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Determinants of Freshmen' Behavioral Intention and Use Behavior of Ubiquitous Learning in Chengdu, China: A Case of Three Universities

Jia Cheng*

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Abstract

Purpose: This study aims to explore the factors that influence first-year students' behavioral intention and use behavior when using ubiquitous learning in Chengdu, Sichuan Province. The key variables are understanding u-learning, assimilating u-learning, applying u-learning, perceived usefulness, e-learning motivation, social influence, behavioral intention, and use behavior. **Research design, data, and methodology:** Quantitative methods and questionnaires were used to collect sample data from the target population. The sampling methods are purposive, quota, and convenience sampling. The index of item-objective congruence and Cronbach's Alpha pilot tests were used to test the validity and reliability of the content before the questionnaire was distributed. Confirmatory factor analysis and structural equation model were used to analyze the data, verify the model's goodness of fit, and confirm the causal relationship between variables for hypothesis testing. **Results:** The findings indicate that the conceptual model can effectively predict behavioral intention and usage behavior. Assimilating u-learning, applying u-learning significantly influence perceived usefulness. Perceived usefulness, e-learning motivation, social influence significantly influences behavioral intention towards use behavior. In opposite, understanding u-learning has no significant influence on perceived usefulness. **Conclusions:** It is found that the conceptual model of this study can predict and explain the behavioral intent and usage behavior of college students when using u-learning.

Keywords : Ubiquitous Learning, Perceived Usefulness, Social Influence, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The potential of short video learning to become a major learning method depends on three things: first, many people with learning needs (Richmond et al., 2008). Second, most people easily access internet content (Schmidt, 2008). Third, verified iPod and iTunes infrastructure devices or users can access relevant content of academic conferences that have been used for storage (Rosell-Aguilar, 2007). This study aims to present learners with life experiences, describe description schemes, and describe the emphasis of structure on the nature of learning through short videos (Moustakas, 1994). While the researchers found that short videos have a place in education in recent forms, such as YouTube, they conducted primarily ethnographic studies, mainly describing customs and outcomes (Mullen & Wedwick, 2008). A short video is a new media form, and short video learning is also a new U-Learning mode; the speed of researchers building theories is far slower than the speed of a short video, constantly showing its advantages. Therefore, the current research project still requires researchers to solve some essential problems using these short videos for learning.

Sam et al. (2021) thought ubiquitous learning (u-learning) means daily learning, regardless of time or place, through mobile or e-learning and social media. Network short video learning is Ubiquitous learning to learn short video content anytime and anywhere on the network. In the past, short videos for learning were rare in educators' teaching resources and means (Jans & Awouters, 2008). However, DelSignore et al. (2016) believe that video-based e-learning is increasing,

1*Jia Cheng, Chengdu Polytechnic, China. Email: 992319165@qq.com

and preliminary research shows that watching video (independent of answering test questions) can focus on the presented content to improve the learning effect. Therefore, the research on u-learning, assimilation of u-learning, and application of u-learning of network short video learning in this paper mainly comes from the research on u-learning and e-learning. In order to study students' acceptance of network short video learning, it is necessary to understand students' acceptance of U-Learning and determine the factors affecting their intentions to use short video learning.

Ubiquitous learning is a new learning mode with modern, interactive, and integrated characteristics. The learning environment needs to provide how to enable learners to learn anytime and anywhere in their daily lives. This also depends on the development of computers in all aspects (Lyytinen & Yoo, 2002). Therefore, we usually define U-learning as "delivery learning techniques using ubiquitous computing" (Gwo-Jen, 2006). Finally, pan-learning is considered by e-learning and complementing skills such as intelligence, GPS, information systems, sensors, and natural user interfaces (sensors), including applications in context, computing, artificial intelligence, and interaction and context interactions (Friedewald & Raabe, 2011).

The first year of college or university is a critical transition period for students. They are adapting to a new academic environment, encountering new teaching methods, and developing study habits. Understanding how freshmen engage with and perceive u-learning during this formative year can provide insights into how these technologies can be integrated effectively into higher education. Therefore, the research study aims to explore the factors that influence first-year students' behavioral intention and use behavior when using ubiquitous learning in Chengdu, Sichuan Province.

2. Literature Review

2.1 Understanding U-learning

Therefore, U-Learning will help improve the learning effect (Ogata & Yano, 2004). Most previous U-learning research was conducted in natural science or language training courses (Liu & Chu, 2010). Chen et al. (2000) pointed out that the most important thing about technological innovation is the ability of people to absorb this kind of technology. Since students can access complete U-Learning resources for free at any time, it is necessary to check whether U-Learning is accepted. Lin (2013) believes this new learning technology can be learned by integrating personal absorptive capacity into Tam. In addition, if you want to maintain a successful pan-learning environment, you need to pay attention to understanding the technical components (perceived usefulness and ease of use) and the ability of each student's U-learning, which is the ability to understand, absorb, and apply U-learning. The individual's understanding of U-learning and the ability to assimilate and apply it will affect students' perception of its practicality and ease of use and, in turn, affect the intention to use it (Lin, 2013).

H1: Understanding u-learning has a significant influence on perceived usefulness of u-learning.

2.2 Assimilating U-learning

U-learning may have new functions compared to traditional functions (such as ubiquity, mobility, and flexibility). Online Learning environments like U-learning depend as much on technology as the individual (McElroy et al., 2007). Park et al. (2007) understood the absorptive capacity, including assimilation and applied u-learning. Perceived usefulness and ease of use are greatly affected by the absorptive capacity of understanding, absorbing, and applying U-Learning (Lin, 2013). Simelane-Mnisi (2015) recognized that people perceive and assimilate information, make decisions, and solve problems in various ways. Thus, how they receive and process information impacts everything they do, including how they prefer to learn and, communicate with and manage others. Rodrigo and Luisardo (1992) found that participants with learning styles of Assimilating and Diverging, as measured by the KLSI, were perceived by others on the ESCI-U as significantly higher in self-awareness. Those with a strong learning preference for either Assimilating or Diverging styles were perceived as having lower achievement orientation and adaptability levels on the ESCI-U. The individual's understanding of U-learning and the ability to assimilate and apply it will affect people's perception of its practicality and ease of use and, in turn, affect the intention to use it (Lin, 2013).

H2: Assimilating u-learning has a significant influence on perceived usefulness of u-learning.

2.3 Applying U-learning

Digital learning will affect the degree of knowledge or skills obtained by applying knowledge management tools (absorption capacity) (Lau & Tsui, 2009). The idea of U-learning in terms of applied absorbency means that if students can use U-learning and have a certain amount of basic knowledge and confidence in their operational abilities, u-learning can improve learning (Lin, 2013). Park et al. (2007) understood the absorptive capacity, including assimilation and applied u-learning. Gwo-Jen (2006) found that "context-aware U-learning" was appropriate when defining the term U-learning. The information gathered from sensors and RFID can be applied to the learning environment (Jun et al., 2007). Tsai (2017) believes that a flexible U-

Learning mobile application is helpful for students to access materials.

H3: Applying u-learning has a significant influence on perceived usefulness of u-learning.

2.4 Perceived Usefulness

The perceived usefulness of individuals is greatly influenced by their ability to absorb learning, which mainly includes the ability to understand, absorb, and apply (Lin, 2013). The individual's understanding of U-learning and the ability to assimilate and apply it will affect students' perception of its practicality and ease of use and, in turn, the intention to use it (Elkaseh, 2015). With the application of technology in all aspects of our lives, we hope that PU is essential when dealing with any new information system (Merhi, 2015). perceived usefulness significantly impacts users' decisions when accepting new social networking technologies. Researchers have found that perceived usefulness is important in accepting and using Facebook for educational purposes (Chen & Tsai, 2012). Perceived usefulness positively impacts the adoption of Facebook for educational purposes and continues to be used as a learning tool for academic purposes (Moghavvemia et al., 2015). Hsu and Lu (2004) found that perceived usefulness is an important factor that can greatly affect the user's attitude, thus leading to whether he accepts and adopts the system in learning.

H4: Perceived usefulness has a significant influence on behavioral intention to use u-learning.

2.5 E-learning Motivation

Researchers believe that technical reasons will have an important impact on online learning motivation. On the contrary, the use of technology will affect students' e-learning motivation (Kim & Malhotra, 2005). Keller (1987) suggested that traditional learning motivation will be considered in the teaching design, but it differs greatly from Internet learning motivation. For example, in developing countries, the environment of electronic learning provides electronic learning through mobile, digital, and IP TVs. In the future, research can understand the degree of acceptance of other electronic learning technologies in school students by exploring the motivation of electronic learning (Paola et al., 2011). In electronic learning, students' motivation significantly impacts learning effects (Conati, 2002). Li et al. (2019) believes that the motivation behind students' intention to use mobile learning is the ease of use or performance expectation and the satisfaction and fun of using it. It is believed that behavior is mainly based on two factors: Extrinsic motivation and intrinsic motivation (Alotaibi & Wald, 2013).

H5: E-learning motivation has a significant influence on students' behavioral intentions to use a short video.

2.6 Social Influence

In the case of compulsory use, the role of social influence will diminish with time and ultimately has nothing to do with the continued use of technology (Venkatesh & Davis, 2000). Paola et al. (2011) found that social influence has a meaningful influence on behavioral intentions, accounting for 64% of the differences in behavioral intentions. Previous studies have shown that college students' judgments are often influenced by important people around them, such as teachers or family members (Abu-Al-Aish & Love, 2013). Therefore, even if they participate in certain behaviors, they do not mean that they want to participate in them (Venkatesh et al., 2003).

H6: Social influence has a significant influence on behavioral intention.

2.7 Behavioral Intention

The three dimensions of the perception of absorptive capacity have a significative influence on the behavioral intention of learning using u through the usefulness and ease of perception, and the absorptive capacity of perceptual comprehension u-learning is more explanatory than the perceptual absorption or the absorptive capacity of applied u-learning Use intention (Lin, 2013). Alzeban (2016) discussed the importance of social influence in the behavioral intention of intervention. Social influence has a direct impact on behavior intention. The opinions of others easily influence people. Therefore, even if they participate in certain behaviors, it does not mean they are willing to participate (Venkatesh et al., 2003). The opinions of others can affect people's willingness to use an information system (Zhou, 2011). Behavioral intention determines users' desire to use e-learning systems (Salloum et al., 2018).

H7: Behavioral intention has a significant influence on u-learning use behavior.

2.7 Use Behavior

Li et al. (2011) discussed that convenience conditions and behavioral intentions positively influence the use of web-based question-and-answer services. Šumak and Šorgo (2016) thought that the post-interactive whiteboard adopters among teachers have a positive attitude, and their behavioral intentions are supported by appropriate convenience, which leads to the active use of the whiteboard. For e-government services, convenience conditions influence usage behavior (Agudo-Peregrina et al., 2014). For university education, the habit of writing self-reporting positively influences the frequency of using the electronic learning system. Gupta and Arora (2020) found that positive behavioral intentions lead to positive use of something. The use behavior of online Q&A services is significantly affected by convenience and behavior intention (Li et al., 2011). In addition, for business schools, appropriate convenience conditions and positive behavioral intentions lead to the active use of enterprise resource planning software (Chauhan & Jaiswal, 2016).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this research is developed based on existing theoretical and empirical studies, as presented in Figure 1. This research aimed to study factors influencing university students' behavioral intention and use behavior to use u-learning in Chengdu, China—the conceptual framework presented all the variables used in this study. The researcher applied three major theories (TAM, UTAUT, and UTAUT2) and three major previous research frameworks to support and develop a conceptual framework for this research. For the previous research framework, the first previous research framework was conducted by Lin (2013). It studied the understanding of u-learning, assimilating u-learning, applying u-learning, perceived usefulness, and behavioral intention. The second previous research framework was conducted by (Paola et al., 2011). It provided the study of motivation, social influence, and behavioral intention. The third previous research framework was conducted by (Badri et al., 2014). It provided the study of behavioral intention and use behavior. So, the conceptual framework of this research was developed based on eight variables. The only dependent variable for this study is behavior, which is the heart of this research. This study aims to identify factors influencing university students' behavioral intentions and use behavior to short video learning platforms in Chengdu, China.

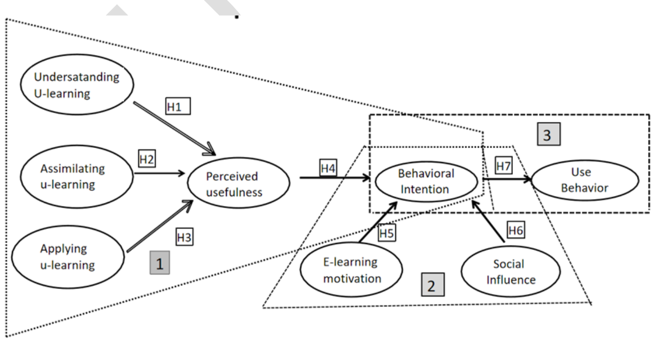

Figure 1: Conceptual Framework

H1: Understanding u-learning has a significant influence on perceived usefulness of u-learning.
H2: Assimilating u-learning has a significant influence on perceived usefulness of u-learning.
H3: Applying u-learning has a significant influence on perceived usefulness of u-learning.
H4: Perceived usefulness has a significant influence on behavioral intention to use u-learning.
H5: E-learning motivation has a significant influence on behavioral intentions to use u-learning.
H6: Social influence has a significant influence on behavioral intention to use u-learning.
H7: Behavioral intention has a significant influence on u-learning use behavior.

3.2 Research Methodology

A conceptual framework is proposed as a quantitative study based on previous research. The conceptual framework of this study consists of 8 variables and seven hypotheses. In addition, a well-considered and standardized questionnaire was designed, including screening questions, demographic questions, and measurement items. Before using the questionnaire to collect data and test the assumptions among variables in the conceptual framework, the IOC test and Cronbach's test were conducted, and the Alpha test was adopted to ensure the reliability of the content. Two scale items failed the IOC test, and the rest of the scale items all passed the Cronbach's Alpha test in the preliminary test. Confirmatory factor analysis and structural equation model were used to analyze the data, verify the model's goodness of fit, and confirm the causal relationship between variables for hypothesis testing

Before the IOC test, there were 29 scale items, but 2 of them failed the IOC test, and the remaining 27 scale items all scored above 0.6 and passed the IOC test, which can be used for the following research. Furthermore, the standard of Cronbach's Alpha value acceptable in this study is greater than 0.70 (George & Mallery, 2010). A pilot test (n=30) was conducted to check the alpha value of each variable. As a results, Cronbach's Alpha value of Assimilating u-learning, Behavioral intention, Motivation, and social influence exceeded 0.9, getting the "Excellent." In general, all the scale items of the questionnaire design passed the pilot test and had high content reliability.

3.3 Population and Sample Size

The final questionnaire had two screening questions, two demographic questions, and 27 measurement items. Daniel Calculator recommended a minimum sample size of 444, but the researcher decided to collect 500 samples. Therefore, three universities from Chengdu were selected for the survey.

Questionnaires are mainly distributed through the online questionnaire website WJX. Data collected from the questionnaire were analyzed using quantitative research tools, including Confirmatory Factor Analysis (CFA) and Jamovi. Therefore, the relationship and hypothesis among all variables can be tested to explain further the factors that affect the behavioral intention and use behavior of Chengdu college students in u-learning.

3.4 Sampling Technique

This study applied purposive sampling to select freshmen from three universities in Chengdu, China. In addition, quota sampling ensures that various researchers reflect the subgroups in the studied population in the correct sample characteristics (Zikmund et al., 2013). Burns and Bush (2019) suggested that quota sampling would ensure that convenient sampling must be carried out according to the proportion of specific respondent groups. The size of quota sampling is also determined by researchers' confidence in each sample's relative size to define the population survey object category, as illustrated in Table 1.

Table 1: Sample Units and Sample Size

Grade	Population Size	Proportional Sample Size
Chengdu Polytechnic	4349	160
Chengdu Textile College	4238	156
Chengdu Vocational & Technical College of Industry	5018	184
Total	13605	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The overview of the 500 participants in the demographic target is shown in Table 2. Firstly, these 500 respondents are all freshmen, 67.2% female, and 32.8% male. of people have experience using short videos for learning, with 63% frequently using TikTok, 5.6% using Quick Hand, 2.4% using Quick Hand, and 29% using other short videos.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	164	32.8%
	Female	336	67.2%
Frequently used network short videos	TikTok	315	63%
	Quick hand	28	5.6%
	Tencent video	12	2.4%
	Other	145	29%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a crucial first step in the SEM (Hair et al., 2010). By Joreskog (1969), confirmation factor analysis was created. CFA is a group of specialized advanced factor analysis techniques frequently used in social science research and helps distinguish between the factor structure that the researchers are persuaded the phenomenon follows One benefit of confirmatory factor analysis (CFA) was the ability to assess the reliability and validity of both variables (Byrne, 2010). The CFA differs from other hypothetical idea testing methods since it can measure complex hypotheses in the deductive simulation pattern (Hoyle, 2012). Consequently, Cronbach's Alpha value acceptable in this study is greater than 0.70 (George & Mallery, 2010). Furthermore, the acceptable threshold for factor loading is 0.5 or higher (Hair et al., 2006). According to Fornell and Larcker (1981), CR and AVE values are acceptable at 0.6 or higher and 0.4 or higher.

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
Understanding U-learning (UU)	Lin (2011)	3	0.811-0.829	0.861	0.862	0.676
Assimilating U-learning (ASU)	Lin (2011)	2	0.914-0.917	0.912	0.717	0.559
Applying U-learning (APU)	Lin (2011)	4	0.774-0.817	0.876	0.877	0.641
Perceived Usefulness (PU)	Lin (2011)	3	0.787-0.830	0.856	0.856	0.665
Behavioral intention (BI)	Paola et al. (2011)	4	0.816-0.823	0.890	0.890	0.670
E-Learning Motivation (EM)	Paola et al. (2011)	5	0.763-0.829	0.901	0.902	0.648
Social Influence (SI)	Paola et al. (2011)	3	0.819-0.862	0.875	0.875	0.701
Use Behavioral (UB)	Samsudeen and Mohamed (2019)	3	0.808-0.840	0.863	0.864	0.679

When studying structural models, CFA plays a crucial role in all potential variables (Alkhadim et al., 2018). Since the data provided by the initial model meets acceptable thresholds and is consistent with CFA, there is no need to modify the model. Table 4 shows that all model fit values of the initial model are within acceptable thresholds, including CMIN/df=1.341, GFI=0.946, AGFI=0.931, NFI=0.956, CFI=0.988, TLI=0.986, RMSEA=0.026. Based on the criteria for the index listed below, GFI received an acceptable output, which indicated that the model gets model fit in SEM.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	<3 (Hair et al., 2006)	1.341
GFI	>0.90 (Bagozzi & Yi, 1988)	0.946
AGFI	>0.85 (Sica & Ghisi, 2007)	0.931
NFI	≥ 0.95 (Hair et al., 2006)	0.956
CFI	≥ 0.90 (Hair et al. 2006)	0.988
TLI	≥ 0.90 (Hair et al., 2006)	0.986
RMSEA	< 0.08 (Pedroso et al., 2016)	0.026
Model Summary		**In harmony with empirical data**

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Discriminant validity is confirmed when AVE's square root is greater than any interrelated construct's coefficient (Fornell & Larcker, 1981). In this study, the discriminant validity values were greater than all internal construction factor correlations, so the discriminant validity was considered acceptable.

Table 5: Discriminant Validity

	UU	ASU	APU	PU	BI	EM	SI	UB
UU	**0.822**							
ASU	0.462	**0.747**						
APU	0.520	0.397	**0.800**					
PU	0.405	0.470	0.511	**0.815**				
BI	0.503	0.427	0.538	0.501	**0.818**			
EM	0.542	0.511	0.464	0.522	0.537	**0.804**		
SI	0.517	0.429	0.498	0.473	0.537	0.474	**0.837**	
UB	0.553	0.454	0.485	0.456	0.415	0.489	0.467	**0.824**

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 researcher used AMOS software to examine the proposed model and got outputs as follows: c2/df=1.810, GFI=0.927, AGFI=0.910, NFI=0.939, CFI=0.971, TLI=0.967, RMSEA=0.040. Based on the criteria for the index listed below, only NFI did not receive an acceptable output, which indicated that the model did not get model fit in SEM and needed to be adjusted.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/df	<3 (Hair, et al., 2006)	1.810
GFI	>0.90 (Bagozzi & Yi, 1988)	0.927
AGFI	>0.85 (Sica & Ghisi, 2007)	0.910
NFI	≥ 0.95 (Hair et al., 2006)	0.939
CFI	≥ 0.90 (Hair et al. 2006)	0.971
TLI	≥ 0.90 (Hair et al., 2006)	0.967
RMSEA	< 0.08 (Pedroso et al., 2016)	0.040
Model Summary		**In harmony with empirical data**

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The importance of each variable is based on its standardized path coefficient (β). Check the t-value, as shown in Table 7. This study validated the substantive effects of H1, H2, H3, H4, H5, H6, and H7. The results indicate that the hypothesis of H1 is insignificant, while the other six hypotheses are significant and supported.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: UU →PU	0.078	C.R.=1.322	Not Supported
H2: ASU→PU	0.313	6.133*	Supported
H3: APU→PU	0.424	7.290*	Supported
H4: PU→BI	0.261	5.546*	Supported
H5: EM→BI	0.306	6.168	Supported
H6: SI→BI	0.350	6.959*	Supported
H7: BI→UB	0.523	10.350*	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

For research group, standardized path coefficients (β) and t-values were utilized to examine the significance of each variable. According to table 5.16 and figure 5.8, **H1** was not supported because its T-value value does not meet the requirements, C.R.=1.322, less than 1.98, and P's data is 0.186, less than 0.5, the value of β = 0.078. **H2** was accepted at the importance of β 128 = 0.313 and t-value = 6.133***. **H3** was supported by the significance of β = 0.424 and t-value = 7.290***. For **H4**, the influence of perceived usefulness on attitude toward using English u-learning was reflected in the matter of β = 0.261 and t-value = 5.546***. **H5** was supported at the value of β = 0.306 and t-value =6.168***. Moreover, **H6** was accepted at the value of β = 0.350 and t-value = 6.959***. **H7** was supported at the value of β = 0.523 and t-value = 10.350***. In summary, for study group 1, the hypothesis of H1 is insignificant, while the other six assumptions are significant and supported.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The study set out to explore the factors influencing first-year students' behavioral intention and use behavior in the context of ubiquitous learning in Chengdu, Sichuan Province. The investigation encompassed critical variables including understanding u-learning, assimilating u-learning, applying u-learning, perceived usefulness, e-learning motivation, social influence, behavioral intention, and use behavior. The research design and methodology adopted quantitative methods and questionnaires to collect data from the target population.

Before distributing the questionnaires, the study rigorously assessed the validity and reliability of its content. This was achieved through the application of the Item-Objective Congruence (IOC) index and Cronbach's Alpha pilot tests. These measures ensured that the questionnaire items effectively measured the intended constructs and exhibited the necessary internal consistency and reliability.

The results of the study provided valuable insights into the factors influencing behavioral intention and usage behavior in the context of ubiquitous learning among first-year college students. Several noteworthy findings emerged from the analysis:

The study revealed that assimilating u-learning and applying u-learning significantly influenced perceived usefulness. This implies that when students successfully integrate and apply ubiquitous learning principles into their academic routines, they are more likely to perceive it as a valuable and practical tool. This underscores the importance of practical application and integration of technology in the learning process.

Perceived usefulness, e-learning motivation, and social influence significantly influenced behavioral intention towards use behavior. When students perceive ubiquitous learning as beneficial, are motivated to engage with it, and are influenced by their social networks, they exhibit a greater intention to utilize this learning approach. These findings highlight the pivotal role of perceived utility, motivation, and social connections in driving students' engagement with new educational technologies.

Interestingly, the study found that understanding u-learning did not have a significant influence on perceived usefulness. This suggests that simply comprehending the concept of ubiquitous learning may not necessarily translate into a heightened perception of its practical utility. It emphasizes that practical experience and application of the technology play a more substantial role in shaping perceptions.

In conclusion, this study has provided valuable insights into the factors that influence first-year students' behavioral intention and use behavior when utilizing ubiquitous learning in Chengdu, Sichuan Province. The conceptual model employed in this research effectively predicts and explains students' tendencies in this context.

The findings underscore the significance of assimilating and applying ubiquitous learning principles in influencing perceived usefulness. They also emphasize the importance of perceived usefulness, e-learning motivation, and social influence in shaping behavioral intention towards use behavior. These results align with the broader literature on technology adoption and highlight the importance of practical application and social factors in driving technology adoption in educational contexts.

The finding that understanding u-learning does not significantly impact perceived usefulness suggests that educators and institutions should focus on practical integration and real-world application of ubiquitous learning to enhance students' perceptions of its utility.

Ultimately, this study contributes to the understanding of how students engage with and perceive ubiquitous learning. It can inform educators and institutions in Chengdu, Sichuan Province, and beyond in designing effective strategies for the adoption and integration of ubiquitous learning technologies, ultimately benefiting student learning experiences and outcomes.

5.2 Recommendation

Ubiquitous learning, characterized by the seamless integration of technology into educational experiences, holds tremendous promise for transforming the way college students engage with their studies. In a recent study conducted in Chengdu, Sichuan Province, the factors influencing the behavioral intention and use behavior of first-year college students in the context of ubiquitous learning were explored. The study revealed valuable insights into the dynamics of ubiquitous learning adoption and offered an opportunity to develop recommendations for educators, policymakers, and institutions seeking to optimize the ubiquitous learning experience.

One key recommendation is to invest in activities that enhance students' understanding and assimilation of ubiquitous learning principles. Orientation programs or workshops can be designed to introduce students to the concept of ubiquitous learning, its benefits, and how it aligns with their educational goals. Furthermore, providing accessible resources and materials that facilitate a deeper understanding and assimilation of these principles into their academic routines can be invaluable.

To encourage students to actively apply ubiquitous learning concepts, instructors should integrate these principles into their courses. This integration should create opportunities for students to apply what they have learned in real-world contexts. Collaborative projects, experiential learning activities, and other interactive pedagogical approaches can be designed to leverage ubiquitous learning technologies and promote active application.

Perceived usefulness is a crucial factor in determining students' willingness to engage with ubiquitous learning. To enhance this perception, institutions should showcase the practical benefits and advantages of ubiquitous learning. This can be achieved by highlighting its relevance to academic success and future career prospects. Continuously collecting feedback from students to identify areas where improvements in perceived usefulness can be made is essential for ongoing enhancement.

Motivation is a key driver of student engagement in any learning context, including ubiquitous learning. Institutions should recognize and reward students' efforts and achievements in ubiquitous learning to boost motivation. Additionally, introducing gamification elements or interactive features in ubiquitous learning platforms can make the learning experience more engaging and foster a sense of accomplishment.

The influence of peers and social networks plays a significant role in shaping students' attitudes and behaviors. Institutions can foster a sense of community among students engaged in ubiquitous learning by facilitating peer-to-peer interactions and collaboration. Encouraging students to share their positive experiences with ubiquitous learning on social media and other platforms can further amplify its influence.

Effective integration of ubiquitous learning into the curriculum requires well-prepared instructors. Providing training and professional development opportunities for faculty is essential to ensure they can effectively utilize ubiquitous learning technologies and methods. Creating a supportive environment for faculty to experiment with innovative teaching approaches and technologies is equally crucial.

To ensure the sustained success of ubiquitous learning initiatives, institutions should implement continuous assessment mechanisms. Regularly gathering feedback from students through surveys, focus groups, or course evaluations can provide valuable insights into the effectiveness of ubiquitous learning implementations. This feedback should inform iterative improvements in the design and delivery of ubiquitous learning experiences.

Resource allocation is fundamental to the success of ubiquitous learning initiatives. Institutions should allocate resources, both technological and financial, to ensure the availability and accessibility of ubiquitous learning tools and platforms. Investments should be made in maintaining and upgrading infrastructure to support seamless ubiquitous learning experiences.

The field of ubiquitous learning is continuously evolving with the emergence of new technologies and best practices. Institutions should encourage and support ongoing research in this field. Collaborations with industry partners and experts can open new avenues for innovation and ensure that ubiquitous learning remains at the forefront of educational advancements.

Lastly, institutions should develop a comprehensive, long-term strategic plan for the integration of ubiquitous learning into their educational landscape. This plan should align with the broader educational goals and objectives of the institution, ensuring a cohesive and sustainable approach to ubiquitous learning adoption.

The recommendations outlined above provide a roadmap for institutions and stakeholders seeking to enhance ubiquitous learning for first-year college students. By implementing these strategies, institutions can create an environment that fosters the effective adoption of ubiquitous learning, ultimately benefiting students and preparing them for success in a rapidly evolving educational landscape. Ubiquitous learning, when harnessed effectively, has the potential to empower students with the skills and knowledge needed to thrive in the digital age.

5.3 Limitation and Further Study

Firstly, a limitation of this study may be attributed to the population of researchers selected for research. The target population of this study is first-year students; compared to third-year college graduates, if they choose students from other grades, they may have different results. This study selected three vocational schools in Chengdu as the research subjects. All three schools are three-year vocational schools and do not have sufficient representativeness. Secondly, another limitation may be the limitation of potential variables. Therefore, in this case, future research may include additional variables to examine their relationship with behavioral intention. Finally, this study only uses quantitative methods to collect and analyze data, which inevitably has some limitations. Therefore, in future research work, qualitative research methods will be used.

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