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Factors Influencing Behavioral Intention and Use Behavior of Junior Students to Use Ubiquitous Learning in Chengdu, China

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Abstract

Purpose: The purpose of this study is to investigate the factors that influence the behavioral intention and behavior of third year college students 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:** The researcher employed quantitative techniques and questionnaires to gather data from the designated population. Our sampling approach encompassed purposive, quota, and convenience sampling methods. Prior to questionnaire distribution, we assessed content validity and reliability through pilot tests, utilizing the Item-Objective Congruence Index and Cronbach's Alpha. To scrutinize the data, assess model fit, and validate the causal relationships among variables for hypothesis testing, we conducted Confirmatory Factor Analysis and Structural Equation Modeling. **Results:** The findings indicate that the conceptual model can explain the behavioral intention and usage behavior. understanding u-learning and applying u-learning significantly influence perceived usefulness. Perceived usefulness, e-learning motivation, social influence significantly influences behavioral intention towards use behavior. Nevertheless, assimilating u-learning has no significant influence on perceived usefulness. **Conclusions:** The adoption of ubiquitous learning among third-year college students holds the promise of enhancing their educational experience and preparing them for the challenges of the digital age.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Short video contains pictures, music, and text. Because a short video contains dynamic content, it is usually short, simple, and vivid. So, we can see the product visually. Such products can affect the emotional resonance of consumers and stimulate their shopping. It is much more engaging than still images and text (Huang et al., 2021). Network short video is a new pattern of network media. Because its video duration is very short, it differs from traditional network video. The difference is reflected in their video's length, communication form, and ability. Network short video not only relies on its strong communication ability to promote the continuous growth of user scale but also the younger trend of its user structure and the long-term participation of users continue to provide strong vitality for the development of the short video industry. Xu et al. (2020) found that short videos are a unique form of social networking and are easy to post. The new media has designed small-scale video marketing by expanding the educational scope of students in school. Using short videos to learn is useful to improve leadership because this media can effectively convey information. In addition to entertaining and educating, short videos have become a tool for political dialogue between top human leaders, such as Barack Obama (Castells, 2009). Short videos became the standard way for business and political leaders to communicate when leaders communicated with different people via the Internet (Straubhaar & LaRose, 2008).

With the emergence of mobile Internet social networks,

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the digital dissemination of short videos on the Internet has become increasingly large. Because of network technology and communication development, short videos can be released quickly (Li, 2020). In a broad sense, all platforms that can provide infrastructure for the production and dissemination of short video on the Internet can be used TikTok, Kwai Kong, is called the short video platform, such as micro-blog, bullet screen comments, etc. the narrow network short video platform refers to some App that specializes in making and sharing short videos of the network, and makes profits for them, such as "shaking" and "fast." From the content characteristics, the short video on the Internet generally refers to video content that takes the Internet as the carrier and uses the terminal to shoot up to more than 5 minutes. The push frequency is high. It is published on the new media platform after editing and processing. From the perspective of network technology, network short video refers to "WMV, RM, RMVB, and other types of video files that can be played through specific players."

Despite the growing adoption of ubiquitous learning (u-learning) in educational settings, there is a notable gap in the existing literature regarding the factors that influence the behavioral intention and behavior of third-year college students when using u-learning in Chengdu, Sichuan Province. This gap arises from the fact that most previous research in this field has primarily focused on understanding u-learning from a technical and pedagogical perspective, neglecting the vital aspect of how students' attitudes, motivations, and social factors impact their adoption and utilization of u-learning. To address this gap, this study aims to investigate the various factors influencing third-year college students' behavioral intention and actual behavior when using u-learning in the context of Chengdu, Sichuan Province, China. Therefore, this study investigates the factors that influence the behavioral intention and behavior of third year college students when using ubiquitous Learning in Chengdu, Sichuan Province.

2. Literature Review

2.1 Understanding U-learning

First, understanding is students' ability to understand U-Learning and their belief in the value of U-Learning (Lin, 2013). Learning is a circular process in which learning is considered a series of behaviors that increase cognitive experience, such as specific experience, reflection and observation, abstract concepts and generalization, positive experiments, and so on (Honey & Mumford, 1986). Ngcapu et al. (2013) believes that U-learning (ubiquitous learning) is a more advanced learning mode because it can perceive the current situation of learners and act accordingly. Harrington and Guimaraes (2005) also believe that poor ability to understand the system and incorrect system may make it difficult for users to use it. Chu et al. (2010) believes that using sensor technology can record and detect students' learning behaviors in the real world and the network.

Harrington and Guimaraes (2005) also believed that users may need help using it due to poor system understanding and incorrect information. In the same way, early research on management education shows that the lack of understanding of the electronic learning system may reduce the evaluation of services. Therefore, this study suggests a hypothesis:

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

2.2 Assimilating U-learning

Assimilating u-learning, that is, students' beliefs in their operational abilities learning and this assimilation capability includes technical support, adaptation to content and information, service provision, and even self-management and personalized learning environment (Lin, 2013). In addition, Lin (2013) also pointed out that improving absorptive capacity can expand students' knowledge and ability base, so improving students' ability to absorb and use future information can ultimately improve their academic performance. Assimilation of learning preferences is a specific and logical way. These people like RO and abstract experience and need clear explanations rather than actual changes (Cheng, 2016). They are good at understanding large amounts of information, broad information and organizing it into a clear and logical form (Cheng, 2016).

To carry out technological innovation, it is important to absorb related technical knowledge; this is very important (Pinsker, 2008). It has been found that these professional roles tend to learn and absorb knowledge from project reports and gain experience through successful and failed project outputs (Muraliraj et al., 2017). Therefore, this study suggests a hypothesis:

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

2.3 Applying U-learning

Applying U-Learning, that is, the students' behavior of applying U-Learning to solve learning problems and achieve learning goals in practice. Lin (2013) applied the concept of absorptive capacity to the adoption of U-Learning, which means that students need to have basic knowledge related to U-Learning and confidence in system operation ability to use U-Learning. In addition, using U-learning can improve the learning effect (Lin, 2013). The application of U-learning by students with higher perceptual absorptive capacity will lead to higher perceptual usefulness and ease of use of U-learning (Kim et al., 2018).

It is also useful to apply such a formal and centralized structure to impart knowledge to employees across the organization (Matusik & Heeley, 2005). Individuals are based on the intrinsic value of knowledge, and under certain circumstances, they will take action to apply knowledge (Valaei & Jiroudi, 2016). Therefore, this study believes that when applying U-Learning, students with higher cognitive absorption ability will also have higher perceived usefulness and ease of use of U-Learning (Lin, 2013). Therefore, this study suggests a hypothesis:

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

2.4 Perceived Usefulness

Davis (1989) defined perceived usefulness as a person's trust in the system and belief that it would improve a person's job performance. The ability to perceive absorption is considered an individual's view of learning and solving problems (Kim, 1998). The ability to perceive absorption is the ability to understand the value of new knowledge, absorb new knowledge, and use personal beliefs to absorb new knowledge based on personal beliefs to absorb new knowledge (Cohen & Levinthal, 1990). Perceived usefulness means the user's perceived effectiveness of the system. It shows that utilizing the information system improves performance (Tantiponganant & Laksitamas, 2014). Teo et al. (2003) believed a simpler system would encourage people to participate and use more loyalty. Venkatesh and Bala (2008) believed that an important regulatory factor in the technology adoption environment is the user experience because the user's response to the system may change over time. For students with more mobile experiences, although perceived ease of use does not play a significant role in generating positive U-Learning intention, perceived ease of use will still produce good perceived usefulness. Therefore, this study suggests a hypothesis:

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

2.5 E-learning Motivation

The researchers defined the e-learning motivation structure as the tendency of students to look for useful and easy-to-use e-learning systems and attempt to obtain the expected academic interests. The E-learning motivation concept consists of the items used in the motivation, performance, and effort expectations concept, which directly affect the intention of use (Moon & Kim, 2001). Students' grades, academic performance, and satisfaction are profoundly affected by e-learning or learning through online information and communication technology tools (Katz, 2002).

In order to achieve the effect of flipping classroom teaching, this method sorts out the effects of cooperative learning models on learning motivation and effects (Sultan, 2018). Motivation is a psychological factor that encourages students to practice learning (Demircioglu & Ucar, 2015). E-learning motivation plays an important role in the behavioral intention of technology acceptance. In turn, the use of technology will also affect students' e-learning motivation (Kim & Malhotra, 2005). Therefore, this study suggests a hypothesis:

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

2.6 Social Influence

Important factors for predicting technical and use behavior are considered social influence (SI) (Venkatesh & Davis, 2000). There were many forms, not only to change the intention of people's behavior but also to make the individual affected by the existence of others (Hill et al., 1977). Social influence influences and affects an individual's thoughts, feelings, attitudes, or behaviors (Baker et al., 2007). There were many forms, not only to change the intention of people's behavior but also to make the individual affected by the existence of others (Hill et al., 1977).

Social influence is one of the predictors of behavioral intention to use ICT (Venkatesh et al., 2003). Venkatesh and Davis (2000) found that one of the important factors in predicting the intention and use of technology is social influence. UTAUT defines social influence as "the situation where one thinks others think he should use the new system" (Venkatesh et al., 2003). Murillo-Maldonado et al. (2011) thought that social influence positively influences behavioral intention, accounting for 64% of behavioral intention variation. Therefore, this study suggests a hypothesis:

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

2.7 Behavioral Intention

Behavioral intention (BI) is considered a pioneer in usage behavior, indicating that the user is ready to perform a specific action (Samsudeen & Mohamed, 2019). Ajzen (1988) believes that the behavior attitude and subjective norms jointly affect a person's behavior intention, which is established to predict and guide the actual behavior. Therefore, the actual behavior can be determined by the behavior intention. TRA confirms that behavior is determined by behavioral intention (Hill et al., 1977).

Use behavior and behavior intention are high-order structures based on the Hierarchical Latent variable model (Gupta & Arora, 2020). Convenience and behavioral intention positively influence Web-based question-and-answer services (Li et al., 2011). Chauhan and Jaiswal (2016) considered that for business schools, appropriate convenience and positive behavior intention lead to the active use of Enterprise Resource Planning Software. Therefore, this study suggests a hypothesis:

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

2.8 Use Behavior

Use behavior can be defined as the intensity of a user's use of technology (Venkatesh & Bala, 2008). Use behavior is usually measured by the actual frequency of technology use. Several studies have been conducted on technologies that use "use behavior" (Venkatesh et al., 2012). Williams et al. (2015) showed that many technology adoption models have been developed to explain technology use behavior. Intention is defined as a people's psychological attitude to pursue a specific behavior, which means the commitment of an individual to achieve the goal behavior (Shapero & Sokol, 1982). The used behavior is the interaction between an individual and a specific system; in other words, it refers to the duration, frequency, and intensity of a person using a specific system (Venkatesh & Bala, 2008). A comprehensive analysis of the literature by Salim and Yadav (2012) suggested that social media use behavior in Egypt is positively influenced by behavioral intent.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this research is built upon existing theoretical and empirical studies, as depicted in Figure 3.4. This research aimed to examine the factors that influence university students' behavioral intention and use behavior towards a short video learning platform in Chengdu, China. The conceptual framework encompasses all the variables utilized in this study. The researcher incorporated three major theories (TAM, UTAUT, and UTAUT2) and three previous research frameworks to support and develop the conceptual framework.

The first previous research framework, conducted by Lin (2013), explored the understanding of u-learning, assimilating u-learning, applying u-learning, perceived usefulness, and behavioral intention. The second previous research framework, Paola et al. (2011), focused on motivation, social influence, and behavioral intention. The third previous research framework, conducted by Samsudeen and Mohamed (2019), examined behavioral intention and use behavior. Therefore, the conceptual framework of this research was formulated based on these eight variables.

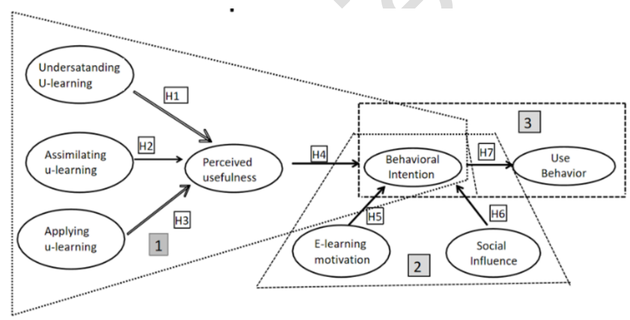

Figure 1: Conceptual Framework

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

The proposed conceptual framework for this quantitative study builds upon previous research. It comprises eight variables and seven hypotheses. A meticulously designed and standardized questionnaire was created to collect data and examine the assumptions among the variables in the conceptual framework. The questionnaire includes screening questions, demographic questions, and measurement items. Before implementing the questionnaire, the IOC test and Cronbach's test were conducted to ensure the reliability of the content. Two scale items did not pass the IOC test in the preliminary test, while the remaining items successfully passed the Cronbach's Alpha test.

Prior to conducting the Item-Objective Congruence (IOC) test, the questionnaire initially comprised 29 scale items. However, upon conducting the IOC test, it was observed that 2 of these items did not meet the required criteria and were consequently excluded. This resulted in a set of 27 scale items that all exhibited IOC scores exceeding 0.6, thus passing the IOC test. These 27 scale items were deemed suitable for use in subsequent research endeavors.

Moreover, it is important to note that, in accordance with the criteria established by George and Mallery (2010), the acceptable standard for Cronbach's Alpha value in this study was set at a threshold greater than 0.70. To ascertain the internal consistency and reliability of each variable, a pilot test involving a sample size of 30 participants was conducted. The results of this pilot test revealed that Cronbach's Alpha values for assimilating u-learning, behavioral intention, motivation, and social influence all significantly exceeded 0.9, thereby attaining an "Excellent" rating.

3.3 Population and Sample Size

The final questionnaire consisted of a total of 31 items, comprising two screening questions, two demographic inquiries, and 27 measurement items. In order to ensure an adequate sample size for robust statistical analysis, Daniel Calculator recommended a minimum of 444 participants. However, the researcher opted to collect data from 500 respondents to enhance the study's statistical power and reliability.

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	4125	**162**
Chengdu Textile College	3979	**156**
Chengdu Vocational & Technical College of Industry	4622	**182**
Total	12726	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The respondents were 500 junior college students from Chengdu. Among them, women account for 61%. 95.2% of these students have experience using short videos for learning. 57.8% of them often choose TikTok short video platform.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	195	39%
	Female	305	61%
Frequently used network short videos	TikTok	289	57.8%
	Quick hand	34	6.8%
	Tencent video	17	3.4%
	Other	160	32.0%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is an essential initial step in Structural Equation Modeling (SEM) (Hair et al., 2010). Joreskog (1969) introduced CFA as a specialized form of advanced factor analysis commonly employed in social science research. It is particularly useful in distinguishing and confirming the factor structure that researchers believe the phenomenon adheres to. One advantage of CFA is its ability to assess the reliability and validity of variables (Byrne, 2010). Unlike other methods used for testing hypothetical ideas, CFA allows for the measurement of complex hypotheses within a deductive simulation framework (Hoyle, 2012).

As per the established criteria for this study, the acceptable Cronbach's Alpha value should exceed 0.70, in alignment with the guidelines set forth by George and Mallery (2010). Additionally, the acceptable threshold for factor loading is stipulated to be 0.5 or higher, as recommended by Hair et al. (2006). Furthermore, in accordance with the criteria outlined by Fornell and Larcker (1981), both the Composite Reliability (CR) and Average Variance Extracted (AVE) values are considered acceptable when they attain levels of 0.6 or higher for CR and 0.4 or higher for AVE. These established benchmarks ensure the robustness and reliability of the research measures employed in this study.

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)	Hsiu-Fen Lin (2011)	3	0.797-0.807	0.845	0.844	0.644
Assimilating U-learning (ASU)	Hsiu-Fen Lin (2011)	2	0.880-0.841	0.850	0.882	0.714
Applying U-learning (APU)	Hsiu-Fen Lin (2011)	4	0.806-0.823	0.885	0.888	0.665
Perceived Usefulness (PU)	Hsiu-Fen Lin (2011)	3	0.806-0.820	0.854	0.854	0.661
Behavioral intention (BI)	Paola et al. (2011)	4	0.811-0.848	0.895	0.896	0.682
E-Learning Motivation (EM)	Paola et al. (2011)	5	0.795-0.829	0.906	0.907	0.660
Social Influence (SI)	Paola et al. (2011)	3	0.784-0.824	0.842	0.843	0.641
Use Behavioral (UB)	Samsudeen and Mohamed (2019)	3	0.709-0.820	0.817	0.821	0.606

CFA plays a critical role in examining potential variables within structural models (Alkhadim et al., 2018). In this study, the data obtained from the initial model meets the acceptable threshold and demonstrates consistency with CFA, indicating that no modifications are necessary. Table 4 presents the model fit values for the initial model, all of which fall within acceptable thresholds. These values include CMIN/df=1.380, GFI=0.944, AGFI=0.929, NFI=0.949, CFI=0.985, TLI=0.982, and RMSEA=0.028. Among these indices, GFI yields a satisfactory result, indicating that the model achieves a good fit in the context of SEM, based on the specified criteria.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	<3 (Hair et al., 2006)	1.380
GFI	>0.90 (Bagozzi & Yi, 1988)	0.944
AGFI	>0.85 (Sica & Ghisi, 2007)	0.929
NFI	≥ 0.90 (Hair et al., 2006)	0.949
CFI	≥ 0.90 (Hair et al. 2006)	0.985
TLI	≥ 0.90 (Hair et al., 2006)	0.982
RMSEA	< 0.08 (Pedroso et al., 2016)	0.028
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

To assess discriminant validity, it is considered acceptable when the square root of the Average Variance Extracted (AVE) is greater than the coefficient of any interrelated construct (Fornell & Larcker, 1981). In this study, the values for discriminant validity exceeded all correlations among the internal construction factors, indicating that the discriminant validity was deemed acceptable.

Table 5: Discriminant Validity

	UU	ASU	APU	PU	BI	EM	SI	UB
UU	**0.802**							
ASU	0.193	**0.844**						
APU	0.412	0.269	**0.815**					
PU	0.340	0.149	0.379	**0.813**				
BI	0.442	0.278	0.450	0.384	**0.825**			
EM	0.445	0.281	0.411	0.373	0.427	**0.812**		
SI	0.359	0.292	0.403	0.358	0.364	0.329	**0.800**	
UB	0.435	0.267	0.345	0.433	0.401	0.406	0.343	**0.778**

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 follow: CMIN/df= 1.867, GFI=0.924, AGFI=0.907, CFI=0.965, NFI=0.928, TLI=0.960, RMSEA=0.042. Based on the criteria for the index listed below, no index received 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)	1.867
GFI	>0.90 (Bagozzi & Yi, 1988)	0.924
AGFI	>0.85 (Sica & Ghisi, 2007)	0.907
NFI	≥ 0.90 (Hair et al., 2006)	0.928
CFI	≥ 0.90 (Hair et al. 2006)	0.965
TLI	≥ 0.90 (Hair et al., 2006)	0.960
RMSEA	< 0.08 (Pedroso et al., 2016)	0.042
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 significance of each variable is determined by its standardized path coefficient (β), as indicated in Table 7. In this study, the substantive effects of H1, H3, H4, H5, H6, and H7 were validated. The results reveal that H2 hypothesis is not significant, whereas the remaining six hypotheses are significant and supported. Additionally, the t-values were checked to verify the significance of these hypotheses.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: UU →PU	0.271	4.750*	Supported
H2: ASU→PU	0.037	C.R.=0.734 P=0.463	Not Supported
H3: APU→PU	0.315	5.429*	Supported
H4: PU→BI	0.259	5.386*	Supported
H5: EM→BI	0.312	6.394*	Supported
H6: SI→BI	0.241	4.855*	Supported
H7: BI→UB	0.485	9.426*	Supported

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

For research group 2, according to table 7 and figure 5.9, **H1** was supported at the value of β = 0.271 and t-value = 4.750***. **H2** was not accepted at the value of β = 0.439 and C.R.=0.734 less than 1.98, P=0.463, less than 0.5. **H3** was supported at the value of β = 0.315 and t-value = 5.429*. **H4** was reflected at the value of β = 0.259 and t-value = 5.386***. For **H5,** E-learning motivation significantly influences students' behavioral intentions to use a short video. was supported at the value of β = 0.312 and t-value =6.394***. In addition, **H6** was accepted at the value of β = 0.241 and t-value = 4.855***. Moreover, Behavioral intention significantly influences use behavior, which was reflected at the value of β = 0.485 and t-value = 9426**, which reported the strongest significance. Thus, **H7** was supported. In summary, for research group 2, the H2 is insignificant, while the other six hypotheses are significant and supported.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study delves into the factors influencing the behavioral intention and use behavior of third-year college students when engaging with ubiquitous learning in Chengdu, Sichuan Province. The study considered a comprehensive set of key variables, encompassing understanding u-learning, assimilating u-learning, applying u-learning, perceived usefulness, e-learning motivation, social influence, behavioral intention, and use behavior. The research design, data collection, and analytical methodology employed were comprehensive and rigorous, yielding significant insights into the dynamics of ubiquitous learning adoption among college students.

Before delving into the key findings, it is important to acknowledge the robustness of the research methodology. The thorough evaluation of content validity and reliability through pilot tests, utilizing both the Item-Objective Congruence (IOC) Index and Cronbach's Alpha, underscores the meticulous approach taken in developing the research instrument. This ensures that the questionnaire items accurately measure the intended constructs and that the data collected is reliable and consistent.

Influence of Understanding U-Learning and Applying U-Learning: The study's results revealed that understanding u-learning and applying u-learning significantly influenced perceived usefulness. This finding underscores the critical role of comprehending the principles of ubiquitous learning and effectively applying them in influencing students' perceptions of its utility. It highlights that theoretical knowledge alone may not suffice; practical application and integration into the learning process play pivotal roles in shaping students' perceptions.

Perceived usefulness, e-learning motivation, and social influence were found to significantly influence behavioral intention towards use behavior. When students perceive ubiquitous learning as beneficial, are intrinsically motivated to engage with it, and are influenced by their social networks, they are more inclined to intend to use this learning approach. These results align with prior research indicating that perceived utility and social factors play key roles in technology adoption.

Interestingly, the study found that assimilating u-learning had no significant influence on perceived usefulness. This finding suggests that the mere integration of ubiquitous learning principles into the student's academic routine may not directly impact their perception of usefulness. It prompts further exploration into the nuances of assimilation and its potential role in influencing perceptions.

Practical Application and Integration: Educators should emphasize not only understanding the theoretical aspects of ubiquitous learning but also practical application and integration into the learning process. This approach can enhance students' perceptions of the technology's utility. Promoting the practical benefits and relevance of ubiquitous learning remains crucial. Demonstrating how it can positively impact academic and future career prospects can heighten perceived usefulness.

Fostering intrinsic motivation and leveraging social networks can be key strategies for encouraging the behavioral intention to use ubiquitous learning. Peer influence and social connections can play a significant role in technology adoption. The finding that assimilating u-learning did not directly influence perceived usefulness warrants further investigation. Future research can delve into the nuances of assimilation and its potential role in shaping perceptions.

In conclusion, this study provides valuable insights into the factors influencing the behavioral intention and use behavior of third-year college students when using ubiquitous learning in Chengdu, Sichuan Province. It underscores the significance of practical application, perceived usefulness, motivation, and social influence in shaping students' engagement with this innovative learning approach. These findings contribute to our understanding of how students interact with ubiquitous learning and offer guidance for educators and institutions seeking to optimize its adoption and integration. Ubiquitous learning, when implemented with a focus on practicality and relevance, holds the potential to significantly enhance the educational experiences and outcomes of college students.

5.2 Recommendation

Ubiquitous learning, characterized by the seamless integration of technology into education, offers immense potential for transforming how college students engage with their studies. A recent study conducted in Chengdu, Sichuan Province, aimed to investigate the factors influencing third-year college students' behavioral intention and use behavior in the context of ubiquitous learning. This research examined key variables, including understanding u-learning, assimilating u-learning, applying u-learning, perceived usefulness, e-learning motivation, social influence, behavioral intention, and use behavior. Drawing from the study's findings and conclusions, this essay presents a set of recommendations for educators, institutions, and policymakers to enhance the adoption of ubiquitous learning among third-year college students.

To foster a deeper understanding and practical application of ubiquitous learning, institutions should develop and implement comprehensive training programs. These programs should equip students with the knowledge and skills needed to effectively navigate and apply ubiquitous learning concepts in their academic pursuits. Hands-on experiences and practical applications should be emphasized, allowing students to realize the value of this innovative approach.

Educators and institutions should actively promote the perceived usefulness of ubiquitous learning. Clear communication about the practical benefits and advantages of this technology is essential. By highlighting its relevance to academic success and future career prospects, educators can instill a sense of purpose and motivation among students.

To maintain students' enthusiasm and engagement with ubiquitous learning, educators should employ motivational strategies within the learning environment. Gamification, rewards, recognition, and interactive elements can be integrated to create a motivating and enjoyable learning experience. These strategies should be tailored to the preferences and needs of third-year college students.

Social networks and peer influence play a crucial role in shaping students' attitudes and behaviors. Institutions should encourage students to form study groups or online communities where they can share their experiences with ubiquitous learning. Highlighting the positive experiences of early adopters can serve as a powerful tool for influencing their peers positively.

Implementing regular assessments and feedback mechanisms is essential for gauging students' perceptions and experiences with ubiquitous learning. Feedback collected should be used to make continuous improvements in the design and delivery of ubiquitous learning. This iterative approach ensures that the technology remains responsive to student needs.

To make ubiquitous learning an integral part of the educational experience, it should be seamlessly integrated into the curriculum. Course materials, assessments, and activities should be designed with ubiquitous learning principles in mind, demonstrating its practical relevance and applicability.

Educators play a pivotal role in facilitating the adoption of ubiquitous learning. To equip them with the necessary skills and knowledge, institutions should offer training and professional development opportunities. Faculty members should be well-prepared to effectively integrate and support ubiquitous learning in their courses.

Establishing mechanisms for ongoing monitoring and evaluation of ubiquitous learning implementation is crucial. Regular assessments should measure the technology's impact on student outcomes, and feedback from both educators and students should be used to make data-driven decisions for continuous improvement.

In conclusion, the adoption of ubiquitous learning among third-year college students holds the promise of enhancing their educational experience and preparing them for the challenges of the digital age. The recommendations presented in this essay provide a roadmap for educators, institutions, and policymakers to optimize the adoption of ubiquitous learning. By addressing factors related to understanding, motivation, and social influence while ensuring practical relevance, institutions can create a supportive and effective learning environment. In doing so, they empower students to harness the full potential of ubiquitous learning, ultimately contributing to their academic and professional success. Ubiquitous learning, when implemented effectively, becomes a valuable tool in preparing students for the dynamic and evolving landscape of education.

5.3 Limitation and Further Study

Firstly, a limitation of this study may be attributed to the selection of the researcher population. The study focused on first-year students, but the results may have varied if students from different grades or backgrounds were included. Future research could consider selecting multiple universities at various levels within the Chengdu region to enhance the representativeness and accuracy of the findings.

Secondly, there may be limitations regarding the potential variables considered in this study. In investigating behavioral intention, particularly within the technology acceptance model, it is important to include other influential factors such as attitude, environment, and habits, in addition to the variables of electronic use motivation and social impact examined in this study. Therefore, future research could incorporate additional variables to explore their relationship with behavioral intention.

Lastly, this study solely relied on quantitative data collection and analysis methods, which inherently comes with certain limitations. Future research could consider employing qualitative research methods such as in-depth interviews to gain a more precise, in-depth, and comprehensive understanding of the factors influencing college students' use of short visual frequency for learning. This would provide valuable insights into the topic.

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