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EURASIA Journal of Mathematics, Science and Technology Education, 2019, 15(9), em1747
ISSN:1305-8223 (online)
Research Paper https://doi.org/10.29333/ejmste/108483

Exploring the Switching Intention of Learners on Social Network-based Learning Platforms: A Perspective of the Push–Pull–Mooring Model

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Received 11 March 2018 ▪ Revised 9 June 2018 ▪ Accepted 30 July 2018

ABSTRACT

Social media or social networking sites have been used to support online learning with good interactive features. If an existing system can retain current users and attract new users, it can provide greater benefits and influence in the field of online learning. However, most previous studies focus on learner participation intention, and rarely note their switching intention. Therefore, this study attempts to analyze and discuss the learner switching intention from the perspective of Push-Pull-Mooring Model. A research framework was proposed for examining the switching intention of learners in social network-based learning platforms. A total of 371 valid samples were used to examine the research framework using the partial least squares approach. The results show that switching intention is significantly affected by the push effects (social interaction and service quality), mooring effects (switching costs and prior switching experience) and pull effects (attractiveness of new services and social effect). To retain and attract users, platform providers can raise switching costs through improving service quality and system capabilities and educators can develop appropriate approaches to enhance social interaction and social effects.

Keywords: social network-based learning platform, migration theory, push-pull-mooring model, switching intention, online learning

INTRODUCTION

The increased popularity of social media or social networking sites (SNSs) has established new trends for integrating into online learning platforms (called Social Network-based Learning Platforms), providing learners with a feedback mechanism that can enhance learning performance (Chen, 2017; George, Michel, & Ollagnier-Beldame, 2016). Learners are shifting an increasingly large percentage of their social activity to SNSs, where they can exchange knowledge and encourage inspire each other to engage in learning processes (Peng, 2017). These platforms allow people with shared learning interests to enhance interpersonal communication and relationships (Nistor et al., 2015).

Over the past decade, many studies have demonstrated the validity and importance of cooperative learning methods, finding that cooperative learning can facilitate the development of self-effectiveness, and improve learning motivation and attitudes while strengthening social interaction skills (Lavy, 2017; Lin, Lai, & Lai, 2016). Interaction on SNS websites allows learners to share their ideas, mutually encourage each creativity and innovation, and receive real time feedback. Meanwhile, SNSs provide a quick and convenient means of self-expression through text comments, photos, videos and music, thus helping learners establish cooperative relationships and learning communities.

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Contribution of this paper to the literature

- An alternative framework based on push-pull-mooring model was proposed to investigate what factors have influences on the learner's switching intention of social network-based learning platforms.
- The results show that switching intention is significantly affected by the push effects (social interaction and service quality), mooring effects (switching costs and prior switching experience) and pull effects (attractiveness of new services and social effect).
- To retain and attract users, platform providers can raise switching costs through improving service quality and system capabilities and educators can develop appropriate approaches to enhance social interaction and social effects.

The emergence of new educational technologies requires teachers and learners to devote considerable time and effort to training and familiarization, thus emphasizing the importance of factors affecting learner migration among different learning platforms. If an existing system can retain current users and attract new users, it can provide greater benefits and influence in the field of online learning. In other words, increasing learner intention to remain with their current platform and reducing switching intention is a critical consideration for the successful use of social network-based platforms for learning. However, most previous studies focus on learner participation intention and rarely note their switching intention. Such switching intention can be regarded as a migration behavior in the virtual world of social communities. Therefore, this study attempts to analyze and discuss the learner switching intention from the perspective of migration behavior.

The Push-Pull-Mooring (PPM) model (Moon, 1995) was applied to develop a research framework for examining the switching behavior of learners in social network-based learning platforms. This study can help platform providers and educators understand the main factors that affect learning platforms to retain existing learners and attract new learners.

LITERATURE REVIEW

Social Network-based Learning Environment

Cooperative learning is the application of organized and systematic teaching and learning strategies within a group (Estébanez, 2017). Stevens, Slavin and Farnish (1991) pointed out that cooperative learning can be conducted through panel discussions, peer support and guidance, emphasizing individual responsibility and the interdependence of group members. In addition to strong interaction, cooperative learning methods better facilitate knowledge sharing and problem solving and help improve learning motivation and learning attitudes. During the cooperative learning process, teachers will assign learners of different abilities, gender and social-economic backgrounds to a single group to learn and work together. Mutual encouragement will enhance individual learning performance, thus enhancing overall group performance. A social network-based learning environment is ideal for supporting cooperative learning strategies.

Previous studies have indicated that the proper use of cooperative learning strategies in teaching can enhance learning achievements and relationships between peers (Estébanez, 2017; Johnson & Johnson, 1987). Advances in network technologies have changed interaction patterns between people and created new modes of social interactions. Online learning communities allow for remote knowledge sharing, allowing each participant to be both a provider and recipient of information, thus gradually constructing new knowledge through interaction and exchange with people from different professional backgrounds (Su, Ding, & Lai, 2017). Moreover, similar to traditional social networks, online social networks allow implicit and explicit knowledge to be shifted to each learner, thus increasing the professional knowledge and abilities of each participant (Huang, 2017). On such interpersonal networks, members can exchange messages with each other, share experiences, and develop a sense of community and identity.

Push-Pull-Mooring Model

Demographic migration is defined as the movement of inhabitants between two places in a certain period of time (Hou et al., 2011). Human migration is an important research issue in demographic statistics. The movement of humans from an origin to a new destination can be regarded as a type of switching behavior, and learners' switching between learning platforms can be also regarded as a type of migration behavior. Bogue (1959) argued that migration was the result of the interaction between the pushing forces in origin and the pulling forces on the destination. Push effects refer to the factors and perceptions that encourage people to leave the origin (Stimson & Minnery, 1998). These factors can have a significant negative impact on quality of life (Moon, 1995). The pull effects refer to the positive factors that attract people to migrate to a better residence (Moon, 1995). Bogue (1969) argued that pull effects include better opportunities for income and education, along with better living conditions and environment.

Push-pull-mooring (PPM) model is a basic framework for migration research, which considers the factors encouraging people to leave their place of origin and attracting them to move to a new destination. However, PPM model analyzes such migrations at an aggregate level and cannot explain considerations of individuals in the migration decision making process (Lewis, 1982). To address this shortcoming, Longino (1992) proposed a totally different migration decision making influence variable —mooring - which can be regarded as social expressions that allow individuals to realize physical, mental and emotional happiness and well-being (Moon, 1995), and which act to accelerate and impede migration behaviors. These mooring effects have a certain impact on migration intention and behavior. Despite the strength of the push and pull forces, they may be counteracted by mooring effects (Bansal, Taylor, & James, 2005). Moon (1995) furthermore combined the concept and the original push-pull model to develop a PPM model to balance the various factors. Lee (1966) suggested that factors in the act of migration can be categorized into original factors, intervening obstacles, destination factors and personal factors. In general, migration decisions are impacted by negative resistance effects (push), positive attractively effects (pull) and mooring effects.

Migration is a complex decision, and previous studies have suggested several relevant factors to provide a better understanding of switching behaviors of learners (Moon, 1995). Chang, Liu and Chen (2014) applied PPM to explain by bloggers switch between different blogging services, finding that push (i.e., dissatisfaction and regret), pull (i.e., alternative attractiveness) and mooring (i.e., switching costs) factors have varying degrees of effects on switching intention. Sun et al. (2017) pointed out that fatigue with incumbent mobile instant messaging and subjective norms have significant positive effects on the switching intention of mobile instant messaging applications, while inertia negatively affects switching intention. In addition, affective commitment, switching costs and habit have significant effects on inertia. While these studies provide some empirical foundation for migration among virtual online services, they did not focus on learning situations. To better understand the learner switching intentions between social network-based learning platforms, PPM model provides a useful conceptual architecture and can help identify major influencing factors of push, pull and mooring effects.

RESEARCH METHODS

Research Framework and Hypotheses

Learners generally consider online learning platforms as virtual places, and thus switching behaviors between platforms are analogous to demographic migration. Based on this assumption, the push-pull-mooring (PPM) model was adopted as the underlying framework. **Figure 1** illustrates the proposed research framework. Push effects of learning platforms include enjoyment, social interaction and service quality. If learners do not have positive perceptions of the original social network-based learning platform, it is easy to enhance their switching intentions. Two pull factors attract learners to other social network-based learning platforms, including attractiveness of new service and social effect. Mooring effects include switching costs and prior switching experience. The three main factors affecting the switching intention are explained as follows.

Push effects

In the PPM model of demographic migration, push effects refer to some negative factors reducing the quality of life that motivate people to leave their residence (Moon 1995, Stimson & Minnery, 1998). When the positive effects of the original residence are stronger, the push effects on the switching are reduced. As applied in the context of this study, push effects are the negative influences on learning or interaction quality that make the learners switch from the currently used learning platform to others.

When learners perceive the learning platform as providing better amusement value, they are more likely to have a positive impression of it, and would therefore be less likely to switch to another platform. Moreover, learners are willing to use online learning platform that provides a better experience. When learners feel immersed in a learning situation, they tend to feel more in control of the learning process, and thus encourage repeat usage (Csikszentmihalyi, 1995). Additional participation on the platform increases enjoyment and, in extreme situations, can develop into a form of dependency. Conversely, if learners experience low enjoyment using a learning platform, they may opt for alternative learning platforms in search of more enjoyment.

Social interactionism (Shalin, 1986) attempts to describe interactions between social actors largely through examining subjective processes, as opposed to other social theories which focus on large macro-structures and entire social systems. Social interactionism theorists are concerned with how social interaction between people can create meaningful social experiences and the ways in which these experiences can, in turn, manifest in social action.

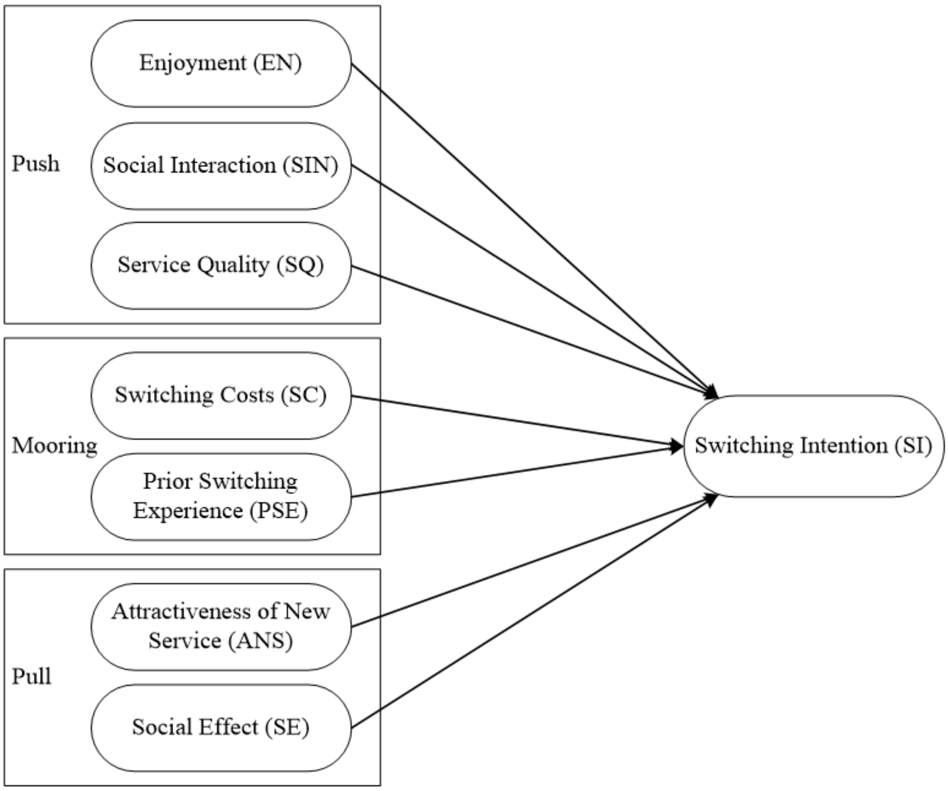

Figure 1. The research framework

In sociology, interactionism is a theoretical perspective that derives social processes (such as conflict, cooperation, identity formation) from human interaction (Herman-Kinney & Reynolds, 2003). Georg Simmel (1950) stated that "society is merely the name for a number of individuals connected by interaction." For symbolic interactionists, the individual is always engaged in socialization or the modification of one's mind, role and behavior through contact with others. Therefore, learners will easily leave the existing platform when they are unable to feel good social interaction on the learning platform.

Service quality is a comparison of expectations with actual performance, and good service quality provides firms with an important competitive advantage over competitors (Ladhari, 2009). When comparing service providers, quality of service can be a key determinant in whether the consumer stays with the current provider or switches to a new one (Bansal & Taylor, 1999; Bansal, Taylor, & James, 2005). This study uses service quality as a basic factor to explore the effects of relevant dimensions on learner intention to switching between social network-based learning platforms. If the learning platform is unable to provide quality services, learners may consider migrating to other learning platforms.

We thus propose the following hypotheses for push effects:

H1: Lower enjoyment on the current learning platform will increase switching intention.

H2: Lower social interactions on the current learning platform will increase switching intention.

H3: Lower service quality on the current learning platform will increase switching intention.

Mooring effects

Migration decision-making is highly complex. Push and pull effects may be mitigated by mooring effects. Switching costs are defined as the cost that customers must pay to switch between alternative products or services. For example, switching to a new telecom provider entails informing friends and relatives of your new telephone number, the paperwork needed to make the switch, and potentially time spent learning how to use the interface of a new mobile phone (Farrell & Klemperer, 2007). Types of switching costs include exit fees, search costs, learning costs, cognitive effort, emotional costs, equipment costs, installation and start-up costs, financial risk, psychological risk and social risk. Thus, a user switching learning platforms assumes switching costs through adapting to a new feature set and interface, and through building a new social group. Excessively high switching costs may deter users from leaving a platform that is less suitable to his/her current needs.

Prior switching experience plays an important role in migration theory. A successful initial migration experience can increase the possibility of a second migration, which is more likely to be successful due to the skills and experience acquired during the first migration (Kuznets & Thomas, 1984). Conversely, an unsuccessful migration experience will discourage future attempts. This phenomenon is frequently cited in the field of consumer marketing, where a buyer's prior switching experience will affect subsequent switching behaviors (Ganesh, Arnold, & Reynolds, 2000). Thus, users who have previous successful switching experience will be more likely to switch to a new one.

We thus propose the following hypotheses:

H4: Higher switching costs will reduce switching intention.

H5: Previous successful switching experience will increase switching intention.

Pull effects

In the decision-making process of demographic migration, if another living place can provide better quality of life, it generates a pull effect on residents. Similarly, if other learning platforms provide better learning or interaction quality, learners will also consider switching to a better one.

Learners may be induced to switch platforms in search of features unavailable on their current platform, in a situation analogous to migrants moving to a new location in search of improved working or educational opportunities (Lee, 1966). Relevant studies have pointed out that the important functional demand of the social networks is one of the motivations affecting the participation in the social network-based learning (Hsu & Lu, 2007). When the learning platform has features that better meet the needs of learners, it will attract them to switch to the learning platform.

Learners may also switch platforms to join friends and/or acquaintances who do not frequent their current platform. Therefore, the greatest challenge of social networking site operators is to give new members a sense of belonging to the virtual community. Relevant studies have pointed out that the user's perception of the attractiveness of a social network is one of the key factors determining user participation in social network-based learning platforms (Hsu & Lu, 2007). For example, based on learning demands, learners must cooperate with others to accomplish given tasks, and social networks play a key factor in this process. The sense of belonging to a community is an important determinant of participation and continued platform use (Hsu & Lu 2007). Therefore, when some members of a given social network are using another learning platform, learners may switch to the new learning platform to stay with the members.

We thus propose the following hypotheses for pull effects:

H6: Relative attractiveness of new services on another learning platform will increase switching intention.

H7: Relatively higher social effect of another learning platform will increase switching intention.

Dimensional Measurement

Regarding scale development, to confirm content validity, all measurement items were developed on the basis of dimensional question items from relevant previous studies, and were generalized with regard to the cooperative learning environment. Without changing the original meanings, the original question items were modified to match the context of this study. The enjoyment (EN) measurement items were based on the enjoyment scale proposed in by Koh and Kim (2003) and Ghani and Deshpande (1994). Social interaction (SIN) used the measurement items proposed by Zeev (1976). Service quality (SQ) used the measurement items proposed by Delone and McLean (2003). Switching costs (SC) used the scale proposed by Ping (1993) and prior switching experience (PSE) was developed from the measurement items proposed by Bansal et al. (2005). New service attraction (ANS) was assessed using the measurement items proposed by Bansal et al (2005). Social effects (SE) used the measurement items proposed by Andrew et al. (2010). Finally, switching intention (SI) was based on the scale proposed by Oliver and Swan (1989). The questionnaire used a 7-point Likert scale, from "strongly disagree" to "strongly agree."

The preliminary questionnaire was evaluated by four domain experts and modified based on their feedback. The formal questionnaire was designed with two parts. The first part collected basic demographic data, including the subject's gender and age. The second part collected data on learner viewpoints about their intention of leaving for any other platform.

Data Collection

University level programming and information technology students were invited to participate in the study. Previous studies examining the use of Google Plus in education have suggested that learners can construct knowledge, obtain meaningful learning experience and improve their cognitive skills through social network-based

Table 1. The analysis results of reliability, convergent validity and discriminant validity

	M	*SD*	*CR*	*AVE*	EN	SIN	SQ	SC	PSE	ANS	SE	SI
Enjoyment (EN)	2.97	0.75	0.85	0.65	0.81							
Social Interaction (SIN)	2.91	0.73	0.84	0.63	0.46	0.79						
Service Quality (SQ)	2.93	0.90	0.90	0.69	0.51	0.45	0.84					
Switching Costs (SC)	3.01	0.79	0.88	0.64	0.50	0.52	0.48	0.80				
Prior Switching Experience (PSE)	4.75	1.17	0.93	0.87	-0.39	-0.36	-0.44	-0.43	0.93			
Attractive of New Service (ANS)	4.86	0.85	0.86	0.68	-0.42	-0.42	-0.50	-0.44	0.43	0.82		
Social Effects (SE)	5.14	0.84	0.88	0.71	-0.63	-0.49	-0.55	-0.54	0.42	0.42	0.84	
Switching Intention (SI)	5.00	1.00	0.90	0.74	-0.33	-0.40	-0.45	-0.44	0.38	0.41	0.41	0.86

Note: 1. AVE is average variance extracted (AVE); CR is composite reliability (CR).
2. The bold characters on the diagonal lines are the square roots of AVE, and the values outside the diagonal lines are the correlations of various dimensions

learning (Garrison & Kanuka, 2004). Erkollar and Oberer (2011) pointed out that Google Plus can help learners organize knowledge and learning experience through cooperative learning. Therefore, Google Plus was used as an originl learning platform. All courses (mainly programming and information technology) have team assignments and projects. Students have to use Google Plus for discussions after class. Learners can access the network through a computer to enter Google Plus and carry out cooperative learning. In order to ensure that students fully experience Google Plus, students were asked to complete the questionnaire after a semester.

A total of 443 copies were collected, of which 72 were invalid, leaving 371 valid samples for a valid return rate of 83.75%. Among valid respondents, 52.5% were male and 47.5% were female, with an average age of 20 years old (ranging from 18 to 26).

RESEARCH RESULTS

Partial Least Squares (PLS) was applied to examine the respondents' dimensional psychological characteristics and verify the research model. PLS has fewer limitations and thus is more beneficial in terms of sample size, measurement scale and data distribution (Rose et al., 2012). Data analysis was conducted on the surveyed sample, including a demographic statistical analysis, reliability and validity analysis of the questionnaire, and verification of the research model and hypotheses.

Reliability Analysis

Reliability refers to the consistency or stability of measurement results. It is the degree of consistency in results when applying different measurements to similar phenomena or groups. Nunnally (1978) argued that the range of high acceptance is a Cronbach's α coefficient value exceeding 0.7. The results of this study indicated that the Cronbach's α coefficients of all the eight dimensions are in the range of 0.72 ~ 0.85, indicating acceptable reliability (see **Table 1**).

Measurement Model

The analysis results of composite reliability, convergent validity and discriminant validity are shown in **Table 1**. All AVE (average variance extracted) values are above 0.80, which is higher than the recommended value of 0.5 (Hair et al., 2006). A high AVE means the dimension has high reliability and convergent validity. In addition, this study compared the AVE and shared variance of individual dimensions to test the discriminant validity (Fornell & Larcker, 1981). The shared variance in between dimensions should be lower than an individual dimension's AVE. Overall, the measurement model has appropriate reliability, convergent validity and discriminant validity.

Structural Model

Statistical software SmartPLS 3.0 was used to test the research model. As PLS does not provide overall model fitness, the explanatory power (R^2) is used to test the predictive ability of the structural path. The bootstrapping method was adopted for parameter estimation. Bootstrapping is an estimation method without parameters. Through data re-sampling, it can estimate the statistical distribution. According to Chin (1998), 500 re-sampling iterations is the basis for the significance test of the estimated value of each structural route. As shown in **Figure 2**, the switching intention variation explanatory power is 31.70%, indicating that switching intention is significantly affected by the social interaction (β = -0.126, *p_value* < .01), service quality(β = -0.170, *p_value* < .001), switching costs

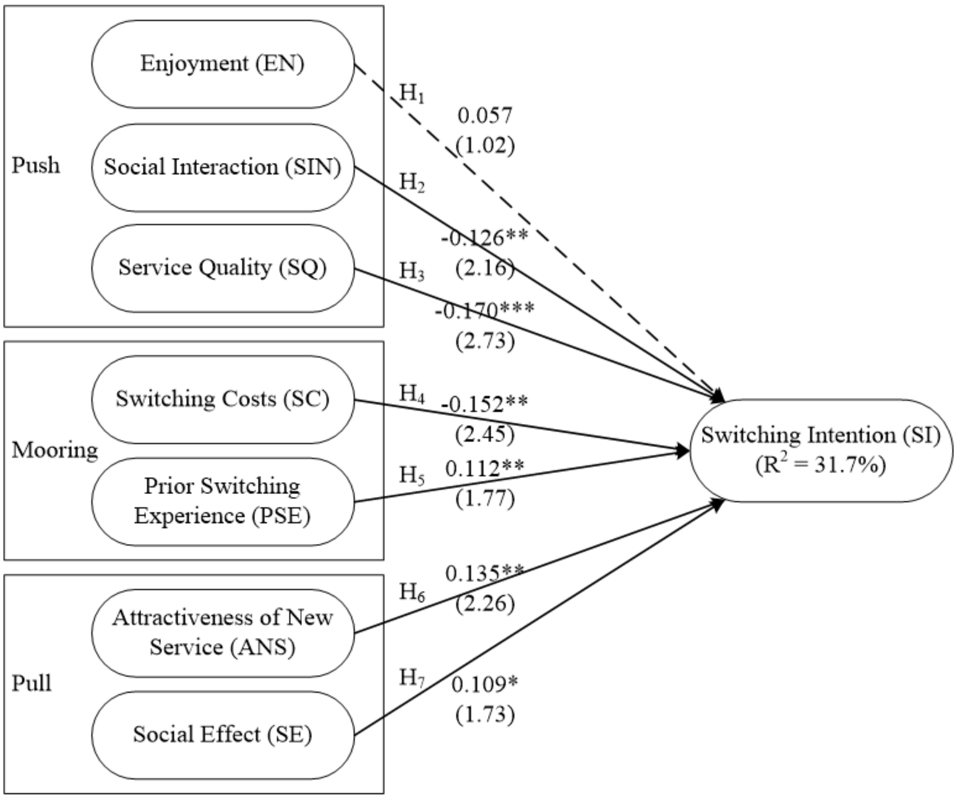

Figure 2. The analysis results of research framework
$^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

(β = -0.152, *p_value* < .01), prior switching experience (β = 0.112, *p_value* < .01), attractiveness of new services (β = 0.135, *p_value* < .01) and social effect (β = 0.109, *p_value* < .05). However, enjoyment (β = 0.057, *p_value* > .05) was found to have no significant impact on switching intention. Therefore, H_2, H_3, H_4, H_5, H_6, and H_7 are all supported.

DISCUSSION AND IMPLICATIONS

Push Effects

Stronger social interactions on the current platform will discourage learners from switching, which is a negative push effect on the migration of learners. Learners indicated that a high degree of platform utility in terms of providing fast feedback or individualized services will enhance platform service quality and thus reduce switching intention. Therefore, social network-based learning platform developers should make a continuous effort to ensure that their platform supports learning methods and content that meet learner needs, and engender a sense of enjoyment through timely knowledge sharing and game-based learning mechanisms. Such underlying mechanisms are the basis of service quality and social interactions, which not only can retain the original learners, but also attract new learners so as to resist the pull effects and reduce switching intention.

In addition, the enjoyment factor was found to have no significant impact on switching intention possibly because learners gradually become accustomed to the services, information and interactions available through the platform. They had to use the platform to complete their team assignments and projects for a long time so that they did not have much difference in enjoyment.

Mooring Effects

Learning platform users gradually build interpersonal relationships and experience which acts to keep them on their current platform, presenting switching costs for those who choose to leave and thus reducing switching intention. Nevertheless, learners who have previously and successfully migrated to a new platform will subsequently have a higher switching intention, while unsuccessful experience will have the opposite effect.

This study found that higher switching costs reduce switching intention, which reflects similar phenomena for consumer migration in real-world products and services. Thus, while most of the current social network-based learning platforms are free of charge, they can still create loyalty through non-financial switching costs.

Pull Effects

When learners perceive another learning platform as having relatively better social effect, they will have a higher switching intention. In fact, one of the most important motivations for participating in the Google Plus learning platform is to interact with friends. Friendship is obviously a crucial factor in selecting and using a social network site. Therefore, if another platform offers increased social effect, it raises motivation to migrate.

According to the research findings, when learners perceive an alternative platform as being more attractive, they will have a higher intention to switching. In fact, one of the most important motivations for learners to participate in the Google Plus learning platform is to access specific services, thus if the learning platform does not satisfy their demands, they will experience dissatisfaction and potentially be induced to switch to other learning platforms. Therefore, learning platform developers should seek to provide new and attractive services.

CONCLUSION

This study investigated the switching intentions of learners using a social network-based learning platform. Empirical results suggest that real-world push-pull-mooring (PPM) model can explain the migration behaviors of learners in such cooperative learning environments. Most previous discussions of social network-based learning platform have mainly focused on learner satisfaction with platform design, functions and intention. Relatively little attention has focused on switching intention, and few empirical studies have been conducted based on widely available existing platforms. Using the underlying PPM model of human migration, this study integrates the concept of service quality from the informational system success model to construct a more complete model for a comprehensive understanding of switching behaviors among users.

To effectively retain learners, social network-based learning platform developers need a better understanding of why learners leave for alternative platforms. Such platforms benefit from a large network effect whereby users are induced to stay on the platform used by a greater number of current or potential friends. Our findings reveal that the forces driving the switching intention are not only from the pull effects of other platforms but importantly from the push effects of the original platform.

Therefore, to appeal to learners and thus reduce switching intention, learning platforms can combine multiple learning and social interaction functions. In addition, switching costs and prior switching experience are perceived by learners as important factors influencing their switching intention. For individual users, switching costs refer not only to the effort required to learn to use a new platform, but also the loss of social assets accumulated in the original platform. Therefore, learning platform developers could consider improvements in the following perspectives. Platforms should provide high service quality and diverse functions to satisfy leaner requirements for learning and cooperation. Such platforms must provide functionality that satisfies user needs for social interaction. Platform providers can also reduce switching intention by facilitating the accumulation of knowledge and social assets which cannot be easily ported to another platform, thus raising switching costs.

The findings are subject to certain limitations. First, the data was collected from university students of similar age, but switching intention may vary with learners in different age groups. Second, this study focused exclusively on users of the Google Plus cooperative learning environment, and future work should seek to validate the findings with other platforms.

ACKNOWLEDGEMENTS

This work was supported by the Ministry of Science and Technology of Taiwan under grant number MOST 107-2511-H-037-003, MOST 107-2511-H-230-003-MY2 and the Kaohsiung Medical University of Taiwan under grant number KMU Q107019.

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