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An Examination of Factors Impacting Attitude, and Intention to Use Mobile Learning Among Female College Students in Guizhou, China

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Abstract

Purpose: The objective of this study is to examine the determinants affecting the attitudes and intentions of female college students in Guizhou, China, regarding the adoption of mobile learning. 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 utilized the quantitative method (n=500), distributing questionnaires to female college students who adopt mobile learning at the Guizhou Institute of Technology. The sampling techniques include judgmental and stratified random sampling in selecting students who adopt three mobile learning platforms. The Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) were adopted for the data analysis, including model fit, reliability, and validity of the constructs. **Results:** The results demonstrate that perceived usefulness and ease of use significantly impact attitude, while compatibility significantly impacts perceived enjoyment, compatibility, perceived enjoyment, attitude, cognitive need, and social influence have a significant impact on intention to use, respectively. **Conclusions:** Educators should provide exemplary courses and models to foster a positive attitude toward technology among students. Furthermore, the study found that cognitive needs and social influence also significantly impact the intention to use mobile learning.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

To address the global spread of COVID-19, various measures have been implemented. One of these measures is the temporary closure of traditional teaching sectors. In order to ensure that students can continue their education, mobile learning has emerged as a viable solution during this challenging time (Mostafa, 2020).

Around 2013, the online education industry in China experienced rapid growth. From 2013 to 2017, the online education market developed quickly and became well-structured by 2018. In 2018, the online education market in China reached a value of 251.76 billion yuan, with 135 million registered customers. The Chinese government has emphasized the advancement of mobile learning, particularly in the K-12 educational system. With the highly developed Internet industry and the increasing number of mobile users in China, the goal of a comprehensive shift in the educational system within the next decade is attainable. This has led to substantial growth in the mobile learning industry, creating more opportunities for market development (Mostafa, 2020).

Since 2013, mobile learning has gained significant popularity at the Guizhou Institute of Technology. The primary mobile learning platform used is Xuetang Online or Rain Classroom, an integrated online platform provided by Tsinghua University. According to statistics from the data

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center at Xuetang Online, the platform has nearly 69 million users globally, with students selecting courses over 193 million times. More than 3,420 courses are currently available on the platform, including 402 national top-quality courses integrated into the curriculum system. The Rain Classroom platform has also seen approximately 51 million student registrations, with 6,220 classes set up specifically for university students (Mostafa, 2020).

At Guizhou Institute of Technology (GIT), the Rain Classroom platform is the primary mobile learning platform. It is utilized by 559 teachers and over 10,000 students across 873 classes. The Rain Classroom platform offers a multifunctional approach to teaching, supporting instructors in three key aspects: pre-class, in-class, and post-class activities. Before the class begins, instructors can provide teaching materials to students for self-study. Additionally, attendance can be recorded using temporary codes, allowing instructors to track student participation. Students can also engage with the teaching content by providing feedback, enabling instructors to assess comprehension and adjust their instruction accordingly.

Furthermore, the platform facilitates instant communication between instructors and students through message forwarding. After the class concludes, students can complete quizzes and assignments on the platform. Instructors are provided with detailed statistics and reports for each class or semester, offering valuable insights into the course's progress and student performance. The Rain Classroom platform at GIT offers a comprehensive and efficient approach to mobile learning, enhancing instructors' and students' teaching and learning experiences.

Guizhou Institute of Technology has adopted Pigai Net, a composition writing revision tool, to assist students in their English writing skills. This platform follows a structured process to help students in writing compositions. Teachers assign writing tasks to students online, who submit their compositions to Pigai Net, which utilizes a vast database of language resources to provide instant revision advice in vocabulary, grammar, and structure. Students can revise their compositions multiple times based on feedback, aiming to achieve excellence in their writing.

Despite the increasing popularity of mobile learning in the educational sector, there is a noticeable research gap in the specific context of Guizhou, China, with a focus on female college students. Limited empirical studies have explored the factors that influence the attitudes and intentions of this specific demographic group towards the adoption of mobile learning. This gap arises from the need to understand the unique sociocultural and educational factors in Guizhou that may impact female college students' readiness and willingness to embrace mobile learning as an educational tool. Addressing this gap is essential to tailor mobile learning strategies that are more gender-sensitive and context-specific. Thus, this study is to examine the determinants affecting the attitudes and intentions of female college students in Guizhou, China, regarding the adoption of mobile learning.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is the extent to which a user believes using a new technology will enhance their performance and productivity, aligning with their intended goals (Chang & Chen, 2019). Cheng et al. (2019) stressed that the perception of usefulness indicates customers' intrinsic requirements for a communication tool. Perceived usefulness can be understood as consumers' desire to determine whether adopting a new service will enhance their performance (Bazel et al., 2018). Perceived usefulness can be interpreted as consumers' inclination to assess whether adopting a new service will improve performance (Bruner & Kumar, 2005; Malhotra & Galletta, 1999). Previous research has highlighted the influence of perceived usefulness on individuals' attitudes towards adopting communication skills (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Yang, 2013). Letchumanan and Tarmizi (2011) also found that attitudes are shaped by perceived usefulness when users decide to use a system. Accordingly, a hypothesis is indicated:

H1: Perceived usefulness has a significant impact on attitude.

2.2 Perceived Ease of Use

Perceived ease of use refers to how users perceive the media as easy to use and navigate (Zakour, 2009). In mobile learning, perceived ease of use reflects a customer's perception of how easily they can use the system for studying purposes (Yang et al., 2012). It signifies the ease with which an individual can adopt a specific system without encountering difficulties (Liu & Li, 2010). In the context of mobile commerce, research has shown that perceived ease of use significantly impacts attitude (Wakefield & Whitten, 2006). Perceived ease of use influences and enhances attitude (Davis et al., 1989). Users are more likely to adopt a positive attitude towards a particular system or skill if they perceive it as easy to use, helpful, and compatible with their lifestyle (Ha & Im, 2014). Accordingly, a hypothesis is indicated:

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

2.3 Compatibility

Compatibility is a living situation towards life and faith (Ha & Im, 2014). Compatibility is the extent to which users think a new media is compatible with the genre of people's perception and action. Compatibility (Com) defines the scale to which a communicating tool is regarded as supportive (Rogers, 2003). Compatibility is vital in new technology situations (Al-Ajam & Nor, 2013; Crespo & del Bosque, 2010; Papies & Clement, 2008). Regarding mobile technology and the entertainment industry, Tan and Chou (2008) suggest that consumers can be influenced by the compatibility of the information they consume and derive enjoyment from it. In the context of technology-based self-service, Dabholkar and Bagozzi (2002) found that if users receive a favorable and compatible service, they perceive it as valuable and are more likely to adopt it. In the study of organizations, Lin and Lee (2006) discovered that compatibility significantly impacted the intention to promote the adoption of new experiences. Moreover, compatibility is an important factor in predicting the intention to use information technology and interactive systems, as supported by robust research conducted through experiments and experiences (Holak & Lehmann, 1990; Plouffe et al., 2001; Van Slyke et al., 2004). Accordingly, a hypothesis is indicated:

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 encompasses the favorable behavior of users in adopting a new service and their affective perception of the technology (Davis et al., 1992; Lee et al., 2005; Teo et al., 1999). Perceived enjoyment reflects the degree to which individuals believe that utilizing a new technology is enjoyable beyond the expected outcomes (Davis et al., 1992). Thong et al. (2006) found that perceived enjoyment significantly impacts intention in the IT field. Lee et al. (2005) suggested tha perceived enjoyment can motivate the intention to use mobile learning platforms. Sun and Zhang (2006) argued that individuals who enjoy adopting new technologies are more likely to have the intention to use them. Accordingly, a hypothesis is indicated:

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

2.5 Attitude

Kaplan (1972) suggests that attitude indicates the likelihood of a positive or negative understanding of a target. Yang et al. (2012) describes customers' biological attitudes as a comprehensive indication of the possibility of a service element. Chen (2013) defines attitude as determining the outcome of an individual's action. Yang and Yoo (2004) conducted research suggesting that intention to use can be predicted by attitude, specifically related to attention and behavior. Cao and Mokhtarian (2005) argued that attitude variables can explain the intention to engage in mobile learning. Dwivedi et al. (2019) stated that attitude can accelerate the behavioral intention to use new technologies. Accordingly, a hypothesis is indicated:

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

2.6 Cognitive Need

Cognitive need reflects customers' desire to satisfy their demands through social media (Bae, 2018). Additionally, cognitive need can be understood as users' requirement for a definite response or solution to a specific question or issue (Kruglanski & Webster, 1996). Othman and Omar (2020) further explain that cognitive need represents the necessity of finding approval or validation elements within a given situation. Numerous research studies have investigated the determinants that impact users' inclination to participate in mobile learning. Lin et al. (2011) studied learners' intention to utilize mobile learning apps, particularly in challenging and critical scenarios. Chen and Chang (2014) explored how users' cognitive styles influence their responses to mobile learning. These studies underscore the significance of employing diverse media formats to accommodate the intentional needs of users (Batts & Herring, 2013). Accordingly, a hypothesis is indicated:

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

2.7 Social Influence

Social influence (SI) refers to how much people believe others expect them to use a specific service or technology (Venkatesh et al., 2003). It represents an individual's belief in adopting a service based on the influence of others (Venkatesh et al., 2012). Social influence reflects an individual's need to conform to societal expectations and gain recognition (Kelman, 1958). Accordingly, social influence significantly predicts behavioral intentions (Oliveira et al., 2014). It substantially impacts the intention to use (Fidani & Idrizi, 2012). Social influence plays a vital role in forecasting mobile learning behavior, which aims to attract attention in terms of technology (Cheung & Lee, 2010). Accordingly, a hypothesis is indicated:

H8: Social influence has a significant impact on intention to use.

2.8 Intention to Use

Intention to use (IU) refers to individuals' perception of their determination and willingness to utilize instruments, skills, or services (Park & Kim, 2013). It represents the possibility that a user will engage with a systematic service (Mohammadi, 2015) and reflects the degree of their willingness to perform a specific action (Ajzen, 1991).

3. Research Methods and Materials

3.1 Research Framework

The proposed conceptual framework is developed by analyzing previous research frameworks and consists of five theoretical structures. Firstly, Huang et al. (2007) examined the influence of perceived usefulness (PU) on attitude (ATT). Secondly, Andoh (2018) investigated the construct of perceived ease of use (PEOU) and its impact on attitude (ATT). Thirdly, Cheng (2014) explored the effects of compatibility (COM) and perceived enjoyment (PE) on intention to use (ITU). Fourthly, Thongsri et al. (2018) identified that cognitive need (CN) and social influence (SI) directly affect the intention to use (ITU) mobile learning in developing countries. Lastly, Park and Kim (2013) discussed the impact of attitude (ATT) on intention to use (ITU). The resulting conceptual framework is visually presented in Figure 1.

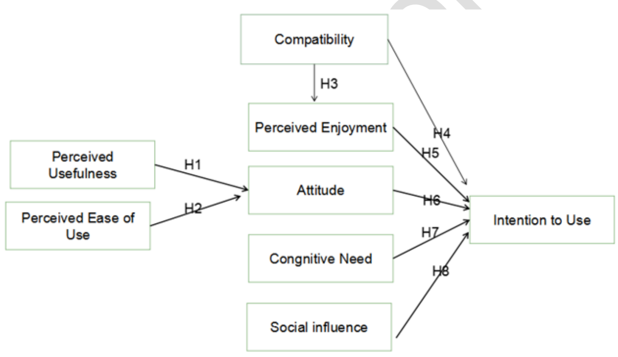

Figure 1: Conceptual Framework

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

For this research, a nonprobability sampling method was employed in the quantitative approach. A questionnaire was distributed to female students using mobile learning in GIT through WeChat and QQ groups. The collected data was then analyzed to identify the key factors significantly impacting the intention to use mobile learning.

The survey consisted of three parts. Firstly, screening questions were utilized to identify the characteristics of the respondents. Secondly, a 5-point Likert scale was employed 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 mobile learning usage.

To ensure the questionnaire's effectiveness, pilot testing was conducted with 31 respondents, and the item-objective congruence (IOC) index was analyzed.

The validity and reliability of the questionnaire were assessed using Cronbach's Alpha approach. After the reliability test, 500 valid responses were collected from the target respondents. The statistical analysis was conducted using statistical tools. The accuracy of convergence and validation were confirmed through Confirmatory Factor Analysis (CFA). The model's validity and reliability were further established through a general test of model fit. Finally, the Structural Equation Model (SEM) was employed to examine the impact of variables.

3.3 Population and Sample Size

The target population in this study refers to the respondents who completed the questionnaire and were surveyed by the researcher to collect statistical data (Ganjeh et al., 2019). Additionally, Mohamed et al. (2020) provided further clarification that the target population comprises individuals who meet the criteria and requirements of the study.

The target population for this research is female college students. The minimum sample size by should be around 200-500. This research identifies the demographical data for analysis. Therefore, female group are selected. After screening, data from 500 female respondents will be selected from each group to analyze the specific factors that impact mobile learning.

3.4 Sampling Technique

This research used nonprobability sampling, specifically purposive or judgmental sampling, to select the target respondents. Purposive or judgmental sampling is a deliberate and intentional approach where the researcher selects participants based on their 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 for the researcher's subjective judgment to determine the selection of participants.

Stratified random sampling involves dividing the population into smaller groups or strata before selecting participants (Ackoff, 1953). In this study, stratified random sampling was used to stratify the students into two groups based on gender - male and female. To obtain specific statistics for this research, 500 students were chosen as the sample from each group.

Table 1: Sample Units and Sample Size

Mobile learning platform	Population Size	Proportional Sample Size
Rain Classroom	2,874	**240**
Pigai Net	1,563	**130**
QQ Classroom	1,563	**130**
Total	6,000	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The profile of the demographic targets 500 female respondents and is concluded in Table 2. In this study, the female participants come from different grades: grade one accounts for 37.8%, grade two accounts for 24.8%, grade three accounts for 23.0% and grade four accounts for 14.4%. 32.4% of respondents majored in Technical and engineering, 36.0% in pure science, 24.4% in Commerce and Management, 7.2% in Mathematics and Statistics. The frequency of using mobile learning varied from five times a week 51.2% to once a week 48.8% respectively.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Grade	Year 1	189	37.8%
	Year 2	124	24.8%
	Year 3	115	23.0%
	Year 4	72	14.4%
Major	Technical/Engineering	162	32.4%
	Pure science	180	36.0%
	Commerce and management	122	24.4%
	Mathematics and Statistics	36	7.2%
Frequency of using mobile learning	Regular (5 times a week)	256	51.2%
	Rare (Once a week)	244	48.8%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is utilized to elucidate the structure of variables and factors in order to examine SEM measurement models (Lei & Wu, 2007). Researchers commonly employ CFA to assess whether data supports the hypotheses (Fox, 2010). In the realm of science and technology research, CFA can be employed to test the relationships between observable and latent variables.

The results of the CFA conducted in this study revealed that all items within each variable were statistically significant and displayed factor loadings that supported discriminant validity. To determine the significance of factor loadings, the guidelines recommended by Hair et al. (2006) were followed, with values above 0.50 and p-values below 0.05 considered acceptable. Additionally, in accordance with the recommendations of Fornell and Larcker (1981), the Composite Reliability (CR) surpassed the cutoff point of 0.7, and the Average Variance Extracted (AVE) was higher than the cutoff point of 0.4. As depicted in Table 3, all variables were found to be significant.

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	0.683-0.738	0.861	0.508
Perceived Ease of Use (PEOU)	Alsaleh et al. (2019)	5	0.841	0.690-0.738	0.841	0.515
Compatibility (COM)	Cheng (2014)	3	0.782	0.721-0.751	0.783	0.545
Perceived Enjoyment (PE)	Cheng (2014)	3	0.769	0.685-0.779	0.770	0.529
Attitude (ATT)	Alsaleh et al. (2019)	4	0.825	0.700-0.756	0.826	0.542
Cognitive Need (CN)	Thongsri et al. (2018)	4	0.822	0.692-0.823	0.824	0.541
Social Influence (SI)	Buabeng-Andoh and Baah (2020)	4	0.802	0.657-0.764	0.802	0.504
Intention to Use (ITU)	Thongsri et al. (2018)	4	0.823	0.709-0.766	0.823	0.538

The square root of the average variance extracted is examined to ensure that all correlations are greater than the corresponding correlation values for that variable, as shown in Table 4. Additionally, various fit indices such as GFI, AGFI, NFI, CFI, TLI, and RMSEA are adopted to assess 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)	740.492/467 or 1.586
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.919
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.903
NFI	≥ 0.80 (Wu & Wang, 2006)	0.899
CFI	≥ 0.80 (Bentler, 1990)	0.960
TLI	≥ 0.80 (Sharma et al., 2005)	0.954
RMSEA	< 0.08 (Pedroso et al., 2016)	0.034
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 plays a crucial role in establishing the construct validity by highlighting the distinctiveness and independence of various constructs within a study (Hubley, 2014). It demonstrates that each construct is not related to or influenced by other constructs, even when variables or conditions are altered (Streiner et al., 2015). The model's strong discriminant validity is evidenced by the fact that the diagonal value of the square root of AVE is greater than the inter-scale correlations listed below it, as indicated in Table 5.

Table 5: Discriminant Validity

	PU	PEOU	COM	PE	ATT	CN	SI	ITU
PU	**0.713**							
PEOU	0.447	**0.717**						
COM	0.489	0.524	**0.739**					
PE	0.331	0.485	0.539	**0.727**				
ATT	0.532	0.403	0.673	0.447	**0.736**			
CN	0.346	0.368	0.313	0.342	0.384	**0.735**		
SI	0.410	0.446	0.455	0.524	0.468	0.383	**0.710**	
ITU	0.463	0.439	0.577	0.553	0.570	0.413	0.503	**0.734**

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 model fit measurement should be less than 5 for the Chi-square/degrees-of-freedom (CMIN/DF) ratio by Awang (2012) and Al-Mamary and Shamsuddin (2015), and GFI should be greater than 0.85 by Sica and Ghisi (2007) and CFI should be higher than 0.8 as introduced by Bentler (1990). The calculation in SEMs and the structure were adjusted by applying SPSS AMOS version 26. The results of the fit index were presented as a good fit, which are CMIN/DF = 2.804, GFI = 0.846, AGFI = 0.822, NFI = 0.813, CFI = 0.871, TLI = 0.860 and RMSEA = 0.060 before adjustment, which indicates an unacceptable model fit. After adjustment, the results of the fit index are CMIN/DF = 2.699, GFI = 0.852, AGFI = 0.828, NFI = 0.822, CFI = 0.879, TLI = 0.868, and RMSEA = 0.058, which demonstrates an acceptable model fit 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)	1365.646/487 or 2.804	1306.304/484 or 2.699
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.846	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.822	0.828
NFI	≥ 0.80 (Wu & Wang, 2006)	0.813	0.822
CFI	≥ 0.80 (Bentler, 1990)	0.871	0.879
TLI	≥ 0.80 (Sharma et al., 2005)	0.860	0.868
RMSEA	< 0.08 (Pedroso et al., 2016)	0.060	0.058
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 significance of each variable in the research model was examined through regression weights and R2 variances. The results presented in Table 6 indicate that all hypotheses were supported with a significance level of $p = 0.05$. Compatibility had the greatest impact on Perceived enjoyment among the variables, with a regression weight of 0.533. Other significant relationships were found between perceived usefulness and attitude (β=0.459), attitude and intention to use (β=0.309), perceived enjoyment (β=0.253), perceived ease of use (β=0.246), compatibility and intention to use (β=0.228), social influence (β=0.187), and cognitive need and intention to use (β=0.177). Therefore, the model demonstrates the factors influencing intention to use mobile learning, as shown in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PU→ATT	0.459	8.071*	Supported
H2: PEOU→ATT	0.246	4.842*	Supported
H3: COM→PE	0.533	8.743*	Supported
H4: COM→ITU	0.228	3.413*	Supported
H5: PE→ITU	0.253	3.765*	Supported
H6: ATT→ITU	0.309	5.725*	Supported
H7: CN→ITU	0.177	3.504*	Supported
H8: SI→ITU	0.187	3.622*	Supported

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

The results from Table 7 provide the following insights:

The first set of sample data in the study of female college students has confirmed that perceived usefulness significantly impacts attitude. The standardized path coefficient for **H1** is 0.459, with a corresponding t-value of 8.071, indicating that perceived usefulness plays a crucial role in the adoption of mobile learning. Perceived usefulness can support female college student's development of a positive attitude toward mobile learning.

The regression results of the sample data in this study confirm that perceived ease of use significantly impacts the attitude of female college students. The normalized path coefficient for **H2** is 0.246, with a corresponding t-value of 4.842, indicating that perceived ease of use plays a crucial role in the utilization of mobile learning. This finding is consistent with previous studies by Abramson et al. (2015) and Peng et al. (2016). If female students perceive mobile learning as easy to use, it will greatly influence their attitude, making them more inclined to engage in the study actively.

Regarding the relationship between Compatibility and perceived enjoyment, the normalized path coefficient of **H3** is 0.533, and the t-value is 8.743. It shows that Compatibility can affect female college students' enjoyment of utilizing mobile learning. If female college students consider this mobile learning service to be very compatible with their requirements, they may feel happy to use it, and this will help them achieve study.

The impact of Compatibility on the intention to use mobile learning is also very positive. The normalized path coefficient value of **H4** is 0.228, and the t-value is 3.413. It can be seen that female students' intention to use mobile learning can be promoted by compatible services and contents so that they may be likely to utilize mobile learning.

Intention to use is significantly influenced by perceived enjoyment; the standardized path coefficient value of **H5** is 0.253, and the t-value is 3.765. The level of feeling of enjoyment can accelerate female students' intention to use mobile learning. For mobile learning, the degree of perception of enjoyment will decide whether they are willing to utilize mobile learning. If they enjoy mobile learning, their intention to use it will be continuously strengthened.

Attitude greatly influences intention to use; the normalized path coefficient value of **H6** is 0.369, and the t-value is 5.725. Attitude is crucial to promote the students' intention to use mobile learning. It can be interpreted that students' attitudes will affect their intention to use mobile learning, and the right attitude will help them utilize mobile learning efficiently.

Intention to use is greatly impacted by cognitive need as well, with the standard path coefficient of **H7** as 0.177 and the t-value as 3.504. It proves that cognitive need can be regarded as an important factor influencing the intention to use. It can be interpreted that female students' appeal to use mobile learning can encourage them to conduct mobile learning easily.

Social influence has greatly influenced the intention to use; the normalized path coefficient value of **H8** is 0.187, and the t-value is 3.622. Social influence is one of the essential factors to impact the intention to use. In conclusion, impacts from important people or social situations can cause female students to adopt mobile learning.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study analyzes the factors influencing female college students' perceived enjoyment, attitude, and intention to use mobile learning at Guizhou Institute of Technology in China. The researcher proposed several hypotheses to examine the impact of perceived usefulness, perceived ease of use, compatibility, perceived enjoyment, attitude, cognitive need, and social influence on intention to use. The study involved distributing questionnaires to mobile learning users at the institute who had previous experience with mobile learning. Confirmatory Factor Analysis (CFA) was used to assess the validity and reliability of the conceptual model, and the Structural Equation Model (SEM) was employed to analyze the factors that significantly influenced the intention to use mobile learning.

The research findings indicate that perceived usefulness significantly impacts attitudes among students who have used mobile learning in their studies. This aligns with research by Huang et al. (2007), which suggests that perceived usefulness plays a more important role than perceived ease of use in influencing attitudes toward mobile learning. Additionally, perceived ease of use is the second most influential factor in shaping users' attitudes toward adopting mobile learning. This finding supports the idea that perceived ease of use is a dominant factor influencing attitude, as highlighted by Andoh (2018). Therefore, perceived ease of use contributes to predicting students' intention to adopt mobile learning.

Thirdly, the findings indicate that compatibility significantly impacts the perceived enjoyment of mobile learning, ranking third among the influential factors. This finding aligns with previous research by Al-Gahtani and King (1999), who found that compatibility is crucial in enhancing enjoyment.

Fourthly, compatibility also significantly affects the intention to use mobile learning. The study conducted by Lin and Lee (2006) revealed that compatibility influences users' intention to use by improving their overall experience with the system.

Fifthly, perceived enjoyment significantly impacts the intention to use mobile learning. This finding aligns with the research conducted by Sun and Zhang (2006), which suggests that individuals who derive enjoyment from using new technology are more likely to have a positive intention to use it.

Sixthly, the results demonstrate that attitude significantly influences the intention to use mobile learning. This is consistent with the findings of Yang and Yoo (2004), who found that users' attitude towards the system is a reliable predictor of their intention to use it.

The study also found that cognitive need significantly impacts the intention to use mobile learning. This suggests that users' motivation to engage with the new technology or service actively can influence their intention to use it. Batts and Herring (2013) found that users can fulfill their needs by adopting different forms of media to express their requirements.

Furthermore, social influence significantly impacted the intention to use mobile learning. This indicates that previous recommendations or the trust placed in certain individuals can influence the adoption of mobile learning. Klobas and Clyde (2001) explained that social influence encompasses various social relationships and aims to anticipate the adoption of technology by social members.

In conclusion, the study successfully identifies perceived usefulness, ease of use, compatibility, enjoyment, attitude, cognitive need, and social influence as significant factors influencing college students' intention to use mobile learning at Guizhou Institute of Technology in China.

5.2 Recommendation

The findings provide valuable recommendations for mobile learning providers, researchers, educators, and institutions interested in mobile learning.

The study highlights the significance of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping individuals' perceptions of mobile learning (Buabeng-Andoh & Baah, 2020). However, the findings reveal that perceived ease of use has a greater impact on individuals' attitudes than perceived usefulness. This suggests that while individuals recognize the importance of mobile learning, they also prioritize the ease of use when considering its adoption. Therefore, mobile learning providers should prioritize the design of user-friendly applications, ensuring that ease of use is maximized alongside the platform's usefulness. Additionally, institutions should create a conducive learning environment for students, including a stable internet connection and uninterrupted power supply, to facilitate the seamless use of mobile learning.

Additionally, the study found that compatibility significantly influences both perceived enjoyment and intention to use mobile learning. Students must select a mobile learning application that aligns with their beliefs, lifestyle, values, previous experiences, and needs. Moreover, students' attitude towards mobile learning directly affects their intention to use it. Therefore, educators should provide exemplary courses and models to foster a positive attitude toward technology among students. Furthermore, the study found that cognitive needs and social influence also significantly impact the intention to use mobile learning. Users may face challenges in integrating their educational information into a cohesive system to address questions and interact with each other effectively. Thus, it is crucial to enhance their skills and abilities to handle questions and collaborate through knowledge sharing (Mondi et al., 2007).

5.3 Limitation and Further Study

While this study has explored various factors influencing female college students' perceived enjoyment, attitude, and intention to use mobile learning, it is important to acknowledge its limitations. For instance, the study did not examine students' family background and individual characteristics, which could significantly impact their behavioral intentions when using any service (Myhill, 2002). Additionally, the role of instructor guidance was not considered, and personal interests and regional differences needed to be accounted for (Park & Kim, 2014). Lastly, using self-reported instruments for data collection may introduce bias and affect the validity of the results (Buabeng-Andoh & Baah, 2020). Future research should address these limitations and explore the influence of these factors on students' perception and intention to use mobile learning.

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