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Key Influences on Mobile Learning Adoption Among Medical Students in Chengdu, China

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Abstract

Purpose: This research aims to examine the factors impacting Chinese medical students' behavioral intentions and actual use of mobile learning. The key influencers are perceived usefulness, perceived ease of use, enjoyment, social influence, attitude, behavioral intention, and actual usage. **Data, methodology, and research design:** Empirical analysis and quantitative approach were employed in this study. The data was collected from 500 Chinese medical students using a questionnaire as the research instrument. Before distribution, the questionnaire's content validity and reliability were tested using item-objective congruence and a pilot test. The data was analyzed using confirmatory factor analysis and structural equation modeling to validate the model's goodness of fit and confirm the causal relationship among variables for hypothesis testing. **Results:** The study found that the medical students' behavioral intention has the greatest impact on their actual usage of mobile learning. Moreover, the perceived usefulness, perceived ease of use, perceived enjoyment, social influence, and attitude of medical students significantly affect their behavioral intention to use mobile learning. **Conclusions:** The study provides valuable insights that mobile learning developers and educators can use for the design of mobile learning systems.

Keywords: Mobile Learning, Medical Education, Behavioral Intention, Actual Use, China

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Electronic learning emerged during the 1990s alongside the growing popularity of the Internet (Benevides, 2011). The study by Papanis (2005) indicates that electronic learning enables faster, cost-effective learning while enhancing access to educational resources and promoting transparency in the learning process. There are several types of e-learning, including online, distance, blended, and mobile learning (Kumar Basak et al., 2018). With the improved performance of mobile devices and the construction of mobile networks, mobile learning has become an indispensable way of learning in people's lives. It has been recognized as a trend in higher education for accessing and sharing information (Sophonhiranrak, 2021).

Four main characteristics can define mobile learning. Firstly, it must be physically based on mobile terminal devices and the mobile Internet (Behera, 2013). Secondly, it is not constrained by temporal or spatial limitations, allowing learners to determine their own pace and location for learning (Huang et al., 2010). Thirdly, learners adopting mobile learning can independently select the content they require for their learning, including medicine learning (Klímová, 2018), language learning (Alkhezzi & Al-Dousari, 2016), special education (Karanfiller et al., 2018), and so on. Furthermore, learners can communicate with teachers and others through mobile devices to form a network-based learning community, thereby achieving common learning goals (Huang et al., 2010). Fourthly, the resources available for mobile learning are becoming increasingly diverse, encompassing text, images, audio, and video, which provide learners with a variety of learning modes (Wang & Shen, 2012). In light of these characteristics, mobile learning may be defined as learning across multiple contexts at any time and place through social and content interactions using

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personal mobile devices (Crompton & Burke, 2018).

Previous studies have demonstrated that mobile learning offers several advantages. For instance, Al-Fahad (2009) demonstrated that mobile learning can effectively enhance students' memory. Murphy (2006) demonstrated that mobile learning facilitates the accessibility, interoperability, and reusability of educational resources and the interactivity and flexibility of learning at any time and in any location. Ratto et al. (2003) demonstrated that using mobile devices for learning enhanced students' critical thinking skills, ability to solve problems in multiple ways, and independent thinking. Chan and Lee (2005) demonstrated that the use of mobile devices in learning was an effective means of reducing students' anxiety during the learning process. Hwang and Chang (2011) demonstrated that mobile learning enhances students' learning interests and attitudes and improves their learning achievement. Furthermore, it was demonstrated that mobile learning effectively means enriching students' learning experiences and collaborative interactions and motivates students at risk of social disengagement (Scornavacca et al., 2009).

The numerous advantages of mobile learning have led to its adoption in numerous medical education contexts. (Chang & Hwang, 2018). Moreover, several studies have been conducted to assess the efficacy of mobile learning in medical education (Chandran et al., 2022; Klímová, 2018). For example, Yoo and Lee (2015) researched the effectiveness of a mobile application in educating on cardiopulmonary assessment. The results demonstrated that mobile applications exhibited comparable efficacy to high-fidelity human patient simulators for teaching and retaining cardiopulmonary assessment abilities. Similarly, Davis et al. (2012) examined the impact of concise, timely mobile learning videos on medical students' chest tube insertion skills. The findings of this study indicated that those who viewed the video demonstrated superior performance in the skills assessment compared to the control group. After a comprehensive review of previous studies, Koohestani et al. (2018) concluded that integrating mobile learning into medical education could offer significant educational benefits and enhance clinical competence, confidence, theoretical knowledge, attitudes, and perceptions toward mobile learning. Similarly, Klímová (2018) posited that mobile learning can effectively acquire new medical knowledge and skills.

Today, research on mobile learning in medical education focuses mainly on the effectiveness and comparison of new and old technologies. Nevertheless, only a few theoretical models explain the acceptance of mobile learning in medical education. (Kalantarion et al., 2022). In recent years, many studies have been conducted to investigate the factors that influence the adoption of mobile learning in medical education. The populations studied in these studies are in different countries, including England, Spain, and Turkey (Briz-Ponce & García-Peñalvo, 2015; Davies et al., 2012; Kucuk et al., 2020). However, there is a paucity of research on the factors influencing the adoption of mobile learning in medical education in China.

The influence of these factors on the adoption of mobile learning depends on the specific research context and the composition of the sampled population. The same factors influence the adoption of mobile learning in different contexts in different countries (Al-Emran et al., 2018). Therefore, this study aimed to identify the factors influencing the actual use of mobile learning by undergraduate students at Chengdu Medical College in China. The findings of this study will inform the development of a model that explains and predicts the actual usage behavior of mobile learning among Chinese medical students. The findings of this study will prompt medical school educators and mobile learning resource developers to comprehend the factors influencing the adoption of mobile learning by medical learners.

2. Literature Review

2.1 Perceived Usefulness

According to the study of Davis (1989), perceived usefulness refers to the extent to which an individual believes that utilizing a specific information system would enhance their job performance in an organizational context. Similarly, Gefen et al. (2003) defined perceived usefulness as a measure of the individual's subjective assessment of the utility offered by the new information technology in a specific task-related context. Recently, Buabeng-Andoh (2021) defined perceived usefulness as the range to which a higher education student perceives that utilizing mobile learning will Improve the outcomes of his/her education.

Perceived usefulness is one of the two main factors that govern the internal beliefs of individuals in the technology acceptance model (TAM) (Davis, 1989). Therefore, perceived usefulness has been considered a crucial factor in positively influencing the intention to use information systems (Legris et al., 2003) and has been employed to predict the usage intention of different technologies and contexts (Al-Emran & Granić, 2021; Buabeng-Andoh, 2021). Pratama (2021) indicated that perceived usefulness significantly determines middle and high school students' intention to use mobile learning. Similarly, a study conducted in China demonstrated that perceived usefulness positively influences university students' intention to use mobile APPs with smartphones (Zhonggen & Xiaozhi, 2019). Based on these studies, the current study addressed the following hypothesis:

H1: Perceived usefulness has a significant impact on behavioral intention.

2.2 Perceived Ease of Use

Davis (1989) stated that perceived ease of use (PEOU) is the degree to which the prospective user expects the target system in a computer to be free of effort. According to the study of Gefen et al. (2003), perceived ease of use referred to an indicator of the cognitive effort needed to learn and utilize new information technology. Recently, Alhumaid et al. (2021) defined perceived ease of use as an individual's perception that using mobile learning will be free from effort.

Similar to Perceived Usefulness, Perceived Ease of Use was a belief factor that can explain the user's motivation, so it was also introduced into the Technology Acceptance Model to predict the usage of information systems (Davis, 1989; Marangunić & Granić, 2015; Venkatesh et al., 2003). Many studies employed TAM confirmed that PEOU positively affects BI (Kamal et al., 2020; Li, 2010). For example, in studies conducted in the United Arab Emirates and Jordan, it was demonstrated that undergraduate students' intention to use mobile learning was positively influenced by PEOU (Al-Hamad et al., 2021; Almaiah et al., 2019). Moreover, Hu and Lai (2019) surveyed undergrad students' adoption of mobile learning in Hong Kong, China. They found that PEOU is a significant determinant of students' usage intention. Therefore, this study addressed the following hypothesis:

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

2.3 Perceived Enjoyment

Davis et al. (1992) defined perceived enjoyment as the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated. Van der Heijden (2004) defined Perceived enjoyment as the excitement and happiness derived from using a system in its own right. Cheng (2014) states that perceived enjoyment means that using mobile learning is fun and beneficial.

According to the motivational theory established by Deci (1976), user acceptance is determined by extrinsic motivation (e.g., Perceived Usefulness) and intrinsic motivation (e.g., Perceived Enjoyment). Therefore, Perceived Enjoyment has been integrated into the extension Technology Acceptance Model in different reach areas (Marangunić & Granić, 2015). In the last decade, mobile learning adoption has widely investigated the relationship between perceived enjoyment and behavioral intention (Al-Rahmi et al., 2021; Fan et al., 2022; Lu et al., 2017; Pratama, 2021). These studies conducted in different countries showed that mobile learning positively affected BI. Therefore, this study addressed the following hypothesis:

H3: Perceived enjoyment has a significant impact on behavioral intention.

2.4 Social Influence

Venkatesh et al. (2003) indicated that social influence is the degree to which an individual perceives that important others believe he or she should use the new system. Tewari et al. (2023) defined social influence as the extent of change in the user's behavior when using a technology under the influence of others. Almaiah et al. (2019) indicated that social influence is the extent to which consumers feel other people think they ought to be using a specific technology, such as mobile learning.

Social influence stems from the subjective norm in the Theory of Reasoned Action (Fishbein & Ajzen, 1975). Although they have different labels, each contains the notion that the individual's behavior is influenced by how they believe others will view them as a result of having used the technology (Venkatesh et al., 2003). It significantly impacts individual behavior and intention regarding information technology (Jambulingam, 2013). In recent studies, social influence was used to predict the adoption of mobile learning (Shorfuzzaman & Alhussein, 2016; Tewari et al., 2023). These studies indicated that undergraduates' intention to use mobile learning was influenced by social influence. Therefore, this study tested the following hypothesis:

H4: Social influence has a significant impact on behavioral intention.

2.5 Attitude

Fishbein and Ajzen (1975) defined the attitude as a learned predisposition to respond in a consistently favorable or unfavorable manner concerning a given object. According to the study of Davis (1989), attitude refers to an individual's positive or negative feelings (evaluative affect) about performing the target behavior. Teo and Zhou (2014) point out that attitude refers to a person's degree of evaluative effect (like or dislike) toward a target behavior (computer use). Alhumaid et al. (2021) state that attitude means one's desire to use mobile learning.

Like Perceived Ease of Use and Perceived Enjoyment, attitude is one of the three factors explaining the user's motivation (Davis, 1985). So, the attitude was introduced into the TAM to predict information technology adoption (Davis, 1989). It was proved that a good attitude is an essential factor for an individual to develop a particular behavioral participation intention (Moon & Kim, 2001). Previous mobile learning studies have indicated that attitude positively impacts individuals' intentions to use mobile

learning systems (Al-Emran et al., 2018; Khanh & Gim, 2014). Furthermore, several studies have shown that attitude was the most significant predictor of mobile learning acceptance (Alhumaid et al., 2021; Park et al., 2012; Shin & Kang, 2015). Therefore, this study proposed the following hypothesis:
H5: Attitude has a significant impact on behavioral intention.

2.6 Behavioral Intention

Fishbein and Ajzen (1975) defined behavioral intention as a person's subjective probability that he will perform some behavior. Then, Davis (1989) concisely defined Behavioral Intention as a measure of the strength of one's intention to perform a specified behavior. Furthermore, in a study about mobile learning, the cognitive picture of a person's preparedness to carry out a certain act was described as behavioral intention (Al-Rahmi et al., 2021).

According to TAM theory, behavioral intention is considered the best predictor of information system usage (Venkatesh & Morris, 2000). Over the past three decades, a respectable number of researches have demonstrated that behavioral intention was a determinant factor of actual usage of different technologies (Al-Emran & Granić, 2021; Chaudhry et al., 2023; Marangunić & Granić, 2015). In the last decade, the behavioral intention of learners to use mobile learning has been demonstrated to be substantially correlated with system acceptability and utilization (Almaiah et al., 2019; Alshurideh et al., 2023; Shin & Kang, 2015). Therefore, this study proposed the following hypothesis:
H6: Behavioral intention has significant impact on actual use.

2.7 Actual Use

Davis (1989) indicated that Actual Use refers to an individual's actual direct usage of the given system in the context of his or her job. Chen et al. (2011) stated that actual use refers to using a technology. In addition, in the study of Lutfi et al. (2022), Actual Use refers to students' actual direct usage of mobile learning in the context of Saudi learning institutions.

Davis (1989) indicated that the actual usage of the system is a response that can be explained or predicted by user motivation, which, in turn, is directly influenced by an external stimulus consisting of the actual system's features and capabilities (Marangunić & Granić, 2015). Actual use has been a fundamental factor in the TAM and applied to the study of various technologies in both organizational and non-organizational settings (Mortenson & Vidgen, 2016). In recent years, actual use is often employed in a modified TAM to predict mobile learning adoption (Alsharida et al., 2021).

3. Research Methods and Materials

3.1 Research Framework

In order to develop a reliable model that could predict the actual usage of any specific technology, Davis (1989) adopted the theory of reasoned action and proposed the TAM. TAM has been acknowledged as a robust and valid model typically employed for elucidating the acceptance of numerous technologies (Chen et al., 2011). The TAM has been employed in numerous investigations to study the adoption of different technologies, such as online banking (Ahmad, 2018), mobile payment (Mondego & Gide, 2022), social media (Al-Qaysi et al., 2020), and mobile learning (Al-Emran et al., 2018) among many others.

The research model is derived from three theoretical frameworks of previous studies based on the TAM and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). The first theoretical framework was developed by Al-Bashayreh et al. (2022). This study confirmed that perceived usefulness, ease of use, and enjoyment significantly impact the behavioral intention to use mobile learning. The second theoretical framework was conducted by Al-Rahmi et al. (2021). The investigation revealed that behavioral intention positively influences the actual use of mobile learning. Furthermore, perceived usefulness, ease of use, enjoyment, and attitude have been demonstrated to influence the behavioral intention of mobile learning significantly. Efiloğlu Kurt (2023) conducted the third theoretical framework. The study demonstrated that the adoption of mobile learning was significantly influenced by perceived enjoyment and social influence. The research conceptual framework is presented in the form of Figure 1.

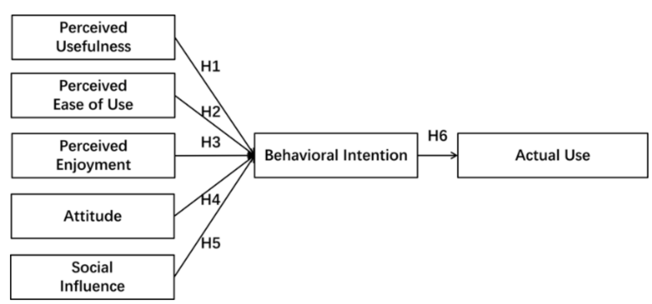

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant impact on behavioral intention.
H2: Perceived ease of use has a significant impact on behavioral intention.
H3: Perceived enjoyment has a significant impact on behavioral intention.

H4: Social influence has a significant impact on behavioral intention.
H5: Attitude has a significant impact on behavioral intention.
H6: Behavioral intention has significant impact on actual use.

3.2 Research Methodology

In this study, an empirical analysis and quantitative method were employed. The sample data were collected from the target population using a questionnaire as an instrument. Before the large-scale data collection, the content validity and reliability of the questionnaire were verified via an Item-Objective Congruence (IOC) test and a pilot test of Cronbach's Alpha. Following the reliability test, the questionnaires were distributed online to undergraduate students from Chengdu Medical College in Sichuan, China. The respondents must have at least one year of experience with mobile learning.

Anderson and Gerbing (1988) proposed a two-step method for the Structural Equation Model (SEM), adopted in this study to analyze the sample data. The first step involved using SPSS and AMOS for Confirmatory Factor Analysis (CFA) to examine the convergent validity of the model. The second step entailed the conduct of an SEM to explore the causal relationships between all constructs in the conceptual model and to test the significance of influences and proposed hypotheses.

3.3 Population and Sample Size

The study's target population was Sophomore, junior, and senior undergraduate students majoring in clinical medicine, anesthesiology, pediatrics, and medical imaging from Chengdu Medical College with at least one year of mobile learning experience. The students in these four majors were selected for this study because their enrollment size has been relatively stable and because they are the main majors for external enrolment at most medical schools.

The A-priori Sample Size Calculator for SEM (Soper, 2006) indicated that a minimum sample size of 425 is required based on the parameters of 7 latent variables and 34 observed variables at a 0.05 probability level. Consequently, the questionnaire was distributed, and 500 valid responses were screened.

3.4 Sampling Technique

The sample was selected using multistage sampling techniques, including judgment, stratified random, and convenient sampling. A judgment sampling technique was employed to select students from four distinct majors at Chengdu Medical College in Sichuan, China. The stratified random sampling method was then used to determine the sample size for each major or sample stratum, as illustrated in Table 1.

The questionnaire was made available online via the questionnaire star website for one month in March-April 2024. The convenience sample was selected in the final stage to reach the intended participants willing to complete the questionnaire. A set of screening questions was used to identify participants with at least one year of experience in mobile learning among undergraduate students. Only those with the requisite experience were included as the target respondents.

Table 1: Sample Units and Sample Size

Selected majors	Number of Students	Proportional Sample Size
Clinical Medicine	1867	324
Medical Imaging	355	62
Anesthesiology	355	62
Pediatrics	300	52
Total	**2877**	**500**

Source: Constructed by author.

4. Results and Discussion

4.1 Demographic Information

Table 2 presents the demographic profile of the total 500 respondents. The respondents comprised 161 females and 339 males, representing 37.2 percent and 62.8 percent, respectively. The respondents were distributed as follows: 40.8 percent were sophomores, 30.6 percent were juniors, and 28.6 percent were seniors.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	161	37.2%
	Female	339	62.8%
Year of Study	Sophomore	204	40.8%
	Junior	153	30.6%
	Senior	143	28.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a statistical technique employed to verify the factor structure of a given set of observed variables (Hair et al., 2010). CFA can measure both variables' reliability and validity (Byrne, 2010). Convergent validity can be statistically measured by Cronbach's Alpha reliability, factor loading, average variance extracted (AVE), and composite reliability (CR) (Fornell & Larcker, 1981; Pallant, 2010).

Factor loading above 0.50 is significant (Hair et al., 1998). As presented in Table 3, the factor loading values of all items in this study were greater than 0.50, with values ranging from

0.723 to 0.838. Composite reliability (CR) was recommended to be at a value of 0.70 or above, while average variance extracted (AVE) was recommended to be greater than or equal to 0.4 (Hair et al., 1998). As shown in Table 3, all estimates were significant, as CR values exceeded 0.7, and AVE values exceeded 0.5.

Cronbach's alpha is a technique used to evaluate the internal consistency of items within a construct (Killingsworth et al., 2016; Taber, 2018). The value of Cronbach's alpha should be at 0.7 or higher to indicate an acceptable level of reliability (George & Mallery, 2003; Hair et al., 2010). As shown in Table 3, all Cronbach's alpha values exceeded the level of 0.8.

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)	(Al-Bashayreh et al., 2022)	6	0.888	0.723-0.780	0.888	0.571
Perceived ease of use (PEOU)	(Al-Bashayreh et al., 2022)	6	0.894	0.734-0.797	0.894	0.585
Perceived enjoyment (PE)	(Al-Rahmi et al., 2021)	5	0.894	0.760-0.838	0.895	0.629
Social influence (SI)	(Efiloğlu Kurt, 2023)	4	0.887	0.801-0.835	0.887	0.662
Attitude (ATT)	(Al-Rahmi et al., 2021)	5	0.884	0.730-0.802	0.884	0.605
Behavioral intention (BI)	(Al-Rahmi et al., 2021)	5	0.885	0.751-0.796	0.885	0.606
Actual use (AU)	(Al-Rahmi et al., 2021)	6	0.898	0.749-0.789	0.898	0.595

The goodness of fit assesses the degree to which the hypothesized measurement model aligns with the observed data. Various fit indices, including CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA, are employed to assess the goodness of fit (Hair et al., 2019). As illustrated in Table 4, the indicators of goodness of fit were found to be greater than the acceptable values and demonstrated the requisite goodness of fit for the measurement model.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	859.203/608 =1.413
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.917
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.904
NFI	≥ 0.80 (Wu & Wang, 2006)	0.923
CFI	≥ 0.80 (Bentler, 1990)	0.976
TLI	≥ 0.80 (Sharma et al., 2005)	0.974
RMSEA	< 0.08 (Pedroso et al., 2016)	0.029
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, CFI = comparative fit index, NFI = normalized fit index, and RMSEA = root mean square error of approximation.

The validity of the discrimination is confirmed when the square root of AVE is greater than the coefficient of any correlated structure (Fornell & Larcker, 1981). As shown in Table 5, the square root of AVE is greater than the inter-construct correlation. Therefore, the discriminant validity is supportive.

Table 5: Discriminant Validity

Variables	PU	PEOU	PE	SI	ATT	BI	AU
PU	**0.756**						
PEOU	0.303	**0.765**					
PE	0.276	0.268	**0.793**				
SI	0.331	0.327	0.344	**0.814**			
ATT	0.322	0.366	0.314	0.381	**0.778**		
BI	0.347	0.365	0.352	0.417	0.413	**0.778**	
AU	0.405	0.392	0.337	0.449	0.404	0.446	**0.771**

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

4.3 Structural Equation Model (SEM)

This study employed a structural equation model (SEM) to analyze the collected data. SEM is a set of statistical techniques for measuring and analyzing the relationships between latent and observed variables (Beran & Violato, 2010). SEM has numerous advantages: Firstly, it was able to explore dependent relationships (Hair et al., 2010) Secondly, SEM examined the causal relationships between latent and observed variables; Thirdly, the introduction of random error in the observed variables enabled the generation of more accurate measurement results; Fourthly, it employed multiple indicators to measure the latent variable; lastly, it could also test hypotheses at the construct level, in addition to the item level (Hair et al., 2010; Wang et al., 2022). The goodness of fit for the structural model was quantified and presented in Table 6. All values of the fit indices were found to be greater than the acceptable values, thereby confirming the model's fitness.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1326.852/623 =2.13
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.859
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.841
NFI	≥ 0.80 (Wu & Wang, 2006)	0.880
CFI	≥ 0.80 (Bentler, 1990)	0.933
TLI	≥ 0.80 (Sharma et al., 2005)	0.928
RMSEA	< 0.08 (Pedroso et al., 2016)	0.048
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, CFI = comparative fit index, NFI = normalized fit index, and RMSEA = root mean square error of approximation.

4.4 Research Hypothesis Testing Result

The degree of the correlation among variables proposed in the hypothesis is quantified by standardized path coefficients of the structural equation model. The research model assesses the significance of the standardized path coefficients based on their t-values and determines the explanatory power of the independent variables on the dependent variable based on R^2. As presented in Table 7, all proposed hypotheses were supported.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU → BI	0.181	3.830*	Supported
H2: PEOU → BI	0.201	4.234*	Supported
H3: PE → BI	0.195	4.125*	Supported
H4: SI → BI	0.254	5.262*	Supported
H5: ATT → BI	0.269	5.569*	Supported
H6: BI → AU	0.496	9.009*	Supported

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

The analysis of H1 indicated that perceived usefulness significantly impacts the behavioral intention of mobile learning, with a standardized path coefficient of 0.181 and a t-value of 3.83. This finding is consistent with the results of Cheng (2014), who found that perceived usefulness is important in affecting learners' intention to use mobile learning. Furthermore, the result of H2 indicated that perceived ease of use affects the behavioral intention of mobile learning with a standardized path coefficient of 0.201 and a t value of 4.234. This corroborates the findings of Alshurideh et al. (2023), which demonstrated that perceived ease of use significantly influences university students' intention to utilize mobile learning systems. The result of H3 indicated that perceived enjoyment also affects the behavioral intention of mobile learning, with a standardized path coefficient of 0.195 and a t value of 4.125. This is consistent with the findings of a previous study, which demonstrated that the behavioral intention of university students to use mobile learning was significantly influenced by perceived enjoyment (Efiloğlu Kurt, 2023). The results of the H4 indicated that social influence had a significant effect on the behavioral intention of mobile learning, with a standardized path coefficient of 0.254 and a t-value of 5.262. This finding is consistent with previous studies that have demonstrated the significant influence of social influence on behavioral intention to use mobile learning (Fatmasari et al., 2018; Wang et al., 2009). The result of H5 indicated that attitude significantly affects the behavioral intention of mobile learning, with a standardized path coefficient of 0.269 and a t value of 5.569. Similar findings have been observed in previous studies, demonstrating that attitude was the most important predictor of intention to use mobile learning (Alhumaid et al., 2021). The result of H6 indicated that behavioral intention significantly affects the actual use of mobile learning, with a standardized path coefficient of 0.496 and a t value of 9.009. This finding is consistent with previous studies that have indicated that the actual use of mobile learning is largely determined by university students' intention to use it (Alhumaid et al., 2021).

5. Conclusion and Recommendation

5.1 Conclusion

This study aimed to examine the factors that influence the Behavioral intention and actual usage of mobile learning among Chinese medical students. A conceptual model was constructed using seven variables: perceived usefulness, ease of use, enjoyment, social influence, attitude, behavioral intention, and actual use. This model proposes six hypotheses regarding the relationships between the variables. Subsequently, the questionnaire was distributed online to undergraduate students with more than one year of mobile learning experience at Chengdu Medical College University in Sichuan, China. The data was analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM) to assess the validity and reliability of the conceptual model and to analyze the proposed relationships among the hypotheses.

The results of this study support all six hypotheses proposed. Firstly, behavioral intention significantly directly impacts actual use, indicating that their behavioral intention largely determines the actual usage of mobile learning by Chinese medical students. Secondly, attitude has the greatest direct effect on behavioral intention, suggesting that if Chinese medical students experience positive feelings toward mobile learning, they are more likely to develop a strong intention to adopt it. Thirdly, social influence has a significant direct effect on behavioral intention. This suggests that if Chinese medical students perceived that important others believed they should use the new system, there was a strong likelihood that they would form a robust behavioral intention to adopt it. Fourthly, perceived enjoyment has a significant direct effect on behavioral intention, suggesting that when Chinese medical students perceive mobile learning as enjoyable, they tend to develop a firm intention to use it. Fifthly, perceived ease of use has a significant direct effect on behavioral intention, suggesting that when Chinese medical students believed using mobile learning would be free of effort, they might form a strong behavioral intention to use it. Sixthly, perceived usefulness has a significant direct effect on behavioral intention, suggesting that when mobile learning was perceived to be useful, Chinese medical students might form a strong behavioral intention to use it.

In summary, this study found that actual usage of mobile learning was strongly impacted by behavioral intention, and the behavioral intention of mobile learning was significantly driven by perceived usefulness, ease of use, enjoyment, social influence, and attitude. Based on TAM, this study introduced new variables. It developed a model to explain the adoption of mobile learning among Chinese medical students and identify the influencing factors that impact their usage of mobile learning.

5.2 Recommendation

This study examined the factors that impact the acceptance of mobile learning by Chinese medical students from their perspective. Hence, it can offer theoretical backing for developing mobile learning applications in medical education and prompt manufacturers and designers to launch products with greater market appeal. Moreover, it can provide recommendations and references for creating medical mobile learning resources and promoting the use of relevant educational resources. Lastly, it can inform faculty and administrators at medical schools about promoting mobile learning.

This study revealed that medical students' actual use of mobile learning is primarily driven by behavioral intention. Consequently, to encourage medical students to use mobile learning, it is recommended that mobile learning app developers, mobile learning resource providers, and medical school educators focus their efforts on the factors that affect behavioral intention. Firstly, this study indicated that students' attitudes are important in determining their intentions to use mobile learning. Consequently, it is important to consider medical students' attitudes towards mobile learning to enhance their positive attitudes. Secondly, the study indicated that social influence significantly affects medical students' intention to use mobile learning. Therefore, medical school administrators should increase the publicity of mobile learning and develop and implement promotional programs to increase the social impact of mobile learning.

Furthermore, university teachers should disseminate information regarding the utilization of mobile learning during lectures or within classroom communication groups. Thirdly, the study provides evidence that perceived ease of use significantly affects behavioral intention.

Consequently, software developers should consider the feedback of university students in software development and curriculum design and develop a humane software platform that conforms to medical students' operating habits. This is also conducive to improving their intention of participating in online education.

Furthermore, it is recommended that medical school administrators enhance the speed and coverage of the campus wireless network to facilitate the intention of mobile learning. Fourthly, it is concluded that perceived enjoyment significantly impacts behavioral intention. It is recommended that mobile application developers optimize the presentation of learning resources, enhance the sense of technology and fashion of the interface to match the aesthetics and interests of contemporary university students, and enhance the sense of the interactive experience of learners. Fifth, perceived usefulness has a significant impact on behavioral intention. Consequently, it is recommended that application developers and university teachers provide and update high-quality courses and learning resources and improve the courses' orientation, objectives, and pedagogical methods. This will contribute to the perceived usefulness of university students.

5.3 Limitation and Further Study

This research has yielded theoretical and practical value and specific results. Nevertheless, it is also evident that the study has certain limitations. Firstly, the population of this study was limited to medical students at Chengdu Medical College in China, and medical students were not included in other regions. Different regions' economic and cultural backgrounds are markedly disparate, which may give rise to divergent research outcomes. Consequently, subsequent studies should include medical students from different regions. Secondly, the study did not consider external variables that might influence the beliefs of medical students towards mobile learning, such as system characteristics, user training, and user participation design (Marangunić & Granić, 2015; Venkatesh & Davis, 1996).

Consequently, future studies should introduce these factors to the conceptual framework model to provide insights for further advancements in predicting medical students' actual usage of mobile learning. Thirdly, this study's use of quantitative data must be revised to provide a clear view of medical students. Consequently, the qualitative method can be proposed to provide a more comprehensive interpretation of the results in future studies.

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