the user believes the new learning management system can improve their learning performance and the system is easier to use, he/she will be more likely to intend to use the new system. In addition, if the user perceives that there is sufficient and effective support around their use of the new learning management system, it is likely that he/she will be willing to use the new system. Finally, if others who are important to the user (such as classmates) believe he/she should use the new learning management system, the user is likely to be more motivated to use it. Therefore, we propose the following group of hypotheses.

> H6a: Users' performance expectancy toward a new learning management system will positively influence their behavioral intention to use it.
> H6b: Users' effort expectancy toward a new learning management system will positively influence their behavioral intention to use it.

H6c: Facilitating conditions supported by a new learning management system will positively influence users' behavioral intention to use it.
H6d: Social influence will positively influence users' behavioral intention to use a new learning management system.

In sum, the proposed research model incorporates the theoretical perspectives of both switching costs and system adoption, with H1-H5 related to the system switching process and H6 (a-d) related to the adoption of the new system.

4 Research method

4.1 Study site

This research was conducted in a major public university in the western part of the United States. During the time of this study, the university was adopting a new learning management system - Blackboard Learn, to replace its previous version - Blackboard Vista. This system transition is mandatory as required by the university. After the transition, the university supports only one learning management system – that is, Blackboard Learn. Users do not have the choice to go back to Blackboard Vista, as it is no longer supported by the university. This mandatory system transition process is consistent with many of the system transitions happening in organizations in general.

Figures 2 and 3 are screenshot examples of the two systems, respectively. Overall, the two systems provide similar functions to assist users' learning activities. For example, both systems enable users to browse and download course materials (such as syllabi and lecture slides), take online quizzes and exams, send messages to instructors and classmates, and view and track their own grades over the semester. The organization of the system functions and features are also similar, both using a two-window display with a list of functions on the left-side window and the main activity window on its right. For both systems, the main activity window organizes and displays course related materials into different folders. The instructor has the control to create, name, and show/hide those folders. The major difference between the two systems is the visual display, such as icons and color themes. Some terms used in the systems are also different. For example, under the instructor view, Blackboard Vista has two groups of functions named "Course Content" and "My Tools," while Blackboard Learn has two similar groups of functions named as the course ID and "Control Panel" respectively. Another difference is that since Blackboard Learn is more recently developed, it is claimed to have a better support on mobile devices. But overall, the two systems share very similar functionality and both can support users' performance of learning related activities in almost the same way. Therefore, we believe the two systems are fairly comparable and the transition between them provides an ideal setting to conduct this study.

4.2 Data collection

To test the proposed research model and hypotheses, a survey was conducted in the weeks before the end of the second semester of the adoption of the new system - Blackboard Learn. We believe that this timing provided a set of respondents who had already explored the new system for a reasonably long time but not long enough for them to have forgotten their experience with the prior system. Students who had used Blackboard Vista (i.e., the prior system) before and were using Blackboard Learn (i.e., the new system) were invited to participate in the study. Their participation was voluntary. Extra credit was given as the incentive. The survey was conducted in a computer lab. Upon agreement to participate, a set of questionnaire instruments related to the constructs in the research model was given to the participants. Participants were also encouraged to provide additional written comments to share their experience and ideas about the two systems.

In total, there are 138 participants in the study, 93 males and 45 females. All of them had the experience of using Blackboard Vista and were using Blackboard Learn at the time of the survey. On average, the participants used Blackboard Vista for 4 semesters and Blackboard Learn for 2 semesters. The average age of participants was 22.7. On average, they had more than 13 years of experience using computers and over 10 years of experience using Web-based information systems.

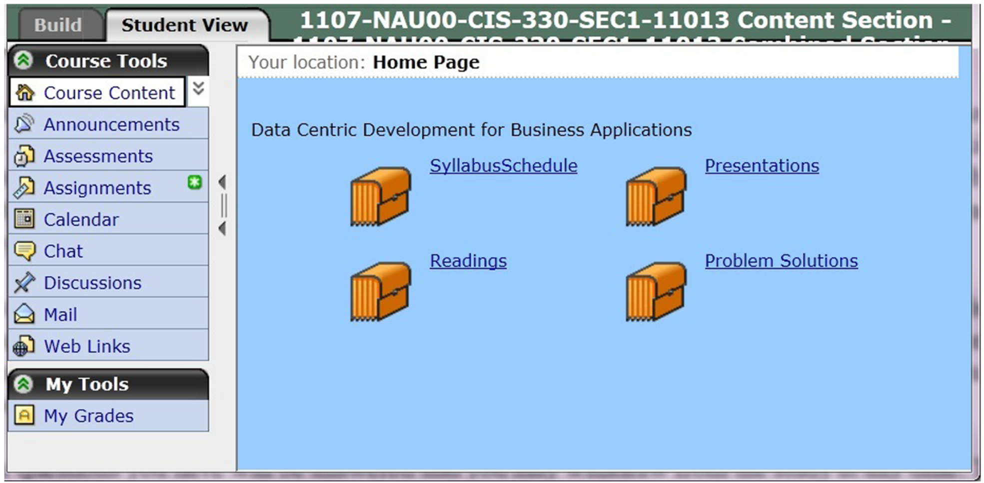
4.3 Measures

To measure the latent variables of emotional costs, learning costs, reduced performance costs, and sunk costs, we adopted measurement items from Kim and Perera (2008) with wording changes to fit the context of this study. The measurement items of perceived switching value were adopted from Kim (2011). We utilized the measurement items from the original UTAUT paper (Venkatesh et al. 2003) to measure performance expectancy, effort expectancy, facilitating conditions, social influence, and behavior intention, with changes to fit our context. All constructs in the research model were measured using the 7-Likert scale. Detailed measurement items are provided in Appendix.

5 Data analyses and results

Structural equation modeling (SEM) techniques were used to assess the research model. In particular, a widely used and robust method for causal model assessment, component-

Fig. 2 Screenshot of blackboard vista



based SEM (PLS) was utilized. Studies have reported that PLS has several advantages compared with other types of model testing techniques in terms of measurement level, sample size, etc. (Chin 1998a, 1998b; Akter et al. 2011; Gao and Waechter 2015; Sharma et al. 2013). In this study, we used Smart PLS 2.0 (M3) beta (Ringle et al. 2005), a widely adopted PLS tool for causal model analysis (Sharma et al. 2013; Hossain and Quaddus 2015).

5.1 Measurement model assessment

Reliability and validity tests were conducted on the latent constructs in the research model. Table 1 shows the reliability test results. Based on item loadings, FC3 and FC4 were dropped from later analyses as they did not pass the threshold value of 0.7 (Au et al. 2008). After that, the Cronbach's alpha values for all constructs were greater than the 0.7 guideline (Hair et al. 1998), and all item loadings were greater than 0.7 and significant at the 0.01 level.

Table 2 shows the descriptive statistics, composite reliability, average variance extracted (AVE), square root of AVE, and correlations among constructs. The composite reliability values of all constructs were above the recommended level of 0.70, indicating adequate internal consistency between items (Au et al. 2008). Convergent validity is demonstrated as the AVE values for all constructs were higher than the suggested threshold value of 0.50, which is the same as the requirement of the square root of AVE to be at least 0.707 (Gefen et al. 2000). Comparing the square root of AVE with the correlations among the constructs indicates that each construct is more closely related to its own measures than to those of other constructs, and discriminant validity was therefore supported (Chin 1998a).

5.2 Structural model assessment

Figure 4 shows the PLS results of the research model. The results show that emotional costs had a significant negative impact on perceived switching value, with a path coefficient

Fig. 3 Screenshot of blackboard learn

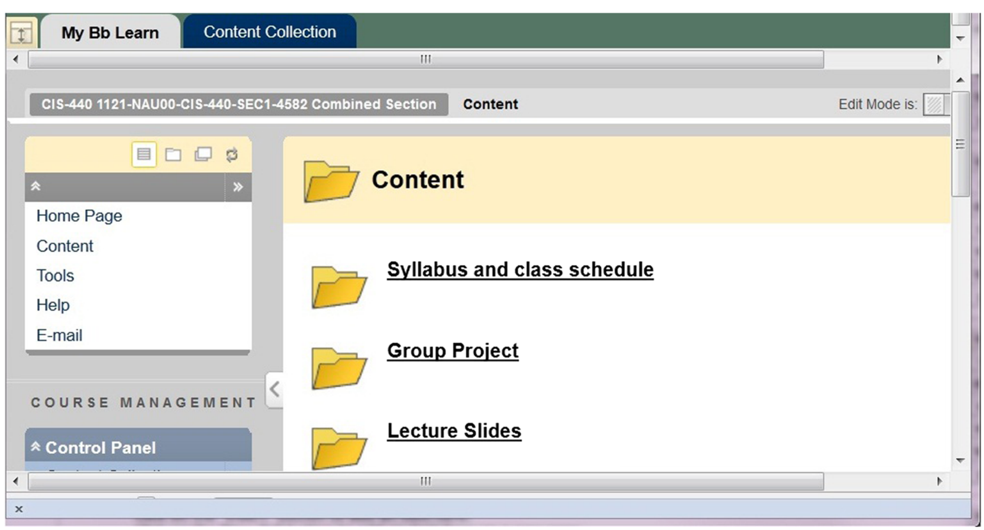


Table 1 Reliability test result

Construct	Cronbach's Alpha	Item	Loading	T-statistics
Perceived switching value (PSV)	0.916	PSV1	0.898	38.209
		PSV2	0.925	41.218
		PSV3	0.952	144.345
Emotional costs (EMC)	0.906	EMC1	0.890	32.266
		EMC2	0.951	114.294
		EMC3	0.910	50.390
Learning costs (LRN)	0.940	LRN1	0.949	126.209
		LRN2	0.957	115.847
		LRN3	0.928	52.860
Reduced performance costs (RPF)	0.959	RPF1	0.935	100.154
		RPF2	0.949	97.548
		RPF3	0.951	90.162
		RPF4	0.939	74.879
Sunk costs (SNK)	0.960	SNK1	0.916	39.036
		SNK2	0.965	139.332
		SNK3	0.939	71.154
		SNK4	0.962	131.438
Performance expectancy (PE)	0.905	PE1	0.888	50.598
		PE2	0.934	87.214
		PE3	0.928	84.274
Effort expectancy (EE)	0.947	EE1	0.923	79.631
		EE2	0.920	64.439
		EE3	0.946	104.625
		EE4	0.928	73.766
Social influence (SI)	0.825	SI1	0.772	20.086
		SI2	0.830	31.261
		SI3	0.820	21.758
		SI4	0.817	20.404
Facilitating conditions (FC)	0.652	FC1	0.909	46.192
	(0.852**)	FC2	0.881	39.511
		*FC3**	*0.390*	*3.863*
		*FC4**	*0.547*	*6.479*
Behavioral intention (BI)	0.976	BI1	0.974	198.726
		BI2	0.974	183.874
		BI3	0.982	331.419

*Dropped

**Reliability after some items dropped

of −0.392 ($p < 0.05$). Therefore, H1 was supported. However, no significant effect was found from learning costs to perceived switching value. This indicates that when adopting a new learning management system, the costs (such as time and effort) associated with learning how to use the system did not play a significant role in influencing learners' perceptions of the value of the system transition. So, H2 was not supported.

Reduced performance costs had a significant negative impact on perceived switching value, with a path coefficient of −0.279 ($p < 0.05$). Therefore, H3 was supported. No significant relationship was found from sunk costs to perceived switching value. Thus, H4 was not supported. The result indicates that the time and effort the learners had already spent to be proficient in using the prior learning management system did not have a strong impact on their perceptions of the value of transitioning to the new system.

Together, the two significant factors, emotional costs and reduced performance costs, together explained 49.9 % of the variance of perceived switching value.

Perceived switching value was significantly associated with users' behavioral intention to use the new learning management system, with path coefficient of 0.195 ($p < 0.05$), in

Table 2 Internal consistency and validity test result

Construct	Mean	Std Dev	Composite reliability	AVE	BI	EE	EMC	FC	LRN	PE	PSV	RPF	SI	SNK
BI	4.601	1.835	0.984	0.954	**0.977**									
EE	5.192	1.560	0.962	0.863	0.781	**0.929**								
EMC	3.599	2.043	0.941	0.842	−0.584	−0.530	**0.918**							
FC	5.482	1.352	0.931	0.871	0.620	0.751	−0.452	**0.933**						
LRN	3.862	1.932	0.961	0.892	−0.395	−0.531	0.638	−0.387	**0.944**					
PE	4.536	1.485	0.941	0.841	0.739	0.718	−0.485	0.638	−0.383	**0.917**				
PSV	4.186	1.818	0.947	0.856	0.702	0.671	−0.677	0.504	−0.508	0.636	**0.925**			
RPF	3.652	1.862	0.970	0.891	−0.608	−0.567	0.817	−0.516	0.573	−0.519	−0.655	**0.944**		
SI	4.721	1.599	0.884	0.657	0.639	0.583	−0.396	0.660	−0.324	0.636	0.603	−0.459	**0.811**	
SNK	3.855	1.801	0.971	0.894	−0.187	−0.267	0.468	−0.162	0.606	−0.128	−0.296	0.354	−0.111	**0.946**

Diagonal elements in bold case are the square root of average variance extracted (AVE) by latent constructs from their indicators; off-diagonal elements are correlations among constructs

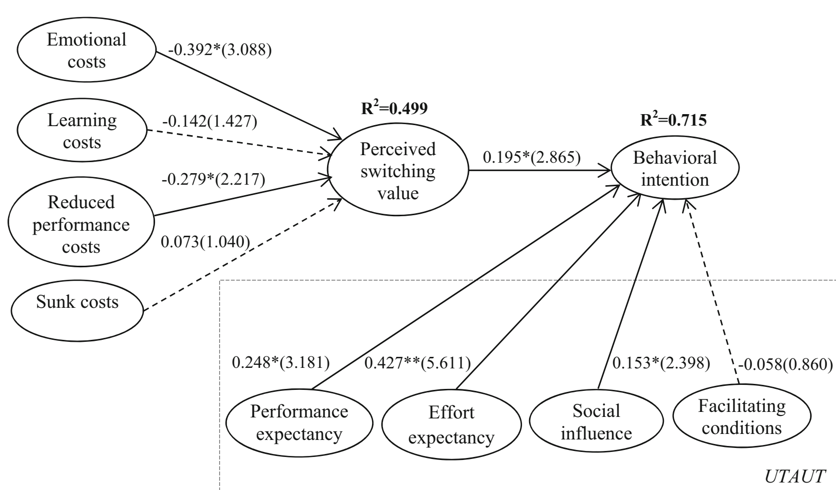
support of H5. Performance expectancy, effort expectancy, and social influence had significant impacts on users' behavioral intention to use the new learning management system, with path coefficients of 0.248 ($p < 0.05$), 0.427 ($p < 0.001$), and 0.153 ($p < 0.05$), respectively. Therefore, H6a, H6b, and H6c were all supported. However, no significant effect was found from facilitating conditions to users' behavioral intention to use the new learning management system. This indicates that the support around learners' use of the new learning management system did not play a significant role on their intention to use the new system. This may attributed to the fact that the two learning management systems shared the same IT support team from the university. Thus, students may not have perceived a significant difference from the support perspective in moving to the new system.

The four significant factors of perceived switching value, performance expectancy, effort expectancy, and social influence together explained 71.5 % of the variance of behavioral intention.

5.3 Summary of written comments

To get a deeper understanding of users' perceptions toward the two systems, we also collected and analyzed written comments provided by the participants. Since both systems aim to support students in performing learning tasks, it is not surprising to see that they share some common features and functions. Some participants saw the two systems as being very similar and did not show a clear preference between them. Examples of comments are: "I find them to [two] very similar," "They are too similar to tell," and "[Blackboard] Learn was almost the same as [Blackboard] Vista's features [,] and function are not that much different."

Fig. 4 Model testing results



Note. * Significant at 0.05 level. ** Significant at 0.001 level

However, other participants did list differences between the two learning management systems, and explained their preference toward certain features and functions in each of the systems. The following two sub-sections summarize the favorable features and functions from each system.

5.3.1 Perceived favorable features and functions in blackboard vista

When asked about what features and functions participants liked more in Blackboard Vista compared with Blackboard Learn, many of them mentioned the feature of change notification (called active alert). This feature helped remind students when class components were newly posted or due as well as when new emails arrived. Some examples of comments are as follows:

> "Only thing that is different from the two is that in [Blackboard] Vista it gave notification with a green asterisk on certain tools/functions that there is something new available like new a [a new] exam or assignment is available."
> "I liked that there were icons that showed when a quiz or email was new [in Blackboard Vista]. Now [with Blackboard Learn] it is very easy to forget when quizzes are open."
> "An alert that new assignment or grades has been on the [Blackboard] vista"
> "The way it organized assignments and informed you of any new assignments with a notification asterisk"

Several participants also said that they preferred the email tool and the grade book provided in Blackboard Vista. Although both systems offer these feature, they felt that the organization and navigation of the two features in Blackboard Vista were better. Some examples of comments are as follows:

> "Blackboard Vista made it much easier to communicate with my instructors and classmates. The chat and e-mail functions were easy to operate and worked well. In addition, it was much easier to view my grades and keep track of my academic progress in [Blackboard] Vista than it is in Bblearn [Blackboard Learn]."
> "The MyGrades tool is easily accessible. The message tool is much easier to find."
> "Email, grades and announcements were more organized in [Blackboard] vista compared to BBlearn [Blackboard Learn]"
> "[Blackboard] Vista made it more convenient to get to the grade and mail tabs for each class. On bblearn [Blackboard Learn] I have to think about where my grades is [are] located to access it."

Other participants expressed a preference for the overall display of Blackboard Vista. They found it was easier to navigate through the system to locate the functions they needed. Although they acknowledged there were more features provided in Blackboard Learn, they still preferred the ease of use associated with Blackboard Vista as some new features offered in Blackboard Learn might not be that popular and could lead to complication and confusion. Examples of comments are:

> "I liked the layout of class pages, [;] it seemed to be a little more logical and took fewer clicks to navigate the page."
> "better interface and easier to find content of the class."
> "When I was first introduced to Bblearn [Blackboard Learn] it was more complex and it was difficult to get adjusted with the system. The thing I missed most about [Blackboard] Vista is the simplicity."
> "Easier to understand, functions are more organized. Class info was easier to access. BBLearn [Blackboard Learn] has lots of tools that I do not understand and are not useful"
> "There are less [fewer] functions in [Blackboard] Vista than in BBlearn [Blackboard Learn]. It is less complicated for me to use [Blackboard] Vista than BBlearn [Blackboard Learn]."

5.3.2 Perceived favorable features and functions in blackboard learn

We also asked participants the features and functions they liked more in Blackboard Learn compared with Blackboard Vista. Many of them stated that there were more tools and resources available in Blackboard Learn that could be very helpful to them. Examples of comments are:

> "The Bblearn [Blackboard Learn] has more functions, [;] some of them is [are] very useful, [.] when [When] I use the Bblearn [Blackboard Learn], I feel it is easier to use. And Bblearn [Blackboard Learn] have many other tools that help my study a lot."
> "BBlearn [Blackboard Learn] has more functions than [Blackboard] Vista. Things are presented in BBlearn [Blackboard Learn] much more clearly."
> "More tools, easier access to different functions of each course."
> "There's a lot more offered."
> "The tools feature that lists all the helpful resources needed."

Some participants also mentioned that they preferred Blackboard Learn because it was more reliable and offered mobile access (such as apps for smart phones and iPads) which was not available in Blackboard Vista. Some examples of comments are as follows:

> "Bblearn [Blackboard Learn] hardly encounters crashes and is extremely easy to use with a far superior interface than [Blackboard] Vista."
> "It is under repair less and is slightly more reliable."
> "it's more reliable, and easier to use"
> "I like the fact that there is an App for blackboard learn."
> "Bblearn [Blackboard Learn] does allow more files to be open on more devices successfully. So it is nice that I can use my ipad/smart phone/and computer to follow my classes"
> "mobile app"

Interestingly, although some participants stated that they preferred Blackboard Vista's email and grade book tools (see the above sub-section), there were also participants who perceived that similar tools offered in Blackboard Learn were better. Examples of comments are:

> "I like the e-mail feature, where on the page it shows you the person [persons] who have e-mails."
> "The system seems to work better as a whole. I like the email function and the ability to communicate with class mates. I also like the being able to access my grades."
> "I like the My Grades function better with BBlearn [Blackboard Learn]. It is more accurate. I also like how you submit assignments, because I have more confidence that the file is actually going to be correctly stored on the server for my professors to retrieve."
> "the grades tool can help me follow the grades and the personal vision is clear"
> "The My Grades section is better in Bblearn [Blackboard Learn]."

Similarly, although some participants expressed their preference for the overall design of Blackboard Vista (see the above sub-section), there were other participants who believed that the overall design of Blackboard Learn was better. Some comments are as follows:

> "The overall organization and feel of bblearn [Blackboard Learn] is much better. I hated that [Blackboard] Vista looked like it was ten years old."
> "I like the layout of Bblearn [Blackboard Learn] more than that of [Blackboard] Vista. All of the different modules and widgets available are neat, but they do take a while to load sometimes. Still, I think Bblearn [Blackboard Learn] made some improvements to user interface over [Blackboard] Vista."
> "I like the ability to navigate through the coursework easier. The organization is much simpler to follow."
> "Everything is a little more streamlined."
> "I like the easy flow of BBlearn [Blackboard Learn] and [it] takes very little effort to learn"

6 Discussion

6.1 Research contributions

This study makes several research contributions. First, this study uses multiple theoretical lenses to investigate the adoption of new information systems. Most existing research related to systems adoption typically utilizes a single research perspective to examine the adoption scenario. However, with the increased popularity and complexity of modern information systems, using one theoretical lens is not enough. These days, when adopting a new information system, most of the organizations already have an existing system that provides somewhat similar functions but will be replaced by the new system. Therefore, when studying the adoption of the new system, it is not enough to only assess it based on factors related to the use of the new system (such as factors stated in UTAUT). Instead, users' perceptions on the system switching process should also be taken into account. Following that line, this study contributes to existing research by combining two theoretical perspectives, systems adoption and switching costs, and leverages them to investigate the adoption of new systems in organizations.

A second contribution of this study is the incorporation of new factors (i.e., switching costs and switching value) in the adoption model. As discussed in the Research Gap section (i.e., Section 2.4), there are two parallel groups of research, focusing on systems adoption and switching costs, respectively. On one hand, studies on systems adoption mainly focus on assessing the performance and success of information systems being used or adopted (Lederer et al. 2000; Wu and Wang 2005; Shareef et al. 2015; Shibl et al. 2013; Miltgen et al. 2013), without specifically considering any potential impacts made by the prior system usage experience. On the other hand, studies on investigating the system switching scenario mainly compares and measures different types of costs in order to understand the level of users' resistance to change and other switching behavior (Wang et al. 2011; Matos et al. 2013; Blut et al. 2014; Kim 2011; Kim and Perera 2008). This body of research rarely considers detailed adoption factors relating to either the prior or new systems. Although there are a few studies that have examined factors related to both switching costs and systems adoption (Chen and Hitt 2003; Zhang et al. 2009; Ye et al. 2008; Hsu 2014), none of them have incorporated a set of detailed types of switching costs along with a detailed set of adoption factors.

This study makes the contribution by developing a research model that integrates both the theoretical perspectives of systems adoption and of switching costs, by examining the effects of a variety of adoption factors and different types of switching costs. Specifically, the model posits that different types of switching costs may negatively influence perceived switching value; while perceived switching value, together with performance expectancy, effort expectancy, facilitating conditions, and social influence about the new system, are direct antecedents of user' intention to adopt the new system. We believe this model is more advanced than existing ones and more balanced toward the two theoretical lenses, thus making a contribution to existing adoption literature.

A third contribution of this study is that it demonstrates the necessity of considering the switching costs perspective when examining the success of modern information systems adoption. The widely accepted adoption theories, such as TAM (Davis 1989) and UTAUT (Venkatesh et al. 2003), and their extensions, such as TAM2 (Venkatesh and Davis 2000), TAM3 (Venkatesh and Bala 2008), and UTAUT2 (Venkatesh et al. 2012), do not specifically consider switching costs related factors. Rather, they focus more on factors related to users' beliefs, attitudes, and behavior toward a particular system being studied. Thus, our proposed research model can be treated as an extension of UTAUT. In addition to the four predicting factors (i.e., performance expectancy, effort expectancy, facilitating conditions, and social influence) of system acceptance as specified in the original UTAUT model, we also find perceived switching value as another determinant which is influenced by different detailed types of switching costs.

In addition, our study contributes to the literature on the adoption of learning management systems. As an important type of systems, learning management systems have been widely adopted in educational institutions as well as other entities (such as corporate training departments). However, relatively fewer studies have been done to examine the adoption of this type of systems. Furthermore, to the best of our knowledge, no study has specifically investigated the system switching process of this type of system. Therefore, our study contributes to existing literature by developing and testing a model focusing on assessing system switching and new system adoption in the context of learning management systems.

The model testing results and the analysis of participants' comments can help educators and system developers better understand learners' systems adoption behavior. The results suggest that, emotional costs and reduced performance costs had a significant negative impact on the value perceived by the learner toward the system transition. In addition, their perceptions of performance expectancy, effort expectancy, and social influence on the new learning management system, as well as perceived value about the system transition, were found to be significant determinants of users' intention to use the new learning management system.

The proposed research model could also be applied to systems other than learning management systems. It is possible that the model could be used to assess other types of information-rich systems, in which a considerable amount of switching costs could be expected during the system transition process. Differences in the nature and usage of the systems being studied might lead to interesting variations in the types of switching costs impacting most significantly on a particular system switch.

From the practical perspective, findings of this study can provide implications to system developers, researchers, and organizations. When designing and/or adopting a new information system, it is important to consider users' experiences (if any) with the prior system. To ensure a successful adoption of a new information system, developers and managers should not only focus on introducing new and advanced features provided by the new system but also take into account the influence of users' prior system usage experience.

To do that, one important factor to consider is the perceived switching value, which is defined as the benefits gained from switching to the new system from the prior system (i.e., the system to be replaced). As indicated in the model testing results, in addition to adoption factors, perceived switching value was found to be a significant indicator of users' intention to adopt the new system. Thus, during the system switching process, it is important for the organization to make clear to their employees the potential benefits that will be brought by the new system compared with the old one. Since in most cases the system transition happening in the organization is mandatory, to make the process smooth, it is better for the organization to spend time and resources helping their employees go through the transition process, instead of making a sudden system change. During that time, promotion strategies (such as the use of demonstrations, seminars, and guest speakers) can be designed and utilized to help demonstrate the positive features and benefits of using the new system.

In addition, since the perceived switching value is influenced by detailed types of costs associated with the system transition process, it is also important to examine various types of switching costs. As shown in this study, certain types of switching costs can lead to negative impacts on users' perceptions about the value of the system transition, which in turn influence their attitude toward the new system adoption. To assure a smooth system transition, developers and managers need to be aware of and put effort into controlling various switching costs associated with the process. For example, offering adequate and easy-to-understand training on how to use the new system, and consistently promoting the new and more advanced features in the new system could be of help.

6.2 Limitations and future directions

This study also has limitations that future research can further address. First, this study was conducted during the system transition process (when the transition had already happened). In order to gain an in-depth understanding on users' switching behavioral over time, a longitudinal study could be more appropriate. By doing this, it is possible to compare users' pre-switching and post-switching adoption behavior. Because of the timing limitation of this study, we only examined users' switching behavior when the system transition had already happened (a short time period after the adoption of the new system). But as mentioned in Section 4.2, we believe the timing of our data collection is appropriate for testing the proposed research model, since this timing provided us a set of respondents who had already explored the new system for a reasonably long time but not long enough for them to have forgotten their experience with the prior system. For future studies, we encourage collecting data both before and after system transition when applicable, and conduct of in-depth, longitudinal comparisons. Second, the measurement items on the four types of switching costs used in this study were adapted from a previous study on examining users' Web browser switching behavior (Kim and Perera 2008). We acknowledge that Web browsers and learning management systems are different in terms of system functionality and utility. However, no prior research on learning management systems has specifically measured these four types of switching costs, and thus it is impossible for us to find existing measurement items particularly designed for this type of systems. In addition, we believe that the measurement items used by Kim and Perera (2008) are applicable to our study, since none of these measurement items focus on specific functions, features, or benefits of the system. Instead, the descriptions of the measures are generic, only focusing on users' perceptions about the process of change. Third, in our research model, we leveraged UTAUT (Venkatesh et al. 2003) as the information systems adoption perspective and only incorporated adoption constructs from that model. There are other popular adoption theories such as DeLone and McLean IS Success Model (DeLone and McLean 1992, 2003) which future research could explore to extend the model developed in this study by incorporating other adoption factors. Fourth, our study involves a mandatory system switch. Students were required to experience the system transition and switch to the new learning management system. Future research can further test and validate the proposed research model in voluntary settings. Fifth, student subjects were used in this study. We believe this is appropriate, since students are the largest group of users of the learning management systems and the ultimate goal of adopting those systems is to better help students in their learning. However, there are other types of users who also interact with the systems, such as instructors and IT support staff. Future research could also study system adoption focusing on those users. Finally, we developed and tested the model in the context of learning management systems. Future research can further expand the model to other information systems adoption settings in order to identify which specific types of switching costs have significant impacts on new system adoption of varied types of systems.

7 Conclusion

In this study, we developed a research model integrating factors related to both theoretical perspectives of information systems adoption and switching costs, and tested the model in the context of learning management system transition. The empirical results showed that emotional costs and reduced performance costs significantly influenced learners' perceived switching value of the system transition, and that perceived switching value together with performance expectancy, effort expectancy, and social influence significantly impacted their intention to use the new system. This study makes contributions to existing literature by leveraging multiple theoretical lenses to investigate the adoption of new information systems, incorporating new factors (i.e., switching costs and switching value) to the adoption model, integrating a variety of adoption factors and different types of switching costs into one nomological network. This model is then systematically and empirically tested producing results that demonstrate the necessity of considering the switching costs perspective when examining the success of modern information systems adoption. In addition, the study also contributes to the literature on learning management systems adoption. Detailed discussions on the data analysis, research contributions, and practical implications are presented in the paper.

Appendix. Measurement Items

Perceived switching value: Adapted from Kim (2011)

- PSV1: Considering the time and effort that I had to spend in getting familiar with Blackboard Vista, the change from Blackboard Vista to Blackboard Learn is worthwhile.
- PSV2: Considering the loss that I incurred when using Blackboard Vista, the change from Blackboard Vista to Blackboard Learn is of good value.
- PSV3: Considering the hassle that I had to experience when using Blackboard Vista, the change from Blackboard Vista to Blackboard Learn is beneficial to me.

Emotional costs: Adapted from Kim and Perera (2008)

- EMC1: I am more comfortable using Blackboard Vista compared with Blackboard Learn.

- EMC2: I miss using Blackboard Vista after changing to Blackboard Learn.
- EMC3: I feel regretful about changing from Blackboard Vista to Blackboard Learn.

Learning costs: Adapted from Kim and Perera (2008)

- LRN1: Learning to use the features of Blackboard Learn, as proficient as I use Blackboard Vista, takes time.
- LRN2: Understanding the features of Blackboard Learn takes time and effort.
- LRN3: Even after switching, it takes effort for me to be proficient with Blackboard Learn.

Reduced performance costs: Adapted from Kim and Perera (2008)

- RPF1: I can lose certain benefits when I change from Blackboard Vista to Blackboard Learn.
- RPF2: Blackboard Vista can provide me with certain benefits that I cannot receive by using Blackboard Learn.
- RPF3: By continuing to use Blackboard Vista, I could receive certain benefits that I could not receive when I switch to Blackboard Learn.
- RPF4: There are certain benefits I cannot retain when I change from Blackboard Vista to Blackboard Learn.

Sunk costs: Adapted from Kim and Perera (2008)

- SNK1: A lot of energy, time, and effort have gone into learning and getting proficient at Blackboard Vista.
- SNK2: Overall, I have invested a lot into learning and getting proficient at Blackboard Vista.
- SNK3. All things considered, I have spent a lot time and effort with Blackboard Vista.
- SNK4. I have invested much in learning and getting proficient at Blackboard Vista.

Performance expectancy: Adapted from Venkatesh et al. (2003)

- PE1: I found Blackboard Learn useful in conducting my learning-related activities.
- PE2: Using Blackboard Learn enabled me to accomplish my learning-related activities more quickly.
- PE3: Using Blackboard Learn increased my productivity.

Effort expectancy: Adapted from Venkatesh et al. (2003)

- EE1: My interaction with Blackboard Learn was clear and understandable.
- EE2: It was easy for me to become skillful at using Blackboard Learn.
- EE3: I found Blackboard Learn easy to use.
- EE4: Learning to operate Blackboard Learn was easy for me.

Facilitating conditions: Adapted from Venkatesh et al. (2003)

- FC1: I have the resources necessary to use Blackboard Learn.
- FC2: I have the knowledge necessary to use Blackboard Learn.
- *FC3: Blackboard Learn is not compatible with other systems I use.
- FC4: A specific person or group (such as the IT help service) is available for assistance with system difficulties.

Social influence: Adapted from Venkatesh et al. (2003)

- SI1: People who influence my behavior (such as classmates, team members, and/or professors) think that I should use Blackboard Learn.
- SI2: People who are important to me (in terms of my schoolwork) think that I should use Blackboard Learn.
- SI3: The department, college, and/or university have been helpful in supporting the use of Blackboard Learn.
- SI4: In general, the department, college, and/or university have supported the use of Blackboard Learn.

Behavioral intention: Adapted from Venkatesh et al. (2003)

- BI1: I intend to use Blackboard Learn for my future learning-related activities.
- BI2: I predict I would use Blackboard Learn for my future learning-related activities.
- BI3: I plan to use Blackboard Learn for my future learning-related activities.

* *FC3 is a reversed item.*

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