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Empirical Study on the Factors Affecting User Switching Behavior of Online Learning Platform Based on Push-Pull-Mooring Theory

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Abstract: Online learning is gaining popularity, but users can easily find alternatives and switch between learning platforms. Reducing users switching behavior is a critical condition for the sustainable development of an online learning platform; therefore, it is necessary to investigate the influence factors of users switching behavior between different platforms to retain users and enhance the competitiveness of enterprises. Push-Pull-Mooring (PPM) theory is adopted to construct a structural equation model of customer switching behavior on online learning platforms and to explore the mechanism of user switching behavior between learning platforms. The model is tested with data collected from 313 online learning users. The results show that information overload and dissatisfaction, as push factors, significantly affect user switching behavior. Functional value and network externality as pull factors positively affect user switching behavior, switching cost, and affective commitment as mooring factors negatively correlate with switching behavior. Further, this study also revealed that there are obvious different influencing factors for different online learning platforms. Overall, this study provides some practical strategies for the online learning platform and can help them to gain a competitive advantage.

Keywords: online learning; user switching behavior; PPM; sustainable development



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1. Introduction

The increasing availability of the Internet and computer technology has transformed the education mode from the traditional way to online learning. People can access information anytime and anyplace that would normally be available only through a traditional classroom [1]. Online learning applies innovative technologies and facilitates, such as smart devices and online technologies, to realize sustainability in education [2]. According to the statistical report on the development of the Internet in China, by June 2020, 381 million online learning users have accounted for 40.5% of the total Internet users. In particular, during the COVID-19 epidemic, online education customers had increased significantly due to the epidemic situation [3] and the marketing development of the online learning market. In order to occupy the market, online learning platforms mostly launch free live classes and other activities to attract customers to experience its services. IResearch data shows that the penetration rate of online learning has reached the ceiling, and the competition for the existing customer is now becoming common. Additionally, the online learning market has become more competitive and the cost of acquiring new customers is high, therefore, how to retain existing users is the key factors for the sustainable development of online learning platforms. Furthermore, the sustainable development of online learning platforms is increasingly important for sustainability in education. According to the goal

of Agenda 2030, the sustainable development of online learning platforms would have significance for building and upgrading inclusive and effective learning environments for all and promote life-long learning opportunities for all.

Due to the continuity of course learning and the switching cost, once users choose a learning platform, they will not quickly change the learning platform in a short period [4]. However, faced with online learning platforms providing more choices, users will have different needs and may be interfered by external factors, such as the recommendations of teachers or other students' adoption. These conditions can result in users switching behaviors, indicating the loss of the existing users and the economic loss for the original platform [1]. Therefore, the online learning platform needs to explore the motivation of online learning user switching behavior and make strategic adjustments to satisfy the needs of users, attracting new users more effectively and retaining the existing users so as to obtain a competitive advantage.

The remainder of the paper proceeds as follows. The second section briefly introduces the relevant literature. Section 3 builds the research framework. Section 4 conducts a quantitative survey to test this model, and the results are provided in Section 5. Finally, this paper makes a summary of the major findings and provide some suggestion for online learning providers.

2. Literature Review

2.1. User Switching Behavior

Switching behavior is defined as consumers' choices from one provider to an alternative. It is usually associated with users' dissatisfaction with the incumbent product or service, along with their perceptions of the relative advantage of substitutes [5]. Early literature focused on user switching behaviors in many industries, like the airline industry [6], hotels [7], and Airbnbs [8]. In line with the growing prevalence of online services activities, the number of studies on the switching behavior of Information Technology (IT) products has increased in recent years [9]. The user's IT product switching behavior is somewhat different from physical products and services. First, IT innovations allow users to switch between different products with almost the same function freely since users can easily download and install other IT products. Second, IT product switch involves not only a complete replacement but also a partial replacement of the use of the former IT products or services.

IT product switching behavior is a special user's post-adoption behavior, one of the most mature streams of information system (IS) research [10]. Previous post-adoption studies focused on user's continued usage. The ultimate success of an IT product or service depends on its continued use. Facing different IT produces, users would compare them and switch from one product to a competitor. For the initial product provider, switching behavior among different alternatives indicates that the users discontinue using the previous product. Therefore, the user's switching behavior is also one stream of post-adoption behavior studies.

This switching phenomenon has been documented in various IT products, such as web browsers [11,12], cloud storage services [10,13], social networks [14], instant message application [15], and other IT services [16,17]. Through the literature review of IT user switching behavior, we found that previous studies mainly investigated switching behavior through the view of IT acceptance and diffusion [10]. Second, most previous studies focused on computer-based IT products, while few studies have focused on user switching behavior in the context of online education. Furthermore, research in the field of online learning has mainly focused on marketing and information systems [18,19], or they have focused on the influencing factors of continuous use intention [20] and paid more attention to the switch from online to offline. There is limited research on the switching behavior between online learning platforms and comprehensively identifying its antecedent factors. With the rapid growth of online learning platforms, exploring the influence mechanism of switching behaviors is of great significance to the sustainable development of online

learning platforms. To address this gap, this paper attempts to explore the influencing user switching behavior in the context of online learning platform.

2.2. Push-Pull-Mooring (PPM)

We now turn to review the literature about the method of studying IT product user switching behavior. Based on the PPM framework of migration theory, we have developed a model around push, pull, and mooring effects to explore the influencing factors on users switching behavior in online learning platforms.

PPM theory is the leading paradigm of population migration research [21]. Migration refers to the movement of humans between two places for a certain period and is produced by the comprehensive influence of the push force of emigration and the pull force of immigration [22]. Online user switching behavior and population migration have the same characteristics, that is, they move from one place to another, so PPM theory can better understand user switching behavior [23]. Many researchers have introduced related theories and concepts based on PPM framework, which were developed to explain human being's immigration behavior [24] and to explore IT switching behavior research [25].

By reviewing pertinent IS literature, some studies have also constructed distinct switching models. For instance, Cheng et al. [26] applied the PPM model to prove that three antecedents were influencing SNS user switching intention: push, pull, and anchor factors. Jung et al. [27] studied the user switching behavior of Korean Airlines and found that the factors in the PPM model affected traveler switching intention. Xia et al. [28] studied the influencing factors of music platform users switching behavior, based on PPM theory. Cheng et al. [10] studied the switching willingness of mobile cloud storage services in the Chinese market based on PPM. All these existing studies have enriched the application field of PPM theory. Therefore, we consider that the PPM framework is a suitable model for our study. In addition, this paper develops a model that examines the influencing factors of online learning user switching behavior based on PPM theory.

3. Research Framework

3.1. Research Foundation

The PPM framework suggests that migration is influenced by the PPM factors [29]. In the PPM framework, factors influencing user switching behavior can be categorized into push, pull, and mooring categories. Push factors refer to the negative factors driving people away from the original area, while pull factors are positive factors attracting people to a destination [30]. Mooring factors refer to all personal or social issues that act to facilitate or hamper migration decisions [29,31]. Push and pull factors can influence the switching behavior directly, while the mooring factors can moderate the effect of push and pull factors [13]. PPM theory has been widely used in the research of consumer behavior but is relatively scarce in the research on online learning context. Various factors have been summarized in the light of prior research about switching behavior in different research contexts [10,13,15,26,32,33]. Based on reviewing the relevant literature, this paper develops a research model based on the PPM theory to investigate the dynamic evolution process of user switching between platforms.

According to the segmentation result of the online learning market, the learning content can be divided into K12 (kindergarten through twelfth grade) education, higher education, language learning, vocational training, quality learning, and comprehensive online school. Higher education and vocational training, as the main body of the online education market, accounts for about 75% of the overall market. The online learning platform has its different characteristics in acquiring new users with other online IT products. Firstly, the decision-making period of users is long, which means it takes a long time for users to determine which platform to use; secondly, K12 education and quality education are multi-person decision programs, and the retention rate of experienced users is low. There must be some other critical factors that facilitate or hamper a user's switching choice.

Therefore, we try to explore and investigate the promoting or resisting factors affecting the user switching behavior from its own unique features.

3.2. Research Model

Based on the above discussion, a research model in the online learning context was developed where the push effects, pull effect, and mooring effect were proposed to be the impetuses to switch the online learning platform, as shown in Figure 1.

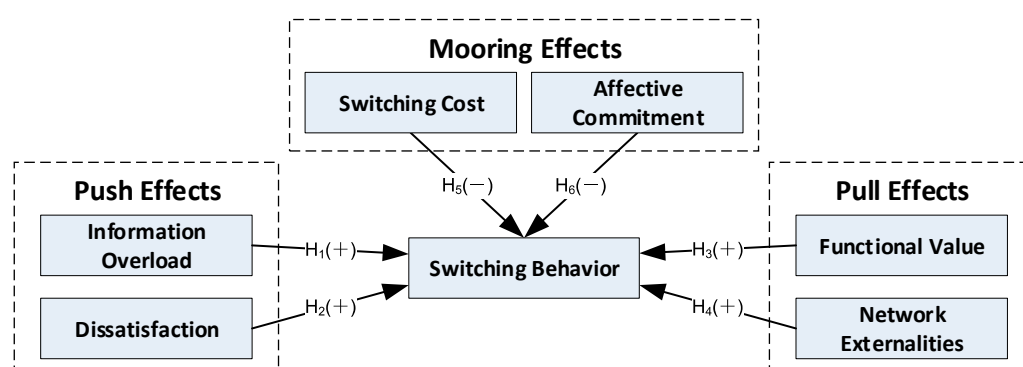


Figure 1. Research model of user switching behavior in online learning platforms.

3.2.1. Push Effects

Push factors mainly include two aspects; information overload in the learning platform and customer dissatisfaction.

Overload is a core factor that results in negative consequences. Information overload occurs when people are exposed to more information than they can accommodate in their capacity for the information process [34]. In the use of the platform, users need to focus on the learning of courses and resources. If the amount of information is too large, redundant information will reduce the learning efficiency of users. When the platform information exceeds the processing capacity, users may have negative emotions such as burnout and pressure [34,35]. Zhang et al. [36] divided perception overload into system function overload, information overload, and social overload, and verified that three types of overloads affect user's continuous use behavior. Zhu et al. [37] believed that perceived information overload has a significant negative impact on the willingness to continue using the government's new media platform. Similarly, social media information overload will lead to the decline of user attention, reduce the efficiency of user information processing, and lead to the loss of social media users.

As a core concept in service post-adoption research, satisfaction is defined as the summary psychological state resulting when the emotion surrounding disconfirmed expectation is coupled with the consumer's prior feelings about the consumption experience [15]. In the study of human migration behavior, satisfaction is also the main reason for residents to leave the original area. More precisely, in the online learning platform, customer satisfaction reflects the degree of a customer's positive evaluation of the learning platform and experience with this platform. In the existing literature, many scholars have found that users' dissatisfaction with the original service leads to switching behavior. For example, Xu [38] found that users' dissatisfaction with social platforms has a positive impact on user switching behavior. Chen et al. [39] also found that there is a significant positive impact between dissatisfaction and user exit intention. Satisfaction is the pre-motivation of whether users continue to use and switching behavior, and improving satisfaction has a significant impact on continuous use behavior [40]. When users are satisfied with the original system, the switching intention is weak.

Therefore, this study takes information overload and dissatisfaction as the factors to promote user switching behavior. As such, in the current study, we suppose that user's

dissatisfaction with the incumbent provider is the push factor that influences user switching intention. Therefore, the following hypothesis is proposed:

Hypothesis 1. *Information overload has a positive impact on user switching behavior.*

Hypothesis 2. *User dissatisfaction has a positive impact on user switching behavior.*

3.2.2. Pull Effects

According to the PPM theory, the attractiveness of the destination will pull the migrants to this place [15]. Attractiveness is defined as the positive characteristics of an alternative service provider. Following [41], the attractiveness of alternatives means the service quality, image, and reputation of the replacing services' providers, which are expected to offer more suitable or superior services than those of the current provider. Several studies [15,26,32,33] have recognized the importance of the attractiveness of alternatives. As for online learning providers, functional value is the main factor of consumer's decision making, reflecting consumers' rational evaluation of products. Online learning platforms provide many complex elements, such as learning resources and activities, instructor's quality, and facilities, and these must be well developed and designed for users to improve their skills and competitiveness [42]. In the competition of similar platforms, if the alternative platform provides better learning resources and modes, users may reduce or stop using the incumbent platform. Fang et al. [4] studied the switching behavior of traditional education platforms to 5G platforms and found that users would consider whether the online platform has artificial intelligence, Internet of things, and other functions or not. The competing platform would offer comprehensive functions to induce the switching behavior. However, when customers were unaware of the alternatives more attractive than their current platform, they were likely to continue using the current provider. Accordingly, the following hypothesis is formulated:

Hypothesis 3. *Functional value has a positive impact on the user switching behavior.*

In addition to its functionality, network externality is also one of the pull factors inducing users' willingness to switch to an alternative, especially under the online environment. Network externality means the increased utility that users obtain from using products and services [43]. The network effect for a user would increase as the number of users on the same platform increases [44]. In our study, the network included peers, friends, colleagues, or others in their social circles who adopt the same learning platform. Users need to share and communicate with more peers; therefore, the network effect is a critical factor for studying online learning platforms. With the increase of platform users, externalities benefit emerges and attracts more users. Other users tend to choose the learning platform with more friends after comparing the price gap, communication convenience, and other factors. It is evident that network externality is an important pulling factor for IT products in many research contexts, such as the study of Cheng et al. (2019) [10] (mobile personal cloud store), Xia et al. [28] (music platform), and Hou [32] (social network sites).

Therefore, the following hypothesis is proposed:

Hypothesis 4. *Positive network externality has a positive impact on the user switching behavior.*

3.2.3. Mooring Effects

Existing research on mooring effects has primarily focused on cognitive-based factors such as switching cost [10]. The factor of affective components may also need to be considered. For this paper, we adopt switching costs and affective commitment as mooring factors.

Switching costs could be defined as the costs incurred when changing one provider to another one [45] or refer to user perceptions of the costs related to changing service providers, and it is throughout the whole switch process [15]. In many studies, switching cost is considered as the mooring effects influencing user switching behavior [10,13,15,45–47].

Users need to compare the switching cost and the benefits after the switch when making the switch decision. The switching cost includes the time, money, and effort paid in the usage of the current platform [13] and the additional money, time, and effort to explore and adopt new resources [48]. If users are sensitive to switching costs, this sensitivity makes users less willing to change and maintain the original state. Even though some customers may feel dissatisfaction with the current platform, they would not switch platforms since they may face a greater switch cost and risk of switching to a new service provider. It is because of the existence of switching costs that users can choose to continue to use the initial service or product. Therefore, from the exit barriers, which is an important factor for long-term retention of users.

Therefore, the following hypothesis is proposed:

Hypothesis 5. *User switching costs of the incumbent provider has a negative effect on switching intention.*

Commitment is defined as an individual's attachment to a particular target, which results in an inclination to maintain a relationship [49]. Affective commitment refers to an emotional attachment to identification with and involvement in the target and reflects a desire to stay in the relationship. Plenty of studies [15,50,51] adopt this core indicator to grasp the affective component in consumer behavior and demonstrate that affective commitment facilitates users to maintain the relationships with the incumbent service because of their emotional bond to the service. In the context of online learning, affective commitment is identified as a crucial factor affecting the online learning continuance intention. Online learning users often interact with platform experts and teachers and establish positive emotions with the incumbent platform, which may lead to users' high level of involvement in the platform [52]. Without a strong sense of affective commitment to the incumbent platform, the users may easily switch to another alternative [51]. Therefore, the following hypothesis is proposed:

Hypothesis 6. *User's affective commitment to the incumbent platform has a negative impact on the switching behavior.*

4. Research Design

4.1. Measurement

There were seven constructs of interest to this study, including information overload, dissatisfaction with the incumbent, alternative attractiveness, network externality, switching cost, emotional commitment, and switching behavior.

All the items were measured by 5-point Likert scales range from "strongly disagree" to "strongly agree". Table 1 lists the measurement scale used in this study. The related literatures are also listed in Table 1.

Table 1. Constructs and measures.

Constructs	Items	Measures
Information overload [34–37,53]	IO1	I feel overwhelmed with the large volume of information everyday.
	IO2	Only a small part of the information is what I need.
	IO3	It is less efficient way of obtaining effective course information.
	IO4	I am frequently disturbed by push information
Dissatisfaction with incumbent platform [15,38–40,54,55]	DS1	Dissatisfied with the quality of teachers and course on the platform.
	DS2	Dissatisfied with the speed and depth of the platform's response to user questions
	DS3	Dissatisfied with the platform's fees, refunds, and other financial protection issues
	DS4	Dissatisfied with the level of protection in personal privacy.
	DS5	Dissatisfied with the inability of timely feedback when using the platform's recording format.

Table 1. Cont.

Constructs	Items	Measures
Functional value [4,42,56]	FC1	I think the learning mode of another platform can bring better value to the capital
	FC2	I think the learning mode of another platform is more scientific, and the scene is more vivid than the incumbent platform.
	FC3	I think the learning resources of another platform are more abundant and high quality.
	FC4	I think another platform will provide personalized services to better meet individual needs.
	FC5	I think the teaching explanation is more closely integrated with technology in another platform.
Network externality [10,28,32,43,44,57]	NE1	Many of my friends are using another platform
	NE2	My respected teachers and friends recommend another platform
	NE3	I anticipate many people will use another platform.
Switching cost [10,13,15,45–47]	SC1	In general, it would spend a lot of money, time, and effort to switch to a new platform.
	SC2	I would lose the accumulated credit and service in the current platform if I were to switch to a new platform.
	SC3	I would lose the benefits of being a long-term user of the current platform if I were to switch to a new platform.
	SC4	It would take a lot of time and effort to evaluate the learning resources and services of the new platform.
Affective commitment [15,50,51,58]	AC1	I value some teachers and courses on the current platform
	AC2	I like to communicate with teachers and other users on the current platform
	AC3	I really like the public image of the current platform.
	AC4	I feel emotionally attached to my current platform.
Switching behavior	SB1	I would spend less time on my incumbent platform.
	SB2	I am considering stopping using my incumbent platform.
	SB3	I am considering switching from my incumbent platform to another.
	SB4	I am determined to switch to another platform, and I am already trying to use another platform.

4.2. Data Collection

To test the research model, an online survey of online education users was conducted. The questionnaire was surveyed and collected in a university in Henan, China. Then the students shared the questionnaire with their friends and families. A total of 313 valid samples were collected.

The demographic characteristics of the final sample are shown in Table 2. Among these valid responders, males accounted for 44.7% and females for 55.3%. In total, 57.8% of responders were between the ages of 18 to 25, which is consistent with young people's strong learning needs and active engagement on the Internet. For education background demographics, most of the respondents had an undergraduate degree or higher.

The use of online learning platforms is shown in Table 3. From the survey results, we found that over half of the sample users had used two or more online learning platforms, indicating that they would switch one platform to another one easily. The proportion of people who use language learning platforms was the highest, followed by higher education platforms and vocational training platforms. It reflects the characteristics of online education platform users' high education level, as well as the demand for professional and effective information and resources, which is in line with the educational level of the sample population.

Table 2. Demographic statistics.

Survey Object	Options	Quantity	Percentage
Gender	Male	140	44.7%
	Female	173	55.3%
Age	Under 18	61	19.5%
	18–25	181	57.8%
	26–40	64	20.4%
	Above 40 years old	7	2.3%
	Postgraduate and above	52	16.6%
Education	Undergraduate	170	54.3%
	Specialist	15	4.8%
	High school and below	76	24.3%
Monthly income (including student allowance)	Below 1000 yuan	102	32.6%
	1001–3000 yuan	90	28.7%
	3001–5000 yuan	66	21.0%
	5001–8000 yuan	32	10.2%
	8001 yuan and above	23	7.5%

Table 3. Analysis of online learning platforms.

Survey Object	Options	Quantity	Percentage
The use situation of online learning platforms	K12 education platform (such as homework help, Xueersi online school, ape tutoring, etc.)	69	22.0%
	Higher education platforms (such as Chinese University MOOC, Postgraduate Entrance Examination Gang, TED, etc.)	226	72.2%
	Language learning platforms (such as Liulishuo, Netease Youdao Dictionary, Momoback words, etc.)	231	73.8%
	Vocational training platforms (such as Zhong Gong Education, Driving Test Baodian, China Accounting Online School, etc.)	140	44.7%
	Comprehensive online school platforms (such as NetEase Open Class, Tencent Class, New Oriental Online, etc.)	102	32.6%
	Quality education platforms (such as Squirrel AI, Programming Cat, etc.)	34	10.9%

5. Result and Discussion

Structure equation modeling has two common methods, covariance-based SEM (CB-SEM) and partial least square SEM (PLS-SEM). This study adopts the CB-SEM due to two considerations.

The first is about the research model—since CB-SEM is a confirmatory approach, the method requires the specification of the full theoretical model prior to data analysis. Further, it is more appropriate for established theory testing and confirmation [59]. In contrast, PLS-SEM is suitable for early-stage theory development and testing [60,61] and is used to explore the constructs and relationships in complex structural models. The model in our study has a sound theoretical foundation (PPM theory), and the direction of the relationship between variables (the influencing factors of users switching behavior in online learning platform) is determined, therefore, CB-SEM should be suitable for this study.

The second is about the research sample size. PLS-SEM works efficiently with small samples and does not need assumptions about distribution. In contrast, CB-SEM requires large samples than PLS-SEM, but CB-SEM has lower variability than PLS-SEM in the case of large sample size. The sample volume in our study is over 300, which is rather larger as fit in the requirement of CB-SEM.

There are two stages during data analysis: (1) measurement modeling for the reliability and validity of the measurement scale, and (2) structural modeling for hypothesis testing.

5.1. Measurement Model

The goal of measurement modeling was to assess the reliability and validity of the measurement scales. The reliability of the measurements was examined using composite reliability (CR) and Cronbach's Alpha. The critical values for CR and Cronbach's Alpha are 0.7 and 0.7, respectively. Table 4 shows the results of CR and Cronbach's Alpha were all higher than the recommended value, indicating that all the constructs were reliable.

Table 4. Reliability and validity.

Constructs	Items	Loading	Cronbach's α	CR	AVE
Information Overload	IO1	0.772	0.841	0.842	0.571
	IO2	0.782			
	IO3	0.758			
	IO4	0.709			
Dissatisfaction	DS1	0.767	0.913	0.914	0.679
	DS2	0.881			
	DS3	0.835			
	DS4	0.811			
Functional Value	DS5	0.822	0.911	0.913	0.679
	FV1	0.774			
	FV2	0.740			
	FV3	0.850			
Network Externality	FV4	0.836	0.878	0.878	0.706
	FV5	0.909			
	NE1	0.855			
	NE2	0.849			
Switching Cost	NE3	0.817	0.932	0.935	0.782
	SC1	0.872			
	SC2	0.901			
	SC3	0.884			
Affective Commitment	SC4	0.879	0.921	0.922	0.747
	AC1	0.887			
	AC2	0.835			
	AC3	0.866			
Switching Behavior	AC4	0.868	0.910	0.911	0.719
	SB1	0.862			
	SB2	0.827			
	SB3	0.900			
	SB4	0.800			

Then, confirmatory factor analysis was used to test the convergent validity and discriminant validity. Convergence validity reflects the correlation degree of the same latent variable, while discriminant validity reflects the difference between different latent variables. The convergent validity of the constructs was examined by average variance extracted (AVE) and item loading significance. The recommended value of AVE is 0.5, and the minimum value of AVE in Table 4 is 0.571. Meanwhile, as shown in Table 4, all item loading were over 0.7, suggesting satisfactory convergent validity.

Discriminant validity can be assessed by correlation matrix and square roots of AVE for all constructs. Good discriminant validity requires that the square root of the AVE of each construct should be higher than the correlation of the specific construct with all the other constructs in the model. Table 5 shows that the square root of AVE value of each construct is higher than the correlation between two other factors, indicating that the measurement model has good discrimination validity.

Table 5. Correlation matrix and square roots of AVE results of the tests.

	IO	DS	FV	NE	SC	AC	SB
IO	0.756						
DS	0.431	0.824					
FV	0.503	0.527	0.824				
NE	0.585	0.504	0.467	0.841			
SC	−0.402	−0.259	−0.312	−0.363	0.884		
AC	−0.305	−0.241	−0.273	−0.291	0.386	0.864	
SB	0.536	0.533	0.536	0.547	−0.475	−0.440	0.848

Note: The bold numbers in the diagonal row represent the square roots of the AVE, and the off-diagonal values represent the correlations of each construct with other constructs.

5.2. Structural Model

The second step is to examine the significances and strengths of each hypothesis and the variable explained to the dependent variable. This part applies to adopt AMOS software and structural equation model (SEM) to carry out the empirical examination of the hypothesis. First, the model's goodness of fit and overall explanatory power was considered. Goodness-of-fit analysis refers to how well a model fits a set of observations [2]. The fitting hypothesis model in this study was evaluated according to the regular fitting indexes provided by AMOS software, shown in Table 6. All meet the recommended values for the indexes [2].

Table 6. Goodness of fit test.

Fitting Index	Recommended Value	Fitting Result
CMIN\DF	<3.0	1.356
GFI	>0.9	0.907
AGFI	>0.8	0.887
CFI	>0.9	0.981
NFI	>0.9	0.932
RFI	>0.9	0.922
IFI	>0.9	0.981
TLI	>0.9	0.978
RMSEA	<0.08	0.034

Figure 2 presents the results of the structural model. All the hypotheses have expected effects on switching intention at different significances, as seen in Table 7.

Table 7. Result of test.

Hypothesis	Path Coefficient	S.E.	C.R.	P	Result
SB←IO	0.158	0.068	2.142	0.032	Positive
SB←DS	0.227	0.055	3.834	***	Positive
SB←FV	0.176	0.059	2.952	0.003	Positive
SB←NE	0.155	0.077	2.2	0.028	Positive
SB←SC	−0.184	0.043	−3.596	***	Negative
SB←AC	−0.174	0.044	−3.58	***	Negative

Note: *** $p < 0.001$.

As expected, dissatisfaction with the incumbent platform has significantly positive effects on switching intention, validating hypothesis 2. It shows that satisfaction is the primary factor of user continuous use behavior. The conclusion is further verified in the online education field. Users will prefer to switch to a more satisfying platform when they are dissatisfied with the incumbent one. Information overloading ($\beta = 0.158$, $p = 0.032$), another one of push factors also has a positive but a weak significance effect on switching intention positively. This conclusion can support hypothesis 2. Information overload

will reduce the user's immersion in the learning process and affect the learning effect. However, it has less impact on user switching behavior compared with dissatisfactory with incumbent one.

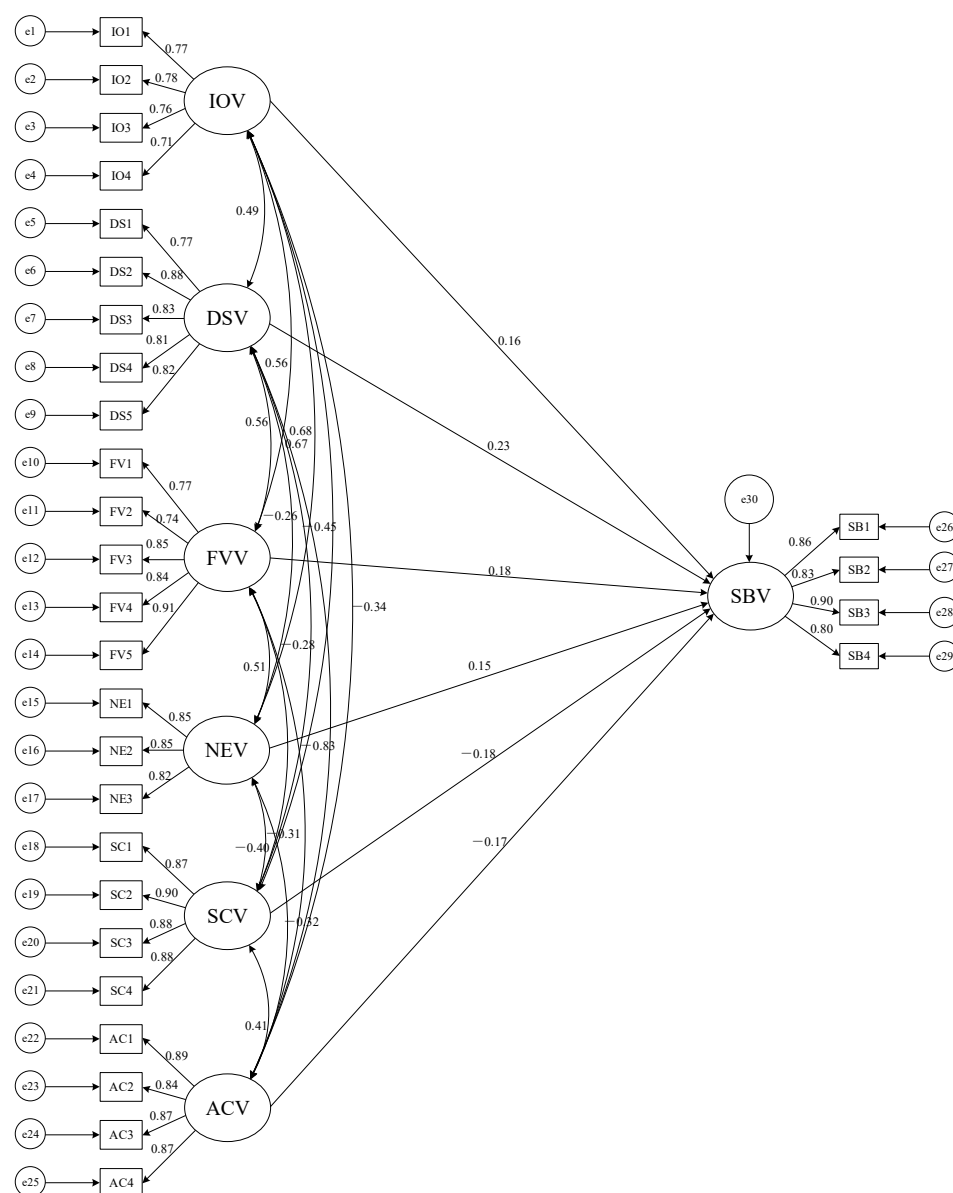


Figure 2. SEM model analysis. Note: IO = information overload; DS = dissatisfaction; FV = functional value; NE = network externality; SC = switching cost; AC = affective commitment; SB = switching behavior.

For pull factors, alternative attractiveness ($\beta = 0.176, p = 0.003$) and network externality ($\beta = 0.155, p = 0.028$), positively affect the switching behavior, indicating that users not only pay attention to the functional value of the alternative platform, but also are affected by personal emotional needs. When the learning resources and teachers' team of the alternative platform are better, the switching behavior is more likely to occur. In other words, the learning resources provided by the current platform cannot meet the users' needs to upgrade, leading users to turn to other platforms. Secondly, users have an emotional connection with other friends through the use of a learning platform. Social networks will convey more information about the alternative platforms by friends around them, thus affecting user switching behavior. This conclusion also confirms the importance of word-of-mouth and promotion. Among the two factors, the significance of functional value is stronger. In this respect, functional value is more important to customers.

On the contrary, for the mooring factors, the switching cost and emotional commitment are found to have significantly negative effects on switching intention, supporting the hypothesis that two mooring factors influence switching intention greatly. The possible reason is that users worry about the uncertain cost in the process of service switching, which not only exists in the search and evaluation cost, but also in the process of learning and understanding effort to adopting a new platform. In addition, the original platform often provides exclusive benefits such as student benefits and points for retained customers, which makes users sensitive in the conversion process and inhibits the occurrence of user switching behavior. In conclusion, the keen emotional commitment to the incumbent platform and perception of high switching costs would make users continue to use the incumbent platform.

Based on the above, users are affected by the interaction of pull, push, and mooring factors in the process of switching. Users of online learning platforms would make the optimal decision after considering all these three factors.

5.3. Expansibility Analysis

The effect of the three factors discussed above on user switching behavior also depends on the type of online learning platform. This study will further analyze the different influence factors and mechanisms of switching behavior for different types of platforms. According to the survey, we know that higher education platforms and language learning platforms have a larger market scale. Therefore, this paper compares the different influence factors for user switching behavior between the two platforms. The test results are shown in Table 8. Model 1 describes the user switching behavior of higher education platforms, and model 2 is for language learning platforms.

Table 8. Result of tests.

	Expansion Variables	Model 1	Model 2
Independent variable	Information overload	0.74	0.190 **
	Dissatisfactory	0.172 **	0.213 ***
	Function value	0.175 **	0.140 *
	Network externality	0.210 **	0.167 *
	Switching cost	−0.219 ***	−1.77 **
	Affective commitment	−0.170 **	−1.56 **
Regression indicators	R ²	0.715	0.745
	Adj R ²	0.498	0.543
	F	38.184	46.479

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In model 1, except for information overload, other factors have a significant effect on the user switching behavior, just as expected. The results show that these factors have the same effect on the users of higher education platforms as with other platform types. However, the item of information overload cannot support the hypothesis, indicating that this item has less effect on the switching intention. The possible reason is that the users of higher education learning need much information and become less sensitive to a large amount of information supply—among them, the switching cost has the greatest influence on such users. The curriculum content of the higher education platform is more professional and coherent, and users pay special attention to the process and results. The switching behavior not only makes users lose sunk costs, but also need to pay new costs to find curriculum resources. The network externality has the second greater influence. Due to the curriculum design and teachers, the decision-making cycle of higher education users is longer and the process is more complex. They are more influenced by the recommendation of teachers and friends. Therefore, the network externality in the higher education platform model has a stronger effect on user switching behavior.

For model 2, all these push, pull, and mooring factors can also have the expected effect on the switching behavior. Among them, dissatisfaction with the incumbent platform has

the greatest influence on the switching intention. Language learning platforms provide users with listening, speaking, reading, writing, translation, and other functions, and users' continuous use depends on whether these functions can meet their needs. Different from higher education platforms, language learning platforms are not a must for most users, and product homogeneity is significant. If users are not satisfied with a certain platform, it is easy for them to switch to other learning platforms.

6. Conclusions

Online learning platforms provide richer resources and diminish the barrier of time and space of traditional teaching mode [62]. Therefore, it is important to ensure that sustainable development and performance enhancement for the online learning platform.

This study attempted to conduct a thorough analysis of influencing factors on user switching behavior to avoid the loss of existing users and effectively retain current users for online platforms, thus maintaining the sustainable development in these platforms. Based on PPM theory, the mechanism of user switching behavior is examined on online learning platforms. First, the results of the empirical study confirm the role of the factors in the hypotheses in shaping learning platform switching intention. Second, among these factors, the dissatisfaction of online learning users has the greatest impact on switching intention, which is consistent with the online learning study of Qian [20]. Moreover, the result also reflects the previous research on immigration theory [24,63]. The mooring factors—switching cost and affective commitment—have a significantly negative impact on switching intention, which is in line with the switching behavior study of Sun [15] and the study of Dong [64]. Third, our study further analyzed the influencing factors for different types of online learning platforms. We found that there were significant differences in the impact of information overload on different types of platforms. For language learning platforms, the user's dissatisfaction is the greatest impact factor, while the network externality and switching cost are the vital influencing factors for high education platforms.

Online learning platforms play a vital role in providing suitable facilities for learners to acquire knowledge and skills and the chances for the learner to be a life-long learner. Fostering life-long learning is crucial not only for improving people's skills but also for the country. It aligns with the Agenda 2030, aiming to "ensure inclusive and equitable quality education and promote life-long learning opportunities for all". Therefore, it is crucial for maintaining the sustainable development of online platforms.

The findings in this study offer new insights and practical implications for the sustainable development of online learning platforms. "Online learning" is a complex multi-dimensional framework system. Promoting the efficient matching of demand and supply is the key to the sustainable development of online education. Therefore, online education needs to increase the functionality of platforms with the help of technology to improve customer satisfaction to strengthen emotional communication with customers through humanistic concerns and to seek sustainable development. To achieve this, they should aim to (1) Meet the diversified needs of users with the application of technology. Compared with the "sense of presence" of traditional classroom teaching, online learning platforms lack real-time interaction and a sense of experience. It is urgent to use artificial intelligence and virtual reality technology to improve the level of interaction in the process of teaching, thus improving the quality of teaching and increasing the attractiveness for users. In the process of online learning, a personalized learning scheme is provided to improve the learning efficiency and emotional experience of users, which can not only meet the individual needs in online learning, but also to enhance user satisfaction of online education services. (2) Strengthen the emotional identity of users with humanistic concerns. Online learning is not only a network of curriculum services but also a network of user-centered communities. It pays attention to the voice and demand of users, helps users to find peers and groups in learning, promotes the exchange between teachers and students, strengthens the communication between the platform and the user. The platform should strengthen the emotional connection with users on the basis of curriculum services and cultivate the

user's sense of identity and belonging in the online learning platform, thus enhancing the user's "stickiness" to the service of online learning platforms.

Some limitations in this paper can be further improved in future studies. The dependent variable was constructed to measure the switching intention based on PPM theory. However, some important factors are not included in this model. Other variables should be considered in future studies that might impact the switching intention. In addition, the samples were restricted to younger adults. Data accounting for teenage and middle age users were not included in this study. If more data covering all age groups are available to conduct future studies on this subject, then better explanations should be drawn. Dependent variables like age and educational background should be considered carefully to obtain more findings.

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