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Factors Impacting Male Student's Attitude and Intention to Use Mobile Learning In Guizhou, China

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Abstract

Purpose: This research aims to examine the factors impacting attitude, and intention to use mobile learning for male college students in Guizhou, China. The conceptual framework proposes a causal relationship among perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, attitude, cognitive need, social influence, and intention to use. **Research design, data, and methodology:** The researcher adopted the quantitative method (n=500), distributing questionnaires to male college students who use mobile learning at the Guizhou Institute of Technology. The sampling procedure includes judgmental and stratified random sampling in selecting students who use three mobile learning platforms. The Structural Equation Model and Confirmatory Factor Analysis were used for the data analysis, including model fit, reliability, and validity of the constructs. **Results:** The results demonstrate that perceived usefulness and perceived ease of use have a significant impact on attitude. Compatibility has a significant impact on perceived enjoyment. Furthermore, compatibility, perceived enjoyment, attitude, cognitive need, and social influence have a significant impact on intention to use. **Conclusions:** Eight hypotheses were proven to fulfill research objectives. So, perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, cognitive need, and social influence are advised to supply an assessment to examine the level of intention to use mobile learning at Guizhou Institute of Technology.

Keywords: Perceived Enjoyment, Cognitive Need, Social Influence, Intention to Use, Mobile Learning

JEL Classification Code: E44, F31, F37, G15

1. Introduction

During the widespread COVID-19 pandemic, many nations have been greatly impacted, such as education, tourism, social life, and economics (Nicola et al., 2020). In terms of education, many nations have chosen to adopt online mobile learning at home by changing the traditional educational methods, which were also regarded as long-distance learning mobile learning. Many universities and colleges have connected their educational activities with technology. Generally speaking, online education has shown that sound and visual images are contained, and it is convenient for researchers to conduct any study on some specific area (Siron et al., 2020). According to a study by McGraw-Hill Education, nearly 81% of students were involved in mobile learning, which increased by 40% in 2015. College students are used to effective adaptive learning technologies. Nearly 66% of college students rely on mobile learning, which is regarded as the most economical way of learning about knowledge.

In order to cope with COVID-19, some methods are being applied to fix the wide spreading virus internationally. Traditional teaching sectors have been closed temporarily. To let students, get involved in teaching and learning activities, mobile learning has been applied as a possible measurement under this situation (Mostafa, 2020).

China's online education industry witnessed fast growth around 2013. The online education market developed

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rapidly from 2013 to 2017 and became well-structured in 2018. In 2018, the online education market accounted for 251.76 billion yuan in China, and the registered customers reached 135 million. The Chinese government paid great attention to the development of mobile learning. For example, the educational system of K-12 will be shifted thoroughly in the next ten years. This goal could be reached due to the highly developed Internet industry and the growing number of mobile users in China. The mobile learning industry welcomes profound growth and supplies more opportunities for market development (Mostafa, 2020).

Mobile learning has been very popular since 2013 at the Guizhou Institute of Technology. The key mobile learning platform is Xuetang Online or Rain Classroom, an integrated online platform supplied by Tsinghua University. Based on the statistics provided by the data engineer from the Xuetang online platform, there are nearly 69 million users, more than 193 million selecting the courses by students globally, and more than 3,420 courses on it. There are 402 national top-quality courses integrated into the curriculum system. Nearly 51 million students registered on the platform of Rain Classroom and 6,220 thousand classes are set up for university students (Mostafa, 2020).

In GIT, Rain Classroom is the main mobile learning platform, with 559 teachers and over 10 thousand students from 873 classes. Most instructors deliver their courses to students through a multi-functional Rain classroom. This mobile learning platform can teach with three aspects: pre-class, while-class, and post-class. Instructors forward teaching materials to students for self-study before class. Meanwhile, students' attendance can be reported according to the temporary code, and students can respond to teaching content to let teachers know whether they can follow the instructions. Besides, they can communicate with students instantly by forwarding messages. After class, students accomplish quizzes and assignments. For each class or semester, the instructors can be reported on the course with detailed statistics.

Despite the growing popularity of mobile learning and its potential benefits for educational outcomes, there is a significant research gap in understanding the factors that influence the attitude and intention to use mobile learning among male college students in Guizhou, China. Existing literature on mobile learning primarily focuses on general populations or students from different cultural backgrounds, and there is limited research specific to the male college student population in Guizhou. Moreover, there is a need to explore the interplay of multiple factors, including perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, attitude, cognitive need, social influence, and intention to use within this specific context. Therefore, this research aims to fill this gap by investigating the determinants of male college students' attitude and intention to use mobile learning in Guizhou, China.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness refers to how users employ communicative methods, and the desired outcome can be achieved effortlessly (Rauniar et al., 2013). Perceived usefulness reflects the perception that adopting something can facilitate individuals in easily utilizing their skills (Davis, 1989). Perceived usefulness refers to how users adopt mass media, inducing a positive user experience (Davis et al., 1989). Perceived usefulness is regarded as understanding individuals' mobile learning experience, which can be illustrated greatly (Huang et al., 2007). Davis et al. (1989) observed that their perceived usefulness influences individuals' attitudes toward adopting a particular skill or media. In the insurance industry, Lee et al. (2015) discovered a strong impact of perceived usefulness on attitude when using mobile applications. Perceived usefulness is crucial in determining a user's intention to utilize a system (Wu & Zhang, 2014).

H1: Perceived usefulness has a significant impact on attitude.

2.2 Perceived Ease of Use

Perceived ease of use means the extent to which a user believes that utilizing a method will be easy with continuous hard work (Davis, 1989; Davis et al., 1989). Huang et al. (2007) considered that perceived ease of use indicates the interpretation of mobile learning, which makes individuals feel comfortable to use. Under the context of communication, perceived ease of use is considered the degree to use any dedication with communicative skills (Pinho & Soares, 2011; Rauniar et al., 2013). Perceived ease of use is an individual's perception of how they respond actively to adopting a new tool (Davis, 1989; Suki & Suki, 2011). Furthermore, Schierz et al. (2010) argue that perceived ease of use has been shown to influence attitudes mediated by perceived usefulness. Therefore, perceived ease of use can also impact students' attitudes and intention towards mobile learning (Peng et al., 2016).

H2: Perceived ease of use has a significant impact on attitude.

2.3 Compatibility

Compatibility refers to how a new service or skill is perceived to align with an individual's beliefs, living conditions, existing values, past experiences, and current desires. The concept of compatibility is closely associated with the favorable adoption of new technology (Rogers, 2003). Phonthanukitithaworn et al. (2016) emphasize that compatibility reflects how new technology fits into individuals' lifestyles and fulfills their needs. Ding and Hampe (2004) define compatibility as the degree to which a new technology aligns with a customer's values, lifestyle, needs, and past experiences. In essence, compatibility refers to the consistency between a new technology and an individual's way of living (Hernandez & Mazzon, 2006).

According to Al-Gahtani and King (1999), compatibility positively impacts enjoyment. In e-textbook applications, compatibility is enhanced through display features, improving perceived enjoyment due to perceived usefulness. This, in turn, leads to an increased intention to use the application for learning purposes (Lai & Ulhas, 2012). Tan and Chou (2008) also found that compatibility actively influences enjoyment.

H3: Compatibility has a significant impact on perceived enjoyment.

H4: Compatibility has a significant impact on intention to use**.**

2.4 Perceived Enjoyment

Perceived enjoyment (PE) refers to the degree to which individuals experience joy and pleasure while engaging in certain activities, which can result in useful experiences (Davis et al., 1992). The definition of perceived enjoyment highlights the extent to which the use of technology is perceived to be enjoyable, in addition to its practical outcomes (Venkatesh, 2000). Perceived enjoyment is also the extent to which individuals find social media communication entertaining (Yap & Lee, 2014).

According to a study conducted by Thong et al. (2006), perceived enjoyment has impacted the intention from the aspect of the IT field. Lee et al. (2005) revealed that perceived enjoyment can motivate the intention to use mobile learning media. Indeed, research has shown that customers who derive enjoyment from using information systems are more likely to have the intention to adopt them (Davis et al., 1992; Sun & Zhang, 2006). Detailed studies have examined the influence of perceived enjoyment on attitude towards mobile learning and its impact on the intention to use (Huang et al., 2007).

H5: Perceived enjoyment has a significant impact on intention to use.

2.5 Attitude

According to Park and Kim (2013), attitude (ATT) refers to an individual's inclination toward selecting skills and media. Davis (1989) defines attitude as a customer's response towards achieving a goal behavior, whether certain or uncertain. Olson and Kendrick (2008) describe attitude as the mental feedback, ideas, and perception of a goal. According to Rogers (2003), attitude can influence the intention to adopt mobile learning during the encouragement phase and impact future behavior. Teo and Pok (2003) studied 11 individuals using WAP (wireless application protocol) for mobile learning. They found that attitude and other social factors greatly influenced the intention to use (such as the availability of resources and opportunities to use WAP-enabled mobile phones). Attitude is important in the intention to use a new system (Davis, 1989).

H6: Attitude has a significant impact on intention to use.

2.6 Cognitive Need

Cognitive need (CN) encompasses the desire to perceive, understand, and engage with various services or matters (Aliberti et al., 2019; Loetscher et al., 2019). It motivates individuals to actively use new technologies or services (Hashim et al., 2015; Mondi et al., 2007). Cognitive need refers to seeking inspiration and fulfilling specific goals while utilizing technology (Hirschman, 1984).

It becomes basic to improve their abilities and acquire new skills to effectively engage with educational content and interact with others (Thongsri et al., 2018). To meet the demand for knowledge acquisition, mobile learning apps can be employed to motivate users to master educational content (Thongsri et al., 2018). Research conducted by Hossain et al. (2020) focused on the usage of learning apps and found that cognitive needs play a significant role in users' satisfaction with mobile learning app usage. This satisfaction, in turn, directly impacts users' intention to continue using mobile learning apps.

H7: Cognitive need has a significant impact on intention to use.

2.7 Social Influence

Social influence includes others' opinions on an individual's decision to adopt a new technology (Bagozzi & Lee, 2002). Social influence is influenced by how individuals perceive others' responses to a new service (Venkatesh et al., 2003). According to Alsaleh et al. (2019), social influence is exerted by significant individuals who provide their opinions on adopting a new service, even if they do not have a strong personal inclination toward it.

Sharma and Srivastava (2020) emphasize the importance of social influence in shaping individuals' opinions and beliefs. Klobas and Clyde (2001) argue that social influence encompasses the impact of various social relationships and aims to anticipate the adoption of technology by social members. Milošević et al. (2015) highlight the influence of individuals related to users, such as teachers, on the intention to adopt mobile learning. In mobile commerce, Chong (2013) suggests that social influence is crucial to users' intention to use a specific system.
H8: Social influence has a significant impact on intention to use.

2.8 Intention to Use

Intention to use is a reliable indicator of individuals' likelihood to adopt and utilize a new service (Liebana-Cabanillas et al., 2018; Zhang et al., 2012). Saha and Theingi (2009) define intention to use as the possibility of individuals adopting a particular behavior, while Zeithaml et al. (1996) suggest that it can indicate whether a customer will adopt a specific technology.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework is proposed by analyzing previous research frameworks. Five theoretical structures shape it. Firstly, Huang et al. (2007) examined the impact of perceived usefulness (PU) on attitude (ATT). Secondly, in a study conducted by Andoh (2018), the construct of perceived ease of use (PEOU) has been discussed to examine the influence on attitude (ATT). Thirdly, the effect of the constructs of compatibility (COM) and perceived enjoyment (PE) have been discussed in the intention to use (ITU) in a study by Cheng (2014). Fourthly, cognitive need (CN) and social influence (SI) can have a direct impact on the intention to use (ITU) mobile learning in developing countries, according to a study by Thongsri et al. (2018). Lastly, in research conducted by Park and Kim (2013), the construct of attitude (ATT) has been discussed on the impact of intention to use (ITU). The conceptual framework of this study is developed in Figure 1.

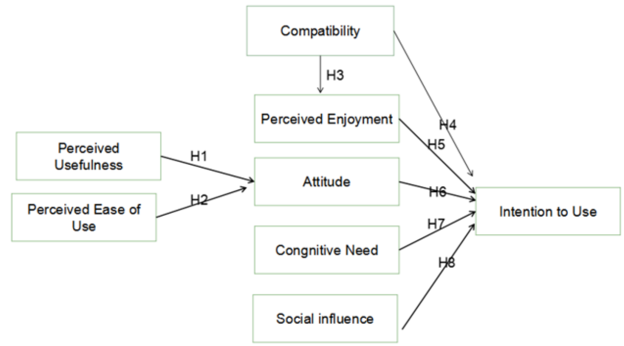

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant impact on attitude.
H2: Perceived ease of use has a significant impact on attitude.
H3: Compatibility has a significant impact on perceived enjoyment.
H4: Compatibility has a significant impact on intention to use.
H5: Perceived enjoyment has a significant impact on intention to use.
H6: Attitude has a significant impact on intention to use.
H7: Cognitive need has a significant impact on intention to use.
H8: Social influence has a significant impact on intention to use.

3.2 Research Methodology

This study employed a nonprobability sampling method for the quantitative approach. Male students who have used mobile learning at GIT were targeted by distributing a questionnaire through WeChat and QQ groups. The data collected was analyzed to identify the key factors that significantly impact the intention to use mobile learning. The survey consisted of three parts. Firstly, screening questions were used to identify the respondents' characteristics. Secondly, a 5-point Likert scale was used to analyze eight proposed variables, ranging from strong disagreement (1) to strong agreement (5) for all eight hypotheses. Lastly, demographic questions were included to gather information on gender, grade, area of education, and frequency of using mobile learning. Pilot testing was conducted on 31 respondents, and the item-objective congruence (IOC) index was analyzed to ensure the accuracy of the survey questions.
To ensure the validity and reliability of the questionnaire, Cronbach's Alpha approach was used for assessment. After the reliability test, 500 valid responses were collected from the target respondents. The statistical analysis was

conducted using JAMOVI 1.6.23 and AMOS Graphics 26.0. The accuracy of convergence and validation was confirmed through Confirmatory Factor Analysis (CFA). Additionally, a general test of model fit was conducted to establish the validity and reliability of the model. Finally, the Structural Equation Model (SEM) was utilized to examine the impact of variables.

3.3 Population and Sample Size

The term "target population" in this study refers to the respondents who completed the questionnaire and were surveyed by the researcher to gather statistical data (Ganjeh et al., 2019). According to Mohamed et al. (2020), the target population consists of individuals who meet the specific criteria and requirements of the study.

In this research, the target population is divided into two groups: male and female. The aim is to compare the gender differences in mobile learning. Following the screening procedure, data from 500 male respondents will be selected from each group to analyze the specific factors that impact mobile learning.

3.4 Sampling Technique

The target respondents for this research were selected using purposive or judgmental sampling, a deliberate and intentional approach where the researcher selects participants based on specific characteristics or expertise (Maxwell, 1996). In this study, students with mobile learning experiences at Guizhou Institute of Technology were chosen as the sample to assist in the research. This sampling method allows the researcher's subjective judgment to determine the selection of participants, ensuring that the sample aligns with the research objectives.

Stratified random sampling is a method that involves dividing the population into smaller groups or strata before selecting participants (Ackoff, 1953). In this study, the stratified random sampling method was employed to divide the students into two groups based on their gender - male and female. To ensure accurate representation, 500 students were selected as the sample from each group to obtain specific statistics for this research.

Table 1: Sample Units and Sample Size

Mobile learning platform	Population Size	Proportional Sample Size
Rain Classroom	8,535	222
Pigai Net	5,328	139
QQ Classroom	5,328	139
Total	**19,191**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the target respondents, consisting of 500 males, is presented in Table 2. The male participants in this study are from different grades, with grade one accounting for 30.4%, grade two accounting for 27.8%, grade three accounting for 29.2%, and grade four accounting for 12.6%. Regarding majors, 54.6% of respondents are from the Technical and engineering field, 38.8% are from pure science, 0.8% are from Commerce and Management, and 5.8% are from Mathematics and Statistics. The frequency of mobile learning usage varies, with 74.0% of respondents using it five times a week and 26.0% using it once a week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Grade	Year 1	152	30.4%
	Year 2	139	27.8%
	Year 3	146	29.2%
	Year 4	63	12.6%
Major	Technical/Engineering	273	54.6%
	Pure science	194	38.8%
	Commerce and management	4	0.8%
	Mathematics and Statistics	29	5.8%
Frequency of using mobile learning	Regular (5 times a week)	370	74.0%
	Rare (Once a week)	130	26.0%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmation factor analysis (CFA) is a statistical method used to examine the structure of variables and factors to assess measurement models in structural equation modeling (Lei & Wu, 2007). Researchers commonly employ CFA to determine whether their hypotheses are supported by empirical data (Fox, 2010). In science and technology research, CFA can be utilized to investigate the relationships between observable and latent variables. The findings of the CFA conducted in this study revealed that all items within each variable were statistically significant and had factor loadings that supported the discriminant validity of the measurement model. The significance of factor loadings was assessed using the guidelines recommended by Hair et al. (2006), with values above 0.50 and p-values below 0.05 considered acceptable. Moreover, following the recommendations of Fornell and Larcker (1981), the Composite Reliability (CR) exceeded the threshold of 0.7, and the Average Variance Extracted (AVE) surpassed the cutoff of 0.4. These results, as presented in Table 3, indicate the importance of all variables in the 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
Perceived Usefulness (PU)	Leon (2018)	6	0.861	0.674-0.746	0.862	0.51
Perceived Ease of Use (PEOU)	Alsaleh et al. (2019)	5	0.850	0.685-0.762	0.851	0.533
Compatibility (COM)	Cheng (2014)	3	0.782	0.733-0.748	0.782	0.545
Perceived Enjoyment (PE)	Cheng (2014)	3	0.791	0.695-0.832	0.795	0.566
Attitude (ATT)	Alsaleh et al. (2019)	4	0.853	0.739-0.787	0.853	0.593
Cognitive Need (CN)	Thongsri et al. (2018)	4	0.807	0.681-0.739	0.807	0.512
Social Influence (SI)	Buabeng-Andoh and Baah (2020)	4	0.811	0.692-0.754	0.81	0.516
Intention to Use (ITU)	Thongsri et al. (2018)	4	0.804	0.644-0.759	0.805	0.508

To establish the study's validity, the square root of the average variance extracted is examined to ensure that all correlations are higher than the corresponding correlation values for each variable, as indicated in Table 4. Additionally, various fit indices, including GFI, AGFI, NFI, CFI, TLI, and RMSEA, are used to evaluate the model fit in the CFA testing.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	717.102/467 or 1.536
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.921
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.905
NFI	≥ 0.80 (Wu & Wang, 2006)	0.903
CFI	≥ 0.80 (Bentler, 1990)	0.963
TLI	≥ 0.80 (Sharma et al., 2005)	0.959
RMSEA	< 0.08 (Pedroso et al., 2016)	0.033
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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation.

Discriminant validity is a vital element of construct validity as it presents the uniqueness and independence of different constructs in a study (Hubley, 2014). It proves that each construct has no relation or is not impacted by other constructs, even under the shift of variables or conditions (Streiner et al., 2015). The excellent discriminant validity of the model is demonstrated by the fact that the diagonal value of the square root of AVE is greater than the inter-scale correlations below it, according to Table 5.

Table 5: Discriminant Validity

	PU	PEOU	COM	PE	ATT	CN	SI	ITU
PU	**0.714**							
PEOU	0.371	**0.73**						
COM	0.164	0.376	**0.738**					
PE	0.446	0.521	0.345	**0.752**				
ATT	0.328	0.500	0.493	0.463	**0.77**			
CN	0.308	0.516	0.438	0.540	0.466	**0.716**		
SI	0.413	0.410	0.374	0.435	0.406	0.412	**0.719**	
ITU	0.320	0.524	0.509	0.517	0.519	0.540	0.504	**0.713**

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

4.3 Structural Equation Model (SEM)

According to Hair et al. (2010), Structural Equation Modeling (SEM) is a statistical method used to analyze the causal relationships among variables in a proposed model, considering measurement errors in the structural coefficients. The goodness-of-fit indices for the SEM model are evaluated as shown in Table 6.

This study conducted the SEM analysis and model adjustments using SPSS AMOS version 26. The final results of the fit indices indicated a good fit: CMIN/DF=2.544, GFI = 0.854, AGFI=0.830, NFI=0.835, CFI=0.892, TLI=0.881, and RMSEA=0.056. These values were compared to the acceptable thresholds mentioned in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1341.359/487 or 2.754	1221.194/480 or 2.544
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.843	0.854
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.819	0.830
NFI	≥ 0.80 (Wu & Wang, 2006)	0.818	0.835
CFI	≥ 0.80 (Bentler, 1990)	0.875	0.892
TLI	≥ 0.80 (Sharma et al., 2005)	0.865	0.881
RMSEA	< 0.08 (Pedroso et al., 2016)	0.059	0.056

Index	Acceptable	Statistical Values Before Adjustment	Statistical Values After Adjustment
Model Summary		**Not in harmony with Empirical data**	**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 = Normed 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 research model was analyzed to determine the significance of each variable using regression weights and R2 variances. As presented in Table 7, the results indicate that all hypotheses were supported at a significance level of p=0.05.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PU→ATT	0.123	2.681*	Supported
H2: PEOU→ATT	0.326	6.575*	Supported
H3: COM→PE	0.347	5.905*	Supported
H4: COM→ITU	0.211	3.938*	Supported
H5: PE→ITU	0.172	2.938*	Supported
H6: ATT→ITU	0.309	5.475*	Supported
H7: CN→ITU	0.239	4.568*	Supported
H8: SI→ITU	0.248	4.781*	Supported

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

Table 7 presents the following findings:

H1: Perceived usefulness significantly impacts attitude, with a standard coefficient value of 0.123. This supports previous research by Letchumanan and Tarmizi (2011) that suggests perceived usefulness influences attitudes when users use a system.

H2: Perceived ease of use significantly impacts attitude, with a standard coefficient of 0.326. This aligns with Teo's (2010) study on pre-service teachers' attitudes toward computers, highlighting the influence of perceived ease of use on attitudes towards newly invented services.

H3: Compatibility significantly affects perceived enjoyment, with a standard coefficient value of 0.347. This finding is consistent with Al-Gahtani and King's (1999) research, which found that compatibility positively influences enjoyment.

H4: Compatibility also plays a significant role in intention to use, with a standard coefficient value of 0.211. This result is consistent with previous studies (Holak & Lehmann, 1990) that emphasize the importance of compatibility in predicting users' intention to adopt new technology.

H5: Perceived enjoyment directly impacts intention to use, with a standard coefficient value of 0.172. This finding supports the research conducted by Lee et al. (2005), which suggests that perceived enjoyment can enhance users' motivation to engage with mobile learning media.

H6: Attitude significantly influences intention to use, with a standard coefficient 0.309. This finding is consistent with the findings of Azizi and Khatony (2019), who also highlighted the significant impact of attitude on students' intention to use mobile learning.

H7: Cognitive need significantly influences intention to use, with a standard coefficient value of 0.239. Although the specific research on learning app usage is not mentioned, this finding suggests that users' cognitive needs are an important factor in their intention to use mobile learning. This aligns with the results of Hossain et al. (2020) study, which revealed that cognitive needs directly impact continuous intention to use.

H8: Social influence significantly affects intention to use, with a standard coefficient value of 0.248. This finding is consistent with Chong (2013) research on mobile commerce, which emphasized the role of social influence in driving users' intention to use a particular system.

These findings provide valuable insights into the factors influencing users' attitudes, enjoyment, and intention to use mobile learning.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research paper attaches great importance to analyzing factors impacting male college students' perceived enjoyment, attitude, and intention to use mobile learning at Guizhou Institute of Technology, Guizhou, China. The hypotheses were suggested as the conceptual framework to examine how perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, attitude, cognitive need, and social influence greatly impact intention to use. The questionnaires were proposed and distributed to the target sample of mobile learning users with a mobile learning experience at the Guizhou Institute of Technology. Confirmatory Factor Analysis (CFA) was applied to measure and examine the conceptual model's validity and reliability. Besides, the Structural Equation Model (SEM) was utilized to analyze the factors that significantly impact the intention to use mobile learning.

The research demonstrates the results as follows. First, perceived usefulness supports the great impact on the attitude of those students who applied mobile learning in their study. The former literature of Huang et al. (2007) reveals that perceived usefulness greatly affects attitude because the user's understanding of usefulness is more important than the perception of perceived ease of use on the influence of attitude in mobile learning. Second, perceived ease of use support shows as the second rank of influencer score on users' attitude toward adopting mobile learning, which supports that perceived ease of use was regarded as the dominant factor influencing the attitude (Andoh, 2018). As a result, perceived ease of use was considered the contributor of effects to predicting students' intention to adopt mobile learning. Third, compatibility support shows as the third rank of influencer score on perceived enjoyment in the context of mobile learning. Al-Gahtani and King (1999) indicated that compatibility has positively impacted enjoyment. Fourthly, compatibility support shows that the extent of compatibility can affect the intention to use mobile learning. It was discovered that compatibility impacted the intention to use to improve the experience distributed in the study of organization (Lin & Lee, 2006). Fifthly, perceived enjoyment support shows that the intention to use can be greatly affected by the extent of the user's enjoyment. Sun and Zhang (2006) presented that people who use new technology enjoyably may have the possible intention to use it. Sixthly, attitude support shows that the user's attitude can significantly influence the intention to use. According to the research by Yang and Yoo (2004), intention to use can be forecasted by attitude related to attention and behavior.

Seventhly, cognitive need support demonstrated that intention to use can be influenced by users' inspiration to actively utilize the new technology or service. It was found that every user can satisfy one's needs by adopting various media forms to convey one's requirements (Batts & Herring, 2013). Lastly, social influence support presented that intention to use can also be impacted by previous indicators or someone strongly trusted that some applications can be adopted. Klobas and Clyde (2001) interpreted that social influence delivers the impact of various social relations and with a general purpose to expect the social members with the ability to adopt the technology.

Generally speaking, the aims of the research are reached that perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, attitude, cognitive need, and social influence are important impactors of intention to use among college students who choose to use mobile learning in Guizhou Institute of Technology, Guizhou, China.

5.2 Recommendation

The researcher found important impactors of perceived enjoyment, attitude, and intention to use mobile learning among college students at Guizhou Institute of Technology: perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, cognitive need, and social influence. The findings of this research have several recommendations for mobile-learning providers and researchers interested in mobile learning as well as educators and institutions. First, perceived usefulness (PU) and perceived ease of use (PEOU) are important elements of individuals' understanding of M-learning (Buabeng-Andoh & Baah, 2020). However, perceived ease of use influences an individual's attitudes more than perceived usefulness, which means that individuals may require an easy way to use mobile learning. At the same time, they precepted that perceived usefulness plays an important role in mobile learning, and this will remind the mobile learning providers that the design of any application needs to consider perceived ease of use carefully if the usefulness has been maximized greatly. In addition, institutions need to provide a comfortable learning environment for students to use m-learning, such as a stable internet connection and a constant supply of electricity. Secondly, compatibility also influences perceived enjoyment and intention to use mobile learning. Students must choose a suitable mobile learning application according to their faith, living standard, existing worth, previous experience, present wishes, and so on. Third, students' attitude influenced their intention to use mobile learning directly. It is significant to arouse students' positive attitudes toward the use of technology. Educators must foster excellent courses and examples to help students develop the right attitude toward mobile learning. Since cognitive need and social influence also have a great impact on intention to use mobile learning, users may encounter some challenges in combining their information of education into an integrated system to deal with the questions, so it is necessary to improve their abilities and new skills in order to deal with questions and interact with each other by adopting their knowledge (Mondi et al., 2007).

5.3 Limitation and Further Study

This study has considered several factors impacting college students' perceived enjoyment, attitude, and intention to use mobile learning. However, there are some limitations of this study. Firstly, for instance, students' family background and factors related to individual characteristics, which may have an important impact on the behavioral intentions of applying for any services, have not been discussed in this study (Myhill, 2002). The significance of the instructor's guidance has not been considered as well. Furthermore, students' personal interests and regional differences have not been considered (Park & Kim, 2014). Lastly, the data collection method is about the self-reported instrument, which may affect the validity of the results (Andoh, 2018).

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