INFLUENCING FACTORS OF SWITCHING INTENTION AND INTENTION TO USE PERSONAL CLOUD STORAGE SERVICES AMONG GRADUATES IN HANGZHOU, CHINA

Pan Li
PhD Candidate of Technology Education and Management, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand.
Email: panl179411503@gmail.com*

Received 30 September 2022
Revised 10 February 2023
Accepted 11 February 2023

Abstract

In China, cloud service leaders such as Alibaba and Tencent provide enterprise-level cloud storage services. At the same time, only a small number of suppliers concentrate on personal cloud storage services (PCSS), and China's most popular PCSS is Baidu Cloud. Therefore, this study investigates the factors influencing switching intentions and intention to use personal cloud storage services, including perceived ease of use, perceived usefulness, perceived risk, attitude, switching cost, intention to use, and switching intention. The data were collected from 517 graduate students using 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. In addition, this study applied confirmatory factor analysis (CFA) and structural equation modelling (SEM). The results show that perceived ease of use significantly impacts perceived usefulness. Perceived usefulness, perceived ease of use, and attitude significantly affect intention to use. The perceived risk significantly affected the switching intention. Finally, switching cost and perceived usefulness significantly affect the switching intention.

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

Introduction

There is a wide variety of personal cloud storage services worldwide, including Dropbox, Google Drive, and OneDrive, which users highly regard. However, owing to national information security concerns on the part of the Chinese government, these services are not permitted to enter the Chinese market (Shen, 2020). China still has outstanding cloud service providers, such as Alibaba and Tencent, despite the absence of competition from foreign cloud service providers (Wu et al., 2017). Alibaba Cloud (Aliyun) is the largest supplier of cloud

services and computing in China and one of the top three on the global market, with over 1 million users (Zhang & Ravishankar, 2019).

Unlike their cloud storage services, Alibaba's cloud services are based on cloud computing or enterprise cloud storage services (ECSS). Baidu Cloud is the market leader for personal cloud storage services in China, with over 80% of the PCSS market. Baidu Cloud provides each registered user with 2 Terabytes of free cloud storage space. However, upload and download speeds will drastically decrease while using the service. Baidu Cloud users must pay and sign up for monthly or yearly subscriptions to get better service. As a result, Baidu Cloud has received mixed reviews on the Chinese market, although users do not have a choice of alternative PCSS.

Literature Review

1. Perceived Ease of Use

In the study on PCSS, perceived ease of use is defined as the extent to which users believe a PCSS is simple to store, modify, and share personal files, as well as the adaptability to multiple systems (Windows, Android, Apple). In the TAM framework, perceived ease of use directly influences people's usage intention and indirectly influences intention by impacting perceived usefulness (Cheng et al., 2019). Wang and Yang (2017) studied the perceived ease of use of PCSS users in the Chinese market and discovered that perceived ease of use has a positive impact on adoptive intention. Hence, this research develops following hypotheses:

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. Perceived Usefulness

The perceived usefulness of an IT product is often defined by the user’s perception of the product's functionality and the consistency of the product's performance (Alharbi et al., 2020). In the study of Personal Cloud Storage Services (PCSS), *perceived usefulness* is defined as the extent to which the service assists users in boosting their learning or work efficiency (Joo & Sang, 2013). Park and Kim (2014) surveyed 1099 undergraduates at a university in South Korea about their use of PCSS and found that perceived usefulness positively influenced users’ usage intention. Wang (2017) indicated that perceived usefulness significantly impacts the switching intention of PCSS users. Hence, this research proposes hypotheses:

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.

3. Perceived Risk

Perceived risks include privacy and security risks. The perceived privacy and security risks of PCSS will influence users’ adoption and switching decisions (Cheng et al., 2019; Takabi et al., 2010). The privacy risk relates to the possibility that PCSS users are concerned about how their personal information and files may be accessed, edited, or deleted without

authorization by cloud providers (Baidu Cloud). Therefore, this research emphasizes a hypothesis:

H5: Perceived risk has a significant influence on switching intention of PCSS.

4. Attitude

There are a few examples of applying attitude to the TAM framework in PCSS research. The causal relationship between attitude and behavioral intention has been well demonstrated and utilized in the study of PCSS (Park & Kim, 2014). Aldiabat et al. (2018) evaluated PCSS usage among 571 students, academics, and staff at the University of Sulaimani. They indicated that users' attitudes toward a particular PCSS positively influenced their intention to use a PCSS. Based on the previous studies, a following hypothesis is assumed:

H6: Attitude has a significant influence on intention to use of PCSS.

5. Switching Cost

According to Wu et al. (2017), most Chinese PCSS users prefer free PCSS and will not pay for cloud services. Therefore, it is not necessary to consider sunk costs since users' investment in the original PCSS is almost negligible. Therefore, the switching cost in this study refers to the continuing cost and learning cost that PCSS users suffer while migrating to an alternative. The greater the switching cost, the lower their intention to switch to a substitute PCSS. Base on the assumptions, the researcher hypothesizes as follow:

H7: Switching cost has a significant influence on switching intention of PCSS.

6. Intention to Use

If a technological product makes a user's work more superficial, the user's intention to use it grows immediately (Mathieson & Keil, 1998; Benjangjaru & Vongurai, 2018). Intention to use PCSS refers to the strong desire of PCSS users to use a certain PCSS, which also indicates the effort users are willing to undertake to adapt to the PCSS (Park & Kim, 2014). Usage intention also reflects the motivational factors of PCSS users for a specific PCSS, which influence the user's usage behavior. The higher a user's intention to use a PCSS, the greater the likelihood of using it (Aldiabat et al., 2018).

7. Switching Intention

Switching behavior happens when customers desire a better product service experience and leave their existing supplier (Ping, 1994). Switching intention refers to customers moving to another substitute when he or she is dissatisfied with the current product or service (Kotler, 2000). As technology advances, users are more likely to abandon the initial IT product in favor of a more utterly functioning substitute (Hsieh et al., 2012). In this research, switching intention refers to PCSS users' desire to abandon Baidu Cloud and choose to use a substitute PCSS.

Research Framework

In Figure 1, the conceptual framework was developed based on four previous theoretical frameworks (Arpaci, 2016; Ogbanufe et al., 2019; Wu et al., 2017; Xu et al., 2017). Dependent variables are perceived ease of use (PEOU), perceived usefulness (PU), perceived risk (PR), attitude (ATT), and switching cost (SC). Independent variables are intention to use (INT), and switching intention (SI).

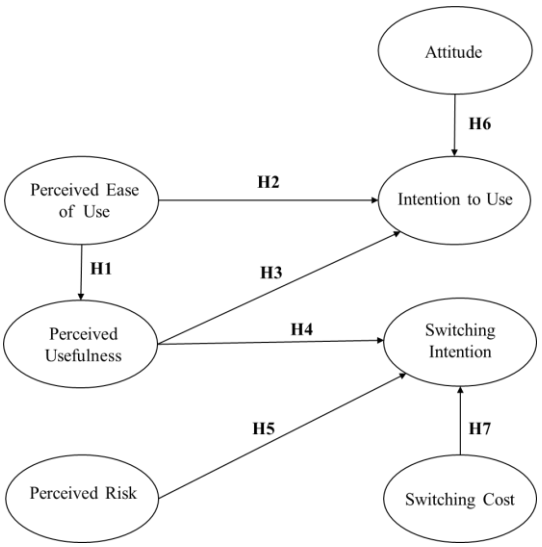

Figure 1 Conceptual Framework

Research Methodology

This quantitative study distributed online surveys to the target group. The questionnaire consisted of three parts; screening questions, demographic questions, and a five-point Likert scale. The results of index of item-objective congruence (IOC) by three experts showed that all items were approved at a score of 0.6 or above. Afterwards, the results Cronbach's Alpha coefficient values indicated the reliability at a score more than 0.7 (Nunnally & Bernstein, 1994). For the data analysis, the researchers used Confirmatory Factor Analysis (CFA) and the structural equation model (SEM).

1. Population and Sample Size

The population of this study is graduate students (Master's and Doctoral's) at Zhejiang University, Zhejiang University of Technology, and Zhejiang Gongshang University. The researcher inputs 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 517.

2. Sampling Techniques

The sampling techniques used are judgmental, stratified random, convenience and

snowball sampling. Firstly, judgmental sampling is to select graduates 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. Accordingly, the questionnaire was distributed between February and June 2022 to over 1,000 students, and 517 responses were retuned. Lastly, snowball sampling is applied to encourage students to share the survey link among their friends.

Results and Discussion

1. Demographic Information

According to the demographic profile of 517 respondents, 51.6% (269 participants) are male, while 48.4% (248 participants) are female. 72.6% (374 participants) of them studying for a master's degree, while 27.4% (143 participants) study a master's degree. 8.1% of students majored in economics (42 participants), 11.6% in engineering (60 participants), 16.4% in management (85 participants), 7.9% in law (41 participants), 6.8% in education (35 participants), 5.6% in literature (29 participants), 11.2% in history (58 participants), 6.0% in science (31 participants), 5.0% in agriculture (26 participants), 4.4% in medicine (23 participants), 10.0 % in philosophy (52 participants), 4.1 % in art (21 participants), and 2.7 percent in other fields (14 participants).

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 1, Cronbach's Alpha coefficient values are valid at a score of more than 0.7 (Nunnally & Bernstein, 1994). Additionally, the composite Reliability (CR) of all model constructs must be more significant 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 be 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 1 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Ogbanufe et al. (2019)	5	0.901	0.7559-0.8342	0.901	0.647
Perceived Usefulness (PU)	Ogbanufe et al. (2019)	4	0.858	0.7284-0.8064	0.859	0.603
Perceived Risk (PR)	Xu et al. (2017)	4	0.922	0.8377-0.8847	0.922	0.748
Attitude (ATT)	Arpaci (2016)	5	0.858	0.7163-0.8574	0.873	0.580
Switching Cost (SC)	Xu et al. (2017)	4	0.858	0.7275-0.8918	0.862	0.612
Intention to use (INT)	Arpaci (2016)	4	0.860	0.7370-0.8262	0.857	0.599
Switching Intention (SI)	Xu et al. (2017)	4	0.885	0.7530-0.8867	0.886	0.661

Source: Created by the author.

As shown in Table 1, 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 2 did not surpass 0.80.

Table 2: Discriminant Validity

	PR	SC	SI	PU	PEOU	ATT	INT
PR	**0.865**						
SC	-0.083	**0.782**					
SI	0.302	-0.570	**0.813**				
PU	-0.140	-0.135	-0.316	**0.777**			
PEOU	0.020	-0.087	0.044	0.375	**0.804**		
ATT	0.032	0.029	-0.034	0.044	-0.040	**0.762**	
INT	-0.002	-0.088	0.029	0.485	0.579	0.399	**0.774**

Note: The diagonally listed value is the AVE square roots of the variables.

3. Structural Equation Model (SEM)

SEM was applied to test model fit, hypotheses, and relationships between variables of the conceptual framework. This research used the goodness-of-fit index to evaluate the measurement model and structural model. The results presented a good fit, as shown in Table 3.

Table 3 Goodness of Fit for Measurement and Structural Model

Index	**Acceptable Values**	**Statistical Values of Measurement Model**	**Statistical Values of Structural Model**
CMIN/DF	< 5.00 (Awang, 2012)	846.5252/384 or 2.2045	942.4382/398 or 2.3679
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.8995	0.889
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.8783	0.870
NFI	≥ 0.80 (Wu & Wang, 2006)	0.9154	0.906
CFI	≥ 0.80 (Bentler, 1990)	0.9517	0.943
TLI	≥ 0.80 (Sharma et al., 2005)	0.9453	0.938
RMSEA	< 0.08 (Pedroso et al., 2016)	0.0483	0.052
Model summary		**Acceptable Model Fit**	**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

4. Hypothesis Testing Result

According to Table 4, the hypothesis results were assessed by SEM, representing standardized path coefficient (**β**) and t-value with the significant value criterion of $p<0.05$ to confirm a structural pathway. Consequently, all seven hypotheses were supported.

Table 4: Hypothesis Results of the Structural Equation Model

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 = 0.4104, CR = 8.0469, 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 = 0.2984, CR = 7.6841, p < 0.001; H2, β = 0.5757, CR = 13.4748, p < 0.001; H6, β = 0.4624, CR = 11.8585, p < 0.001). Perceived risk (PR) positively and significantly affected the switching intention (SI) of PCSS users (H5, β = 0.1997, CR = 5.9681, p < 0.001). Finally, switching cost (SC) and perceived usefulness (PU) negatively and significantly affect the switching intention (SI) of PCSS users (H7, β = -0.3560, CR = -9.4292, p < 0.001; H4, β = -0.7125, CR = -15.0208, p < 0.001).

Conclusions, Recommendations, Limitations and Future Research

1. Conclusions

According to the TAM framework, PEOU should positively impact both perceived usefulness (PU) and intention to use (INT), and the results of this study conform to the TAM framework. The findings indicate that if Baidu Cloud users believe that Baidu Cloud is easy to view, edit, and share their files, they accept that Baidu Cloud can improve their study or work efficiency (Cheng et al., 2019; Xu et al., 2017).

In this study, perceived usefulness negatively impacts PCSS users' switching intention but positively impacts PCSS users' intention to use. If Baidu Cloud users believe it can effectively increase their work and school efficiency. The researcher tested the first hypothesis and discovered that perceived risk (PR) positively influenced PCSS users' switching intentions (Cheng et al., 2019). That is to say if the Baidu Cloud users believe their personal information or files will be unauthorizedly used by Baidu Cloud.

Moreover, TAM often includes attitude, influencing people's intention to use the technology product. According to Aldiabat et al. (2018), users' attitudes positively impact their intentions to use; if users have a favorable view of the PCSS, they are more likely to continue

using that PCSS. Finally, the relationship between switching cost and intention to use is consistent with prior research in which switching cost was also a mooring factor (Cheng et al., 2019). In other words, when Baidu Cloud users switch to using a substitute (new PCSS or traditional hard drive), they need to pay a very high cost.

2. Recommendations

In recent years, cloud service has become a prevalent study topic. However, most academics concentrate on enterprise-level cloud computing and cloud storage services, whereas personal cloud storage services are the subject of relatively few studies. In addition, due to China's strict information security management regulations, there is little competitive competition in China's cloud storage service (PCSS) market, and Baidu Cloud has almost become the only prominent PCSS. In this research, perceived usefulness (PU) is considered not only as a critical variable under the technology acceptance model (TAM) but also as a push factor under the framework of the push-pull mooring (PPM). In order to examine switching intention and intention to use PCSS simultaneously, the researcher combines these two theoretical frameworks and develops a new conceptual framework.

PCSS's privacy and security risks significantly influence cloud users' intentions. Therefore, the risk control of PCSS is essential for cloud service providers. Cloud service providers should invest more in building security mechanisms to avoid hacking and information leakage to entice consumers to use their services. The Chinese government proposed strict regulations on pornography and unlawful publications. It was revealed that many Chinese Baidu Cloud customers had their data deleted without their knowledge, causing many users to abandon Baidu Cloud in favor of traditional hard drives. Some Chinese PCSS users have abandoned PCSS due to the forced deletion of user data and files kept on the Baidu Cloud. Therefore, cloud users should comply with national regulations and use personal cloud storage services legitimately rather than storing and distributing pornographic and unlawful materials via cloud storage services.

There are only a few personal cloud storage services in the Chinese market, making it difficult for PCSS users to switch products; if PCSS users abandon Baidu Cloud, they are more likely to choose conventional hard drives rather than substitute PCSS. Since most non-local PCSS (OneDrive, Dropbox, and Google Drive) cannot enter the Chinese market, there is limited market competition. However, China still has many great cloud service providers, like Alibaba, Tencent, etc. These industry-leading cloud service providers should join the PCSS market so that Chinese PCSS consumers have more options. The development of China's PCSS industry may be aided by healthy market competition, and cloud service providers will endeavor to optimize their services to satisfy the demands of their customers. In addition, the government may encourage some smaller companies to enter the PCSS industry so that the Chinese market for cloud services can flourish.

Most PCSS users who participated in this study rated Baidu Cloud with a high score,

particularly in terms of perceived usefulness and ease of use, indicating that Baidu Cloud is an excellent PCSS. However, as most Chinese cloud services are free or one-time payments, many users believe that Baidu Cloud's paid membership is too expensive, and Baidu Cloud needs to rethink its pricing strategy. For example, for users who are willing to buy out, provide services similar to the one-time purchase of storage space; for users who are willing to pay for a membership, retain the current pricing strategy; for users who want to use the cloud service for free, Baidu Cloud can companion with other products and generate revenue through the mandatory viewing of advertisements. Baidu cloud may increase the upload and download speeds of free users; do not let users think that they cannot use Baidu cloud if they do not pay the membership.

3. Limitations and Future Research

There are two main limitations to the research. Firstly, this study's target population is postgraduate students, so it cannot represent all PCSS users. For students in China, personal cloud storage services (PCSS) are often restricted to storing and sharing learning materials. Consequently, the study's findings may change drastically if the population is changed from students to corporate workers. In the future, researchers may use the same framework to investigate other PCSS users to improve the research findings. Secondly, as this research focuses on a PCSS (Baidu Cloud) in the Chinese market, it isn't easy to apply the findings to other countries. Most of the population PCSS, including OneDrive, Dropbox, and Google Drive, cannot enter the Chinese market because of the government's information security regulations. In the future, researchers might utilize this research model to survey PCSS users in other countries, and the findings could vary considerably from those discovered in the current study.

References

Aldiabat, K., Rashid, A. S. K., Talafha, H., & Karajeh, A. (2018). The extent of smartphone users to adopt the use of cloud storage. *Journal of Computer Science, 14*(12), 1588-1598.

Alharbi, Y., Rabbi, F., & Alqahtani, R. (2020). Understanding university student's intention to use quality cloud storage services. *International Journal for Quality Research, 14*(1), 313-324.

Arpaci, I. (2016). Understanding and predicting students' intention to use mobile cloud storage services. *Computers in Human Behavior, 58*, 150-157. Retrieved from https://doi.org/10.1016/j.chb.2015.12.067

Awang, Z. (2012). *Structural equation modelling using AMOS graphic.* Kota Baru: Penerbit Universiti Teknologi MARA.

Benjangjaru, B., & Vongurai, R. (2018). Behavioural intention of Bangkokians to adopt mobile payment services by type of users. *AU-GSB E-JOURNAL*, *11*(1), 34-46.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238–246. Retrieved from https://doi.org/10.1037/0033-2909.107.2.238

Cheng, S., Lee, S.-J., & Choi, B. (2019). An empirical investigation of users' voluntary switching intention for mobile personal cloud storage services based on the push-pull-mooring framework. *Computers in Human Behavior, 92*, 198-215. Retrieved from https://doi.org/10.1016/j.chb.2018.10.035

Didyasarin, H., Vongurai, R., & Inthawadee, S. (2017). The factors impact attitude toward using and customer satisfaction with elderly health care mobile application services: a case study of people in Bangkok metropolitan, Thailand. *AU-GSB E-JOURNAL*, *10*(1), 167-176.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis*. (6th ed.). Harlow, England: Pearson Education.

Hsieh, J. K., Hsieh, Y. C., Chiu, H. C., & Feng, Y. C. (2012). Post-adoption switching behavior for online service substitutes: A perspective of the push–pull–mooring framework. *Computers in Human Behavior, 28*(5), 1912–1920.

Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: an integrated model of the technology acceptance model and uses and gratifications theory. *Computers in Human Behavior*, 29, 2512–2518.

Kotler, P. (2000). *Marketing Management.* New Jersey: McGraw Hill.

Lei, P.-W., & Wu, Q. (2007). Introduction to structural equation modelling: Issues and practical considerations. *Educational Measurement: Issues and Practice, 26*(3), 33–43. Retrieved from https://doi.org/10.1111/j.1745-3992.2007.00099.x

Mathieson, K., & Keil, M. (1998). Beyond the interface: Ease of use and task/ technology fit. *Information & Management, 34*(4), 221-230.

Ogbanufe, O., Dinulescu, C. C., Liu, X., & Kucuk, C. Y. (2019). It's in the cloud: Theorizing context specific factors influencing the perception of mobile cloud storage. *The DATA BASE for Advances in Information Systems*, *50*(3), 116-137.

Park, E., & Kim, K. J. (2014). An integrated adoption model of mobile cloud services: Exploration of key determinants and extension of technology acceptance model. *Telematics and Informatics*, *31*(3), 376–385.

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40.

Ping, R. A. (1994). Does satisfaction moderate the association between alternative attractiveness and exit intention in a marketing channel?. *Journal of the Academy of Marketing Science, 22*, 364-371.

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modelling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282–286.

Shen, Y. (2020). Baidu net disk overseas edition. *Computer and Network,* 32-33.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M.A. Lange (Ed.), *Leading - Edge Psychological Tests and Testing Research* (pp. 27-50). Nova.

Soper, D. S. (2022, May 24). A-priori Sample Size Calculator for Structural Equation Models. *Danielsoper.* Retrieved from www.danielsoper.com/statcalc/default.aspx

Studenmund, A. H. (1992). *Using Econometrics: A Practical Guide.* Harper Collins.

Takabi, H., Joshi, J. B. D., & Ahn, G. J. (2010). Security and privacy challenges in cloud computing environments. *IEEE Security and Privacy Magazine, 8*(6), 24–31.

Wang, J. (2017). Critical Factors for Personal Cloud Storage Adoption in China. *Journal of Data and Information Science, 1*(2), 60-74. Retrieved from https://doi.org/10.20309/jdis.201614

Wang, W., & Yang, H. (2017). An empirical study of influential factors of personal cloud storage using intention. *Journal of Information Resources Management, 4*, 86-96.

Wu, J.-H., & Wang, Y.-M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728-739. Retrieved from https://doi.org/10.1016/j.im.2006.05.002

Wu, K., Vassileva, J., & Zhao, Y. (2017). Understanding users' intention to switch personal cloud storage services: Evidence from the Chinese market. *Computers in Human Behavior, 68*, 300-314. Retrieved from https://doi.org/10.1016/j.chb.2016.11.039

Xu, F., Tian, M., Xu, G., Reyes Ayala, B., & Shen, W. (2017). Understanding Chinese users' switching behaviour of cloud storage services. *The Electronic Library, 35*(2), 214-232. Retrieved from https://doi.org/10.1108/el-04-2016-0080

Zhang, G., & Ravishankar, M. N. (2019). Exploring vendor capabilities in the cloud environment: A case study of Alibaba Cloud Computing. *Information and Management, 56*(3), 343-355. Retrieved from https://doi.org/10.1016/j.im.2018.07.008