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Switching Intention and Intention to Use Personal Cloud Storage Services Among Chinese Undergraduates

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Abstract

Purpose: As one of the emerging Internet technologies, cloud technology may be broadly categorized as cloud computing and cloud storage. Personal Cloud Storage Service (PCSS) is an important part of cloud technology. Thus, this study investigates the factors influencing Hangzhou undergraduates' switching intentions and intention to use personal cloud storage services. **Research design, data, and methodology:** The data were collected from 515 undergraduates at Zhejiang University, Zhejiang Gongshang University, and Zhejiang University of Technology. The sampling techniques are judgmental, stratified random, convenience and snowball sampling. The item-objective congruence (IOC) and Cronbach's Alpha of the pilot test were approved before the data collection. Afterwards, this study applied confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results:** The findings indicate that perceived ease of use has a significant impact on perceived usefulness. Perceived usefulness, perceived ease of use and attitude significantly affect intention to use. Perceived risk significantly affected the switching intention. Finally, switching cost and perceived usefulness significantly affect the switching intention. **Conclusion:** Personal cloud storage service providers should enhance the security and should continue to improve its PCSS products and optimize the membership price model, enabling free users to use the service by sending them advertisements.

Keywords: Personal Cloud Storage Service, Switching Intention, Intention to Use, Undergraduates, China

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the fast development and advancement of cloud computing, big data, artificial intelligence, the Internet of Things, and other technologies in recent years, human beings have begun to enter the post-mobile era (Wang, 2016). Cloud storage is a new concept that stems from cloud computing and is a product of the network era. Cloud storage service is one of the most prevalent cloud computing services. Users' data will be stored in the cloud data center instead of their complex drive device. They can access and use these resources using various electronic devices, such as desktops, laptops, mobile phones, smartwatches, and so on (Cao et al., 2013). Cloud storage has been widely adopted in all facets of social life and product manufacturing process, such as enterprise management informatization, e-government, online library, online management of personal files, teaching resources sharing, and so on, making it

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become a core issue in the worldwide Information Communication Technology (ICT) industry (Marston et al., 2011).

Users can use the personal cloud storage service (PCSS) for online synchronization management of personal information and files as long as the network is available. The personal cloud storage service (PCSS) generally provides notable features such as ample storage capacity, portable archiving, real-time synchronization, and on-demand information sharing. Cloud-stored files may be accessed in a variety of ways. PCSS Users may access cloud-stored data through web browsers, PC software, and mobile apps. Different Cloud service providers provide varied file-sharing options. Dropbox, for instance, enables users to form sharing groups for file sharing, while Baidu Cloud gives users temporary credentials to access other Cloud users (Wu et al., 2017). Users have a growing need for cloud storage services as the number of Internet users and the sophistication of intelligent gadgets expand. More and more people are turning to cloud storage to store and retrieve their data rather than relying on external storage devices (Yeo et al., 2014).

As cloud technology progresses, more academics are paying more attention to cloud computing and cloud storage. Sun (2013) developed a model for THE adoption intention of personal cloud storage service (PCSS) based on the Technological Acceptance Model (TAM) and task-technology fit (TTF) and discovered that perceived usefulness (PU), perceived ease of use (PEOU), and task-technology fit (TTF). Park and Kim (2014) developed the system by integrating the Technological Acceptance Model (TAM) with various cognitive factors influencing consumers' perspectives towards PCSS and surveyed 1099 respondents. The adoption of PCSS by consumers is shown to be highly dependent on perceived mobility, connectivity, security, service quality, and satisfaction. Park and Ryoo (2013) surveyed personal cloud storage services (PCSS) among students at two South Korean universities. The findings indicate that the intention of PCSS users to use PCSS is positively influenced by expected switching benefits, personal innovation, and expected switching costs.

In the Chinese market, cloud storage services are no longer a new technology; however, the penetration rate of personal cloud storage services in China is meager (Wang, 2016). According to Guo (2014), the Chinese market includes more than 30 personal cloud storage platforms (such as Baidu Cloud, Miui Cloud, Tianyi Cloud, and Tencent Cloud), and their suppliers include Internet service providers, electronic devices providers, and telecom firms. Nonetheless, the growth of cloud storage in China has not been entirely straightforward. Chinese cloud storage service providers lack mature business strategies, yet market competition is severe, resulting in the homogeneity of most cloud storage services. Moreover, the external intervention of the Chinese government and some industry regulations have led to a crisis of trust among PCSS users and extreme concern about releasing personal data (Jing, 2016; Wu et al., 2017).

As China's leading cloud service provider, Alibaba dominates the Chinese cloud industry. However, Alibaba does not provide personal cloud storage services, but Baidu focuses on it; hence, Baidu is the leader in China for personal cloud storage services (Kiran, 2020). Some Cloud storage providers, such as Dropbox, Google Drive, and OneDrive, cannot enter the Chinese market owing to government and regulatory constraints, and Chinese customers cannot use these Cloud services in China (Wu et al., 2017). Accordingly, Baidu Cloud can expand effectively in China. In 2012, Baidu introduced a personal Cloud storage service known as Baidu Cloud, which enables Cloud storage operations on PCs and mobile devices flawlessly and is compatible with all operating systems, including Windows, macOS, Android, and iOS. Using Cloud apps or software, Baidu Cloud users may access and share their data across multiple devices by storing their data in the Cloud. Baidu Cloud has become the most popular personal Cloud storage service in China because it allows many Chinese users (particularly university students) to process and share their data conveniently. Baidu Cloud provides each user with two terabytes of free storage space, but if users do not pay to join the membership, their upload and download speeds will be drastically limited. In order to make better use of the cloud service, many users prefer to pay a monthly or yearly subscription fee, which is too expensive for university students. Thus, Baidu Cloud has received several critiques in China. However, Due to the dearth of cloud storage service providers in mainland China and the immaturity of other providers, Baidu Cloud is still the best cloud storage service in China. Thus, this study investigates the factors influencing Hangzhou undergraduates' switching intentions and intention to use personal cloud storage services.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

The technology acceptance model (TAM) is one of the most prevalently used models for determining if new technology can be adopted. It is a crucial predictive model for adopting various IT tools and systems (Aldiabat et al., 2018). In general, it evaluates the behaviors and attitudes of users while using new technology or system to determine the technology's adoption (Davis et al., 1989). This model can explore whether people would adopt or use a new technology based on their perceptions of its advantages. Derived from the Theory of Reasoned Action, TAM is a prominent model used in recent years to forecast users' behavioral intention for a new system or technology (Bazel et al., 2018). In the field of information technology, Technology Acceptance Models (TAM) have been applied to study a variety of products, including intelligent gadgets (Park & Chen, 2007), online banking (Lee & Chung, 2009), and online games (Ha et al., 2007). Also, the TAM framework has been frequently used in Personal Cloud Storage Services (PCSS) studies to measure the influence of perceived usefulness and perceived ease of use on PCSS users' behavioral intention to use the service (Park & Kim, 2014). According to Malhotra and Galletta (1999), the technology acceptance model comprises the external variables (EV), perceived usefulness (PU), perceived ease of use (PEOU), attitude (ATT), and intention (INT). PU, PEOU, ATT, and INT will be used in this study to conduct an empirical study on personal cloud storage service (PCSS).

2.2 Push-Pull-Mooring (PPM) Theory

In migration research, especially information technology migration study, the Push-Pull-Mooring (PPM) framework is widely recognized (Bansal, 2005). The push and pull factors of the PPM framework originated from 'Laws of Migration' published by Ravenstein (1885), and the mooring factor was introduced by Longino (1992). The PPM framework does not define which factors should come into the push, pull, or mooring categories (Bhattacherjee et al., 2012). Consequently, the PPM framework is highly adaptable and applicable to various studies (Wu et al., 2017).

The push factor refers to the power driving users away from the original place (Moon, 1995). In this research, the push factor is why PCSS users abandon their current PCSS products. The first push factor is the perceived risk in this study, which refers to the PCSS users' perception of the amount of risk they must endure while using the original PCSS product. The second push factor is perceived usefulness (PU), which relates to PCSS users' perception of the original PCSS benefit to work performance. This factor aligns with PU under the TAM framework. The push factor refers to the force that attracts users to new places (Cheng et al., 2019). The pull factor is why PCSS users start using a new PCSS product in this research. The mooring factors that facilitate or impede behavioral changes are personal, environmental, and situational restrictions (Wu et al., 2017). In this study, switching cost (SC) is a mooring factor that refers to all the different costs for a PCSS user to switch to a new PCSS.

2.3 Perceived Ease of Use (PEOU)

Perceived Ease of Use is one of the two components of the Technology Acceptance Model (Bazel et al., 2018). According to Davis (1989), perceived ease of use is the extent to which a user believes that a particular service or product can be used without difficulties. It refers to a person's perception of how simple it is to utilize a particular technology. That is the effort the user requires to use new technology. In this study, PEOU refers to the extent to which students believe PCSS may be used with little effort. If users can transfer, store, and share their data using PCSS, the complexity of PCSS will be lowered, and users' perception of PCSS's PEOU will improve (Bazel et al., 2018). The higher the PEOU, the greater the intention to use the PCSS; The higher the PEOU, the greater the PU of the PCSS (Du et al., 2013; Ratten, 2014). Based on the above discussions, the following hypotheses are developed:

H1: Perceived ease of use has a significant influence on perceived usefulness of PCSS.

H2: Perceived ease of use has a significant influence on intention to Use of PCSS.

2.4 Perceived Usefulness (PU)

Perceived usefulness is a crucial component of the Technology Acceptance Model (TAM). According to the TAM, perceived usefulness is theorized to influence users' behavioral intention to utilize information technology (Davis, 1989). Perceived usefulness is the extent to which individuals agree that particular information technology may enhance their job performance (Davis, 1989). In this study, perceived usefulness is the extent to which a student believes using PCSS would enhance his or her academic achievement. The storage space, upload and download speed, system compatibility of the platform, and ease of file sharing are the most influential factors in students' perceptions of PCSS's usefulness (Bazel et al., 2018). Personal cloud storage services (PCSS) provide more capacity, easier administration, and cheaper costs than conventional hard drives. Mobile cloud storage services significantly enhance users' work performance, and perceived usefulness positively affects PCSS users' intention to use cloud storage services (Park & Kim, 2014). PCSS users will be more willing to switch to a new PCSS if the previous PCSS fails to improve productivity and match user requirements. In this research, perceived usefulness (PU) refers to PCSS users' knowledge of the extent to which the previous PCSS (Baidu Cloud) may enhance job performance and the relationship between PU and PCSS users' intention to switch to a new PCSS (Cheng et al., 2019). Hence, the proposed hypotheses are obtained:

H3: Perceived usefulness has a significant influence on intention to use of PCSS.
H4: Perceived usefulness has a significant influence on switching intention of PCSS.

2.5 Perceived Risk (PR)

The user's uncertainty about the environment or behavior is usually the source of risk. The first type of risk is associated with the file privacy setting of the user. Nowadays, many PCSS users are concerned that the PCSS supplier may repurpose the data they upload to the PCSS without their permission since they lack the power to restrict the PCSS supplier from sharing this information further (Cheng et al., 2019). If files or data uploaded by PCSS users are accessed or utilized without their permission by PCSS providers or the government, PCSS users' intention to continue using the system would be reduced dramatically (Yang & Lin, 2015). The second type of risk is unrelated to the PCSS provider and is affected by network security. According to Cheng and Lai (2012), PCSS is an Internet-based service, and network interaction is frequent, particularly when transferring or sharing data. Therefore, PCSS is susceptible to all Internet-related dangers (such as hacker attempts). The perceived risks in this study will comprehensively consider the above two different types of risk and explore the relationship between these risks and the switching intention of PCSS users. Based on the previous studies, this research hypothesized that:
H5: Perceived risk has a significant influence on switching intention of PCSS.

2.6 Attitude (ATT)

Attitude indicates a person's overall feeling of favorableness or unfavorableness towards a stimulus item (Ajzen & Fishbein, 1977). The user's attitude toward a product refers to the user's emotional reaction to the product (Davis, 1993). According to the Theory of Rational Action (TRA), an individual's intention to engage in a specific behavior is impacted by his or her attitudes (Ajzen, 1991). Attitude refers to a person's approbation and opinion of something (Huang, 2016). Many studies have proven the relationship between attitude and behavioral intention using the Technology Acceptance Model (Phaisuwat & Vongurai, 2017). According to Park and Kim (2014), users' attitude toward a Personal Cloud Storage Service (PCSS) positively influences their intention to use that service. Thereby, a hypothesis is proposed:
H6: Attitude has a significant influence on intention to use of PCSS.

2.7 Switching Cost (SC)

The one-time charges spent by users when switching to a new product or service are referred to as switching costs (Dick & Basu, 1994). According to Jones et al. (2002), switching costs are associated with ongoing costs, learning costs, and sunk costs. Ongoing costs are related to poor performance and uncertainty; learning costs include setup, survey, and measurement costs before switching and behavioral and cognitive costs after switching. *Sunk costs* are costs spent on a prior product that cannot be recovered. In the Chinese market, the sunk cost is generally not high because Chinese PCSS users often only use the free PCSS service (Wu et al., 2017). In this research, switching costs are incurred by users in abandoning the previous PCSS (Baidu Cloud) and training them to use a new PCSS as a substitute. Thus, the assumptions lead to a hypothesis:
H7: Switching cost has a significant influence on switching intention of PCSS.

2.8 Intention to Use (INT)

The degree of effort a user will exert to adapt to a new system or technology is the intention to use it (Mamman et al., 2016). In the context of the research on PCSS, intention to use refers to the level of effort PCSS users is willing to put into learning or resolving problems while utilizing a certain PCSS (Park & Kim, 2014). Perceived usefulness (PU) and perceived ease of use (PEOU) have a significant positive effect on users' intention to use (INT) the system Phyu & Vongurai, 2020). In contrast, INT significantly positively affects users' behavior (Venkatesh et al., 2003).

2.9 Switching Intention (SI)

Switching often happens when the user is dissatisfied with the existing product or service or believes that an alternative product or service is better (Hsieh et al., 2011). Consumers are more likely to abandon previous information technology (IT) products due to new or better products (Hsieh et al., 2011). Hence, IT suppliers must pay more attention to competitors' and users' switching intentions. However, IT users switching behavior is different from users of other products. When IT users switch products, they often continue to use the previous products in tandem with the new ones. Then gradually reduce the usage of the previous services while increasing the use of new alternatives (Keaveney & Parthasarathy, 2001).

3. Research Methods and Materials

3.1 Research Framework

Researchers used four previous theoretical frameworks, the Technology Acceptance Model (TAM) and Push-Pull-Mooring (PPM) Theory, and ultimately chose seven variables to construct the conceptual framework of this study. Variables are perceived ease of use (PEOU), perceived usefulness (PU), perceived risk (PR), attitude (ATT), switching cost (SC), intention to use (INT), and switching intention (SI). The conceptual framework of this study derives from the following four theoretical frameworks:

- Research on the switching intention of Chinese PCSS product users (Wu et al., 2017; Xu et al., 2017)
- A factor analysis of PCSS users' desire to use a particular PCSS product (Ogbanufe et al., 2019)
- Analysis of the intention of university students to adopt PCSS (Arpaci, 2016)

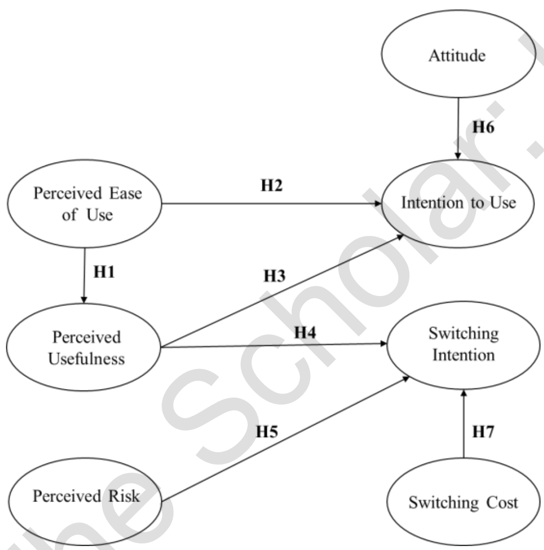

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant influence on perceived usefulness of PCSS.
H2: Perceived ease of use has a significant influence on intention to Use of PCSS.
H3: Perceived usefulness has a significant influence on intention to use of PCSS.
H4: Perceived usefulness has a significant influence on switching intention of PCSS.
H5: Perceived risk has a significant influence on switching intention of PCSS.
H6: Attitude has a significant influence on intention to use of PCSS.
H7: Switching cost has a significant influence on switching intention of PCSS.

3.2 Research Methodology

During the COVID-19 period, the researchers decided to distribute questionnaires online, and participants filled them out online; hence, Wenjuanxing was utilized as the data collecting platform for this research. Wenjuanxing is the most popular commercial questionnaire platform in China, and many Chinese researchers gather data on this site (Mei & Brown, 2017). The questionnaire consisted of three parts. The first part is screening questions, which are used to identify whether the participants are fit for the research. This questionnaire comprises three screening questions. The second part consists of demographic questions, primarily intended to gather participants' personal information. There are five such questions in this questionnaire. The scaling questions in the third part are primarily utilized to quantify the seven variables in this research. Each variable has four to five questions, and a five-point Likert scale is utilized to gather data.

In the pilot test, the validity of the questionnaire was tested by the expert score of item-objective congruence (IOC). The results of IOC by three experts showed that all items were approved at a score of 0.6 or above. Afterwards, the results Cronbach's Alpha coefficients for perceived risk (PR), switching cost (SC), perceived usefulness (PU), switching intention (SI), perceived ease of use (PEOU), attitude (ATT) an intention to use were respectively 0.852, 0.816, 0.850, 0.886, 0.841, 0.853 and 0.962, indicating that internal consistency is valid at a score more than 0.7 (Nunnally & Bernstein, 1994). For the data analysis, the researchers used Confirmatory Factor Analysis (CFA) to determine if the model could be applied to this study. The structural equation model (SEM) was then used to examine the causal relationship between independent and dependent variables.

3.3 Population and Sample Size

The population of this study is undergraduate students at Zhejiang University, Zhejiang University of Technology, and Zhejiang Gongshang University. This study's sample size was calculated using an online SEM calculator. The researcher input the following data into the calculator: anticipated effect size of 0.2, desired statistical power level of 0.8, seven latent variables, thirty observable variables, and a probability level of 0.05 (Soper, 2022). The results indicated that the smallest acceptable sample size was 425, but the minimal sample size chosen by the researchers was 500, and the actual sample size was 515.

3.4 Sampling Technique

The sampling techniques are judgmental, stratified random, convenience and snowball sampling. Firstly, judgmental sampling is to select undergraduates at Zhejiang University, Zhejiang Gongshang University, and Zhejiang University of Technology. Secondly, the stratified random sampling is to proportionally distribute the sample size in three subgroups. Thirdly, convenience sampling is used to distribute online questionnaire. Consequently, the questionnaire was distributed between February and June 2022 to over 1,000 students, and 515 responses were retuned. Lastly, snowball sampling is applied to encourage students to share the survey link among their friends.

Table 1: Population and Sample Size by University

Name of University	Total number of students	Total number of undergraduates (Percentage)	Proportional Sample Size
Zhejiang University	66,772	29,209 (39.42%)	197
Zhejiang University of Technology	30,633	19,383 (26.16%)	131
Zhejiang Gongshang University	30,900	25,500 (34.42%)	172
Total	**128,305**	**74,092 (100%)**	**500**

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

The demographic information of this study includes 515 undergraduate questionnaires from three universities in Hangzhou, which are summarized by the researcher and presented in Table 2.

Table 2: Demographic Profile

Demographic Factors	Frequency	Percentage (%)
Gender		
Male	298	57.9
Female	217	42.1
Student Status		
Freshman	122	23.7
Sophomore	124	24.1
Junior	136	26.4
Senior	133	25.8
Field of Study		
Economics	82	15.9
Engineering	17	3.3
Management	95	18.4
Law	61	11.8
Education	23	4.5
Literature	22	4.3
History	57	11.1
Science	29	5.7
Agriculture	26	5.0
Medicine	40	7.8
Philosophy	24	4.7
Art	26	5.0
Other fields	13	2.5

Source: Created by the author.

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a technique for evaluating the applicability of a model to Structural Equation Modeling (SEM) measurements by assessing a variety of factor structures (Lei & Wu, 2007). As of Table 3, Cronbach's Alpha coefficient values are valid at a score more than 0.7 (Nunnally & Bernstein, 1994). Additionally, composite Reliability (CR) of all model construct must be larger than 0.70 to assure the internal consistency of this study (Hair et al., 2006). According to Fornell and Larcker (1981), the evaluation of convergent validity should include two criteria: first, all factor loadings should be statistically significant ($P < 0.05$) and the value should greater than 0.7; and second, the average variance extraction (AVE) value of all factors in the model should be greater than 0.5.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Ogbanufe et al. (2019)	5	0.852	0.723-0.745	0.852	0.536
Perceived Usefulness (PU)	Ogbanufe et al. (2019)	4	0.831	0.713-0.779	0.833	0.555
Perceived Risk (PR)	Xu et al. (2017)	4	0.863	0.723-0.831	0.865	0.617
Attitude (ATT)	Arpaci (2016)	5	0.934	0.839-0.902	0.934	0.738
Switching Cost (SC)	Xu et al. (2017)	4	0.863	0.724-0.892	0.868	0.624
Intention to use (INT)	Arpaci (2016)	4	0.902	0.797-0.868	0.903	0.700
Switching Intention (SI)	Xu et al. (2017)	4	0.865	0.743-0.869	0.886	0.661

Source: Created by the author.

In the measurement model, CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA are used to indicate the model fitting in CFA testing. The results as stated in Table 4 showed that the model satisfies all criteria of goodness of fit.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Awang, 2012)	710.6748/384 or 1.8507
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.917
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.901
NFI	≥ 0.80 (Wu & Wang, 2006)	0.928
CFI	≥ 0.80 (Bentler, 1990)	0.966
TLI	≥ 0.80 (Sharma et al., 2005)	0.961
RMSEA	< 0.08 (Pedroso et al., 2016)	0.041
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation
Source: Created by the author.

The square root of AVE must always be greater than the cross-correlation values of all factors in this construct for discriminant validity to maintain. As shown in Table 4, the researcher calculated the square root AVE of each factor and concluded that this value was more significant than the correlation values of all factors. Therefore, the discriminant validity was guaranteed. According to Studenmund (1992), this study has no multicollinearity problems because the factor correlations in Table 5 did not surpass 0.80.

Table 5: Discriminant Validity

	PR	SC	SI	PU	PEOU	ATT	INT
PR	**0.785**						
SC	-0.134	**0.790**					
SI	0.508	-0.510	**0.788**				
PU	0.006	0.102	-0.327	**0.750**			
PEOU	-0.050	0.053	-0.242	0.540	**0.732**		
ATT	-0.062	-0.015	-0.122	0.113	0.202	**0.860**	
INT	-0.022	0.098	-0.303	0.574	0.663	0.542	**0.837**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural equation model (SEM) is a collection of statistical techniques used to examine the relationship between observable and latent variables (Beran & Violato, 2010). Before utilizing SEM to determine the causal relationship between variables, it is also required to evaluate the conceptual model. This research uses the goodness-of-fit index to evaluate the structural equation model (SEM).The results of fit index presented good fit which are CMIN/DF = 1.9167, GFI = 0.912, AGFI = 0.897, NFI = 0.923, CFI = 0.962, TLI = 0.958 and RMSEA = 0.042.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Awang, 2012)	762.8397/398 or 1.9167
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.912
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.897
NFI	≥ 0.80 (Wu & Wang, 2006)	0.923
CFI	≥ 0.80 (Bentler, 1990)	0.962
TLI	≥ 0.80 (Sharma et al., 2005)	0.958
RMSEA	< 0.08 (Pedroso et al., 2016)	0.042
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation
Source: Created by the author.

4.4 Research Hypothesis Testing Result

The research hypothesis testing results are measured by the significance of the regression path coefficient according to its t-value and calculates the explanatory ability of the independent variable to the dependent variable according to R2 as demonstrated in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.6454	11.5552*	Supported
H2: PEOU→INT	0.4764	9.4797*	Supported
H3: PU→INT	0.3396	7.2321*	Supported
H4: PU→SI	-0.3590	-9.1314*	Supported
H5: PR→SI	0.5426	13.1258*	Supported
H6: ATT→INT	0.4921	14.1772*	Supported
H7: SC→SI	-0.4845	-11.4026*	Supported

Note: * $p<0.05$
Source: Created by the author.

As summarized in Table 7, all research hypotheses are supported. Perceived ease of use has a significant positive impact on perceived usefulness (H1, β = 0.6454, CR = 11.5552, $p < 0.001$). Perceived usefulness (PU), perceived ease of use (PEOU) and attitude (ATT) positively and significantly affect intention to use (INT) of PCSS users (H3, β = 0.3396, CR = 7.2321, $p < 0.001$; H2, β = 0.4764, CR = 9.4797, $p < 0.001$; H6, β = 0.4921, CR = 14.1772, $p < 0.001$). Perceived risk (PR) positively and significantly affected the switching intention (SI) of PCSS users (H5, β = 0.5426, CR = 13.1258, $p < 0.001$). Finally, switching cost (SC) and perceived usefulness (PU) negatively and significantly affect the switching intention (SI) of PCSS users (H7, β = -0.3590, CR = -9.1314, $p < 0.001$; H4, β =-0.4845, CR = -11.4026, $p < 0.001$).

5. Conclusions and Recommendation

This study investigates the factors influencing PCSS users' intention to use and switch. Using the Technological Acceptance Model (TAM) and the Push-Pull-Mooring (PPM) Theory, this research surveyed and analyzed the usage and switching intentions of cloud storage users (undergraduate students) in Hangzhou, China. As the Baidu Cloud is the only target product in this research, intention to use refers to the intention of users to continue using Baidu Cloud while switching intention refers to the intention of users to switch to a new PCSS. In this study, 515 undergraduates from Zhejiang University, Zhejiang Gongshang University, and the Zhejiang University of Technology were surveyed on the use of PCSS (Baidu Cloud). The main findings of this study are summarized below.

5.1 Conclusion and Discussion

According to the TAM framework, perceived ease of use (PEOU) should influence perceived usefulness (PU) and intention to use (INT). According to the results, perceived ease of use (PEOU) positively influences the usage intention (INT) of PCSS users. In other words, when customers consider Baidu Cloud to be easy to use, their intention to use it will enhance. Moreover, according to Hypothesis seven, perceived ease of use (PEOU) positively influences perceived usefulness. In other words, if PCSS users believe that Baidu Cloud is simple to use, they would also believe that it can enhance their work (learning) efficiency. Numerous studies have proven the relationship between perceived ease of use and the other two factors, and many previous studies have been conducted on the Chinese market (Cheng et al., 2019; Xu et al., 2017).

Perceived usefulness (PU) connects the two theoretical frameworks (TAM and PPM). Perceived usefulness (PU) negatively influences PCSS users' switching intentions (SI). In other words, if PCSS users believe that Baidu Cloud can improve their work (learning) performance, they will be less likely to switch to the new PCSS. This conclusion is consistent with the results of Xu et al. (2017); when users believe that the service increases their performance, they are less likely to adopt a new service. Moreover, according to the fourth hypothesis, perceived usefulness (PU) would positively influence the intention to use (INT) of PCSS users. That is to say; if users believe that Baidu Cloud can improve their work (learning) efficiency, their intention to use Baidu Cloud will also rise. Consequently, this hypothesis is supported by the TAM framework, and a significant number of prior research have demonstrated that the perceived usefulness of PCSS increases users' willingness to use PCSS (Bazel et al., 2018; Park & Kim, 2014).

We can conclude that perceived risk (PR) has a positive and statistically significant effect on PCSS users' intention to switch (SI). That is to say, if a user believes that using Baidu Cloud would compromise the security of their personal information or data, they are more likely to abandon Baidu Cloud in favor of an alternative PCSS. This conclusion is consistent with prior studies. Suppose users believe that their service's security is insufficient, the likelihood of them transferring to alternative services increases (Ye & Potter, 2011). Even if PCSS users adopt and use a certain PCSS, the high risk will cause them to abandon it and switch to a new service (Yang & Lin, 2015).

In the TAM framework, attitude (ATT) is often considered a factor influencing the intention to use (INT). In this study, users' attitudes regarding PCSS will positively influence their usage intentions. If consumers believe Baidu Cloud to be an excellent PCSS and have a favorable view, their intention to use Baidu Cloud will also increase. Aldiabat et al. (2018) researched PCSS, discovered a correlation between users' attitudes toward PCSS and their usage intentions, and demonstrated that users' attitudes positively influenced their usage intentions.

According to the findings, switching costs (SC) have a negative impact on users' PCSS switching intentions (SI). If PCSS user wants to abandon the use of Baidu Cloud and switch to using a new PCSS but must spend a great deal of time and money or forego the benefits of Baidu Cloud, they will be less likely to switch. In China's PCSS market, the switching cost of new PCSS users is highly correlated with their intention to switch (Xu et al., 2017). Although most PCSS on the Chinese market provides free services, most induce users to sign up for a membership or spend money by limiting download speed or storage space. Therefore, after abandoning Baidu Cloud, users must continue to spend money on new PCSS. Moreover, since adopting the new PCSS in China requires real-name verification, service learning, data transfer, and other activities, it will increase users' time. Therefore, the intention of PCSS users to switch to the new PCSS is generally low in China.

5.2 Recommendation

Combining the technology acceptance model (TAM) with the Push-Pull-Mooring (PPM) Theory through perceived usefulness (PU), this study proposes a new research model for investigating the switching intention and usage intention of personal cloud storage services (PCSS) users. This research has the following literature implications. First, increasing numbers of scholars focus on studies concerning the usage and switching of new information technologies. As a component of cloud computing, personal cloud storage service (PCSS) is one of the trendiest fields; nevertheless, few previous studies have investigated the switching and usage intention of the PCSS product simultaneously. Therefore, this study's conceptual framework is unique and applicable to future research. Second, since PCSS services are associated with information security and the Chinese market environment is unique, most overseas PCSS products cannot enter the Chinese market. Baidu Cloud has become a leader in the Chinese PCSS market without intensified competition. In this context, few scholars have comprehensively explored Baidu Cloud users' actual perspectives and intentions.

This study reveals that PCSS users are concerned about the risks posed by PCSS, whether they are private or data risks. If PCSS users deem the risks too high, they would decide to abandon the product, even if there is no better alternative. As a result of the Chinese government's proposed strict regulations on pornography and illegal publications, it was discovered that many Chinese Baidu Cloud users had their data destroyed without their knowledge, causing many users to quit the PCSS and use traditional hard drives instead. Due to account security issues and sharing restrictions, some users believe that Baidu Cloud is a risky PCSS. However, according to the findings, most Baidu Cloud users still feel that Baidu Cloud is safe. PCSS users should comply with the government's regulations and refrain from uploading and sharing pornographic and national security-threatening information. Baidu Cloud should enhance the security of Baidu accounts so that users are confident that their personal information and documents will not be stolen or lost due to account theft, hacking, or other reasons.

In China, PCSS users have relatively limited product choices. Popular PCSS solutions like OneDrive, Dropbox, and Google Drive cannot enter the Chinese market. In addition, Alibaba, Tencent, and these Chinese cloud service leaders concentrate on enterprise-level cloud storage services and cloud computing. In contrast, Baidu Cloud has not faced much competition in the PCSS market and thus holds the vast majority of the PCSS market share in China. Nonetheless, this situation is not beneficial for Chinese PCSS users. According to the research data, the switching cost (SC) of PCSS in China is extremely high, and users are unwilling to abandon the Baidu Cloud they have used for years in favor of an unknown PCSS product. In addition, PCSS users in China generally have low switching intention (SI) since so few PCSS products are available. Considering information security, if it is not feasible to deploy overseas PCSS services, the government might encourage other domestic cloud service providers to offer PCSS so that Baidu Cloud and other PCSS will increasingly satisfy the demands of Chinese users in a competitive market.

Baidu Cloud users provide a positive review of the product's perceived usefulness (PU) and perceived ease of use (PEOU) and consider it a good product. Baidu Cloud offers PCSS users' free space to upload, process, and share their files using different electronic devices. Most users believe that Baidu Cloud fulfills their demands quite well. H however, if users want to upload or download large files, the transferring speed will be drastically reduced, and the speed will not be restored until the premium paid member is activated. Some Chinese PCSS users are likewise dissatisfied with this and wish for a completely free PCSS. Therefore, Baidu Cloud should continue to improve its PCSS products and optimize the membership price model, enabling free users to use the service by sending them advertisements.

5.3 Limitation and Further Study

This study has some limitations. First, as the research participants are university students (undergraduates), the findings may have certain limits. Since students have not yet earned money via working, they may have different views about PCSS product switching costs (SI), and attitude (ATT) compared to those currently working. In addition, students use PCSS primarily for learning or keeping personal data, but after employment, PCSS is more utilized for sharing business information or processing work documents online simultaneously. Future research may be conducted on the enterprise or organization's employees to make this conceptual model more general. Second, all the participant in this research is a Chinese PCSS users. Due to differences in Chinese and international policies and cultures, Baidu Cloud does not need to compete in the Chinese market with globally renowned PCSS products such as OneDrive, Dropbox, and Google Drive. Therefore, the results may not apply to other countries. Consequently, future research may employ this conceptual framework to analyze international markets, and the outcomes may vary considerably from this study.

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