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Uncovering the Key Drivers Behind Undergraduates' Willingness to Embrace Mobile Learning in Sichuan, China

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Abstract

Purpose: The purpose of this research was to explore the effects of perceived ease of use, perceived usefulness, perceived enjoyment, facilitating conditions, social influence, and quality of service on undergraduates' behavioral intention to use mobile learning in Sichuan, China. **Research design, data, and methodology:** The conceptual framework was built to combine the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) theory. A quantitative method with the target population was adopted through distributing questionnaires. After the index of Item-Objective Congruence (IOC), pilot test, Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM), the data of 467 valid responses would be analyzed for testing the research hypotheses proposed. **Results:** The Research results show that the use of mobile learning in higher education and the perceived ease of use significantly influenced perceived usefulness, and both quality of service and perceived usefulness were the main driving factors for undergraduates' behavioral intention. Additionally, perceived enjoyment and facilitating conditions had a certain influence. **Conclusions:** This study's findings supported how higher education institutions urge students to use mobile learning in their life and learning processes. These findings have important implications for prompting the usage of mobile learning in the context of higher education.

Keywords: Mobile Learning, Perceived Enjoyment, Facilitating Conditions, Social Influence, Behavioral Intention to Use

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Since the emergence of mobile learning, its conception has been appropriately modified with adjustments according to development and application scope changes. It emphasized the mobile learning environment, the mobility or portability of learning devices, or a new learning delivery model that enhances the provision of content to students, etc. (Al-Emran et al., 2018; Sharples et al., 2010). Considering the three dimensions of the conceptual evolution of mobile learning: hardware device update and network technical support, learning mobility, and mutual influence in the learning process, there has been more and more research in the educational environment.

In 2000, with mobile learning entering China, many researchers and applications of mobile learning developed rapidly, and the market scale of mobile learning also expanded year by year. There have been various MOOCs (Massive Open Online Courses) for education, such as the national primary and secondary smart education platforms for compulsory education, many mobile learning applications, and various teaching platforms and application software for higher education contexts. It has also been pointed out that the application of mobile learning in education has certain advantages (Gómez-Ramirez et al., 2019; Kukulska-Hulme, 2010). Moreover, with the cost reduction brought by the improvement of supporting conditions from more powerful hardware, technologies, and network environments, it is increasingly welcomed by learners, especially students in colleges and universities (Rui-Ting, 2014).

Nowadays, people, especially young people, have constantly been using mobile devices (Peters, 2007), which made it easier to obtain the target of interaction and positively influence each other, especially for

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undergraduates with more knowledge reserves and learning ability than other learners. Both students and teachers have made gains in the educational environment because of mobile learning (Abachi & Muhammad, 2014; Sarrab et al., 2012). Students can easily access the knowledge they need through advanced mobile devices, and especially for higher education, the students use their personal or university-provided mobile devices as a supportive educational tool (Park et al., 2012).

In recent years, mobile learning has gained significant traction in China's educational environment, particularly in higher education. This trend has sparked a growing interest in the behavioral intention of undergraduate students to use mobile learning, positioning it as a key area of research (Shorfuzzaman & Alhussein, 2016).

2. Literature Review

2.1 Perceived Ease of Use

The PEoU construct was first proposed in the Technology Acceptance Model (TAM) (Davis, 1989) And has been defined as the degree of expected ease when people want to use a technology, namely to an effort expectancy in Acceptance and Use of Technology (UTAUT) model (Hu & Lai, 2019; Venkatesh et al., 2003). Deriving from those theories, the follow-up studies defined it as the degree to which students believed it was easy to obtain and interact flexibly and effortlessly while operating mobile learning (Qashou, 2021). Confining the higher education environment and the technology of mobile learning, Park et al. (2012) defined this construct as the extent to which a university student's degree of belief that using mobile learning can boost personal learning.

Building on the foundational constructs proposed by Davis (1989), the PEoU in universities has been suggested to indirectly influence an individual's acceptance of mobile learning technology through PU (Almaiah et al., 2023). This indirect influence, which has been substantiated in Studie underscores the significant role of PEoU in shaping PU and, consequently, the acceptance of mobile learning technology (Park et al., 2012; Qashou, 2021).

H1: Perceived ease of use has a significant impact on perceived usefulness.

2.2 Perceived Usefulness

Davis (1989) first proposed Perceived Usefulness in the Technology Acceptance Model (TAM) and pointed out that perceived usefulness can effectively reflect the adoption of technology (Davis et al., 1992); it was similar to the performance expectancy construct in the proposal or applications of Unified Theory of Acceptance and Use of Technology (UTAUT) (Al-Rahmi et al., 2022; Venkatesh et al., 2003). Deriving from those theories, in the follow-up studies, this construct was defined as a helpful degree of belief that an individual could obtain from using technology while processing work or learning. (Akbar, 2013).

In the higher education environment, perceived usefulness plays a crucial role in the academic performance of students. It is defined in the minds of students as the degree to which their academic or job performance is improved with the use of mobile learning technology (Qashou, 2021). This concept has been shown to have a significant influence on behavior intention (Iqbal & Qureshi, 2012). When applied to education, perceived usefulness has beneficial characteristics for learners (Al-Adwan et al., 2018; Badwelan et al., 2016; Hassan et al., 2015; Shukla, 2021).

H2: Perceived usefulness has a significant impact on behavioral intention to use mobile learning.

2.3 Perceived Enjoyment

Davis et al. (1992) introduced Perceived Enjoyment as an intrinsic motivation into the Technology Acceptance Model (TAM), a concept similar to the addition of hedonic motivation in the UTAUT 2 model (Venkatesh et al., 2012). In the realm of mobile learning, the concept of perceived enjoyment has sparked increasing interest, with a growing number of studies exploring its role in enhancing TAM (Almaiah et al., 2016; Sánchez Prieto et al., 2016; Su & Cheng, 2015). This surge in interest underscores the dynamic nature of our field and the potential for exciting new discoveries.

When citing the definition of perceived enjoyment, it could be for mobile learning technology (Sukı & Sukı, 2011). Moreover, in the higher education environment, it could indicate that undergraduate students believe they can obtain enjoyment during the processing of mobile learning by ignoring the passage of time, which could lead to the continued intention to use this technology (Efiloğlu Kurt, 2023).

H3: Perceived enjoyment has a significant impact on behavioral intention to use mobile learning.

2.4 Facilitating Conditions

In the UTAUT model, facilitating conditions construct was defined as the degree to which a person believes in supporting for use by the offered organizational and technical infrastructures of a system and considered as the objective factors to make observers easy to accomplish tasks in a certain environment (Venkatesh et al., 2003) or as the resources needed to access information and benefit from the services provided easily (Al-Rahmi et al., 2022).

When the technology environment is mobile learning and the users are university undergraduates, facilitating conditions play a significant role. They include the provision of support, such as resources, self-approved necessity, human guidance, and Internet speed assurance, for undergraduate students to use mobile learning effectively (Efiloğlu Kurt, 2023). It's reassuring to note that facilitating conditions are objective factors that make tasks easier to complete in a specific environment, and they have a significant influence on behavior intention (Iqbal & Qureshi, 2012).

H4: Facilitating conditions has a significant impact on behavioral intention to use mobile learning.

2.5 Social Influence

Davis (1989) acknowledged the need to investigate the effect of social influence construct on usage behavior. Moreover, Venkatesh and Davis (2000) pointed out the necessity of researching social influence in TAM2. The widely cited definition of social influence, deriving from the UTAUT model, was an acceptable degree of one perceived information from one's important person think that one should use a new system (Venkatesh et al., 2003), and it is similar to the social norm in the TAM2 (Venkatesh & Davis, 2000).

Social influence influences users' intention to use mobile learning technology (Mohammadi, 2015). Additionally, social influence is regarded as undergraduate students may need to value the opinions of important people or a certain group in the university that influences their behavior to use mobile learning (Efiloğlu Kurt, 2023).

H5: Social influence has a significant impact on behavioral intention to use mobile learning.

2.6 Quality of Service

The QoS construct was defined as users' evaluation of the overall quality of the provided service (Zeithaml, 1988). As far as its definition was concerned, reliability and response, content quality, and security in the usability research field should be included (DeLone & McLean, 1992), depending on users' requirements and how to fulfill them (Hassanzadeh et al., 2012).

For mobile learning in universities, Quality of Service (QoS) is a key concept. It not only meets the application requirements of undergraduate students with individual needs (Almaiah et al., 2016), but also encompasses the importance, accuracy, and convenience of mobile learning for these students. QoS has been proven to significantly influence behavioral intention when it comes to using mobile learning (Abu-Al-Aish & Love, 2013). Moreover, QoS can explain user satisfaction, which in turn influences behavioral intention. Importantly, there is a direct relationship between QoS and use (DeLone & McLean, 1992).

H6: Quality of service has a significant impact on behavioral intention to use mobile learning.

2.7 Behavioral Intention to use

In the TAM model, the behavior intention to use can be defined as the intention to implement a particular behavioral action (Davis, 1989). In higher education, when the technology was mobile learning, studying the factors influencing the definition's acceptance indicated the usage of undergraduates' behavioral intention (Abu-Al-Aish & Love, 2013; Efiloğlu Kurt, 2023). In a published paper, mobile learning technology has been indicated to have a strong link to this construct (Mohammadi, 2015). By investigating the factors that influence users' acceptance and adoption of mobile learning technology, to show the results and the factors and how extent do these factors influence users' behavioral intention to use this technology, mobile learning (Abu-Al-Aish & Love, 2013; Efiloğlu Kurt, 2023; Qashou, 2021), then achieve the purpose of promoting users' actual use by manipulating these factors.

3. Research Methods and Materials

3.1 Research Framework

Referring to the research results of the three theoretical frameworks constructed based on TAM and UTAUT, a research framework including seven constructs was created. The three theoretical frameworks were all under the university environment, and research on mobile learning technology was conducted to explore the factors influencing students' behavioral intentions. Qashou (2021) verified the link between perceived ease of use (PEoU) and perceived usefulness (PU); The effects of perceived enjoyment (PE), facilitating conditions (FC) and social influence (SI) on behavioral intention (BI) of students had been studied (Iqbal & Qureshi, 2012); And Abu-Al-Aish and Love (2013) pointed out that quality of service (QoS) was an important factor affecting the behavioral intention (BI). A researched conceptual framework is shown in Figure 1.

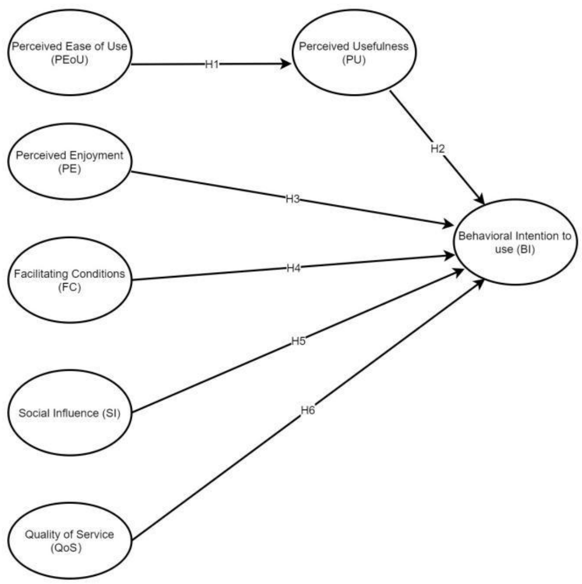

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived usefulness has a significant impact on behavioral intention to use mobile learning.
H3: Perceived enjoyment has a significant impact on behavioral intention to use mobile learning.
H4: Facilitating conditions has a significant impact on behavioral intention to use mobile learning.
H5: Social influence has a significant impact on behavioral intention to use mobile learning.
H6: Quality of service has a significant impact on behavioral intention to use mobile learning.

3.2 Research Methodology

Both probabilistic and non-probabilistic sampling techniques should be used in this research, and the questionnaire survey was completed online and offline. The questionnaire had three parts, including screening questions, demographic information, and factors influencing using mobile learning. Among them, screening questions were used to select qualified survey objects. In contrast, demographic information was used to collect basic information about respondents, such as gender, grade, weekly frequency, and how long they had been using mobile learning. In The last part, questionnaire questions were answered using the five-point Likert scale measuring the extent to which individuals agreed with statements ranging from strongly agree to strongly disagree, which are represented by 5 to 1 respectively.

In this research, three items were deleted to analyze accurate data from the respondents' questionnaires, according to suggestions from three experts with doctorates in IT-related research who provided item objective congruence (IOC) for each scale question. The minimum number for a pilot test was suggested to be 10 percent of the entire study (Saunders et al., 2009); the 50 undergraduate students from designated majors in the target university conducted a pilot test of internal consistency reliability in this research. After carrying out a pilot test, the Cronbach's Alpha score in the results was completed, estimating the internal consistency reliability.

To ensure the validity and reliability of the instrument, the data from 467 effective feedback questionnaires collected were meticulously evaluated by IBM SPSS and AMOS. The research employed confirmatory factor analysis (CFA), which included assessing the factor loading, t-value, composite reliability (CR), and average variance extracted (AVE). The goodness of model fit of SEM was established, and all the hypotheses were rigorously tested by AMOS, leaving no room for doubt about the robustness of the research.

3.3 Population and Sample Size

This research selected a diverse group of undergraduates of random grades majoring in Computer Networks, Software Engineering, and the Internet of Things in the School of Computer Science and Engineering of Sichuan University of Science and Engineering (SUSE) as the population. With the complexity of the research framework also meeting the requirements of the premise, the suggestion from Israel (1992) that a sample size from 200 to 500 should be regarded as a suitable range.

Therefore, the final sample size, comprised of 467 valid data, was found to be from 529 respondents surveyed after the screening questionnaire, filtering step, and quota selection operations.

3.4 Sampling Technique

In the first to third stages, judgment sampling, stratified random sampling, and convenience sampling were used.

The third kind of sampling was carried out, including factors influencing the use of mobile learning by sending online links and paper-based data questionnaires. The first part of the screening questions included the judgments of universities, majors, and those with or without mobile learning experience.

After integrating the received data, 19 erroneous data that did not satisfy screening questions were cleared, and 33 data presented as the most extreme, suggested by Jamovi, were filtered. Thus, 467 valid statistical data met the requirements. The sample units and sizes are given in Table 1.

Table 1: Sample Units and Sample Size

Major	Original Sample Size	Final Sample Size
Software Engineering	227	190
Network Engineering	152	147
Internet of Things Engineering	150	130
Total	**529**	**467**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The second part of the questionnaire was demographic information, with stratified random sampling adopted.

It was carried out, including the gender, grades, majors, and time length and weekly frequency of using mobile learning. The detailed demographic information is shown in Table 2.

Table 2: Demographic Profile

Demographic Information (N=467)		Frequency	Percentage
Gender	Male	333	71.31%
	Female	134	28.69%
Grade	Freshman	8	1.71%
	Sophomore	71	15.20%
	Junior	321	68.74%
	Senior	67	14.35%
Weekly Frequency	1-3 times	188	40.26%
	4-6 times	92	19.70%
	≥ 7 times	187	40.04%
Time Length	2-5 years	224	47.97%
	5-10 years	81	17.34%
	>10 years	162	34.69%

4.2 Confirmatory Factor Analysis (CFA)

Hair et al. (2010) regarded factor loading and acceptance values for all the variables to illustrate the goodness of model fitting, the constituent of scale items, and factor loading counts. Confirmatory factor analysis (CFA) should determine whether matching expectations based on the hypothesis is acceptable; the lowest acceptable value of the coefficient of internal consistency must be 0.7 under the rules of thumb (Dikko, 2016).

According to the scores of Cronbach's Alphas for latent variables in this research, the Perceived Usefulness (PU), Social Influence (SI), Quality of Service (QoS), and Behavioral Intention (BI) were 0.859, 0.822, 0.839, and 0.839 respectively. These values, falling within the range of 0.8 to 0.9, indicate a 'Very Good' association strength evaluation. The remaining variables, Perceived Ease of Use (PEoU), Perceived Enjoyment (PE), and Facilitating Conditions (FC), were 0.789, 0.749, and 0.736, indicating a 'Good' association strength evaluation.

Moreover, all the values of factor loading were more than the threshold of 0.50, the composite reliability (CR) over 0.70, and the average variance extracted (AVE) higher than 0.50 (Sarmento & Costa, 2017).

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)	Qashou (2021)	4	0.859	0.711-0.809	0.861	0.609
Perceived Ease of Use (PEoU)	Qashou (2021)	3	0.789	0.733-0.757	0.793	0.561
Perceived Enjoyment (PE)	Efiloğlu Kurt (2023)	3	0.749	0.667-0.751	0.752	0.503
Facilitating Conditions (FC)	Efiloğlu Kurt (2023)	4	0.736	0.513-0.782	0.750	0.435
Social Influence (SI)	Efiloğlu Kurt (2023)	4	0.822	0.604-0.808	0.774	0.464
Quality of Service (QoS)	Abu-Al-Aish and Love (2013)	4	0.839	0.714-0.83	0.838	0.565
Behavioral Intention to use (BI)	Qashou (2021)	4	0.839	0.664-0.855	0.847	0.584

According to Hair et al. (2006), absolute fit measures indicate how well the whole model fits the observed correlation matrix or covariance. As indicated in Table 4, all the incremental fit evaluations (CFI, NFI, and TLI) requirements and absolute fit indicators (CMIN/DF, GFI, AGFI, and RMSEA) were met. Consequently, every goodness of fit metric used in the CFA evaluation was sufficient.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	529.705/253or 2.094
GFI	≥0.85 (Sica & Ghisi, 2007)	0.918
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.894
NFI	≥0.80 (Wu & Wang, 2006)	0.917
CFI	≥0.80 (Bentler, 1990)	0.954
TLI	≥0.80 (Sharma et al., 2005)	0.946
RMSEA	<0.08 (Pedroso et al., 2016)	0.049
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, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

This research's average extracted variance (AVE) was presented on the diagonal of Table 5, with each value represented respectively by the AVE square root of each corresponding variable. While this value was greater than 0.50, the discriminant validity was ascertained (Bagozzi & Yi, 1988; Hulland, 1999).

Table 5: Discriminant Validity

	PU	PEoU	PE	FC	SI	QoS	BI
PU	0.78						
PEoU	0.599	0.749					
PE	0.299	0.273	0.709				
FC	0.471	0.413	0.238	0.66			
SI	0.449	0.36	0.276	0.438	0.681		
QoS	0.429	0.342	0.294	0.535	0.474	0.752	
BI	0.512	0.536	0.349	0.491	0.419	0.53	0.764

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

4.3 Structural Equation Model (SEM)

After evaluating CFA, the following was to perform a structural equation model (SEM), which was used to explain the causality of research hypotheses by assessing a rigorous combination of linear coefficients. Moreover, SEM not only examined causality between the characteristics of the specified matrix but also accounted for poor evaluations in the coefficient, such as bias or dishonesty (Rattanaburi & Vongurai, 2021). Therefore, as shown in Table 6, the value of the ratio of the chi-square value to degree of freedom (CMIN/DF) was less than 5.00, goodness-of-fit index (GFI) was greater than 0.85, adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), normalized fit index (NFI), and Tucker Lewis index (TLI) were all greater than 0.80, and root mean square errorof approximation (RMSEA) was less than 0.08. Namely, they were all above acceptable limitations that could verify the goodness of fit through adjusting by SPSS AMOS version 26 in this research.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.823
GFI	≥0.85 (Sica & Ghisi, 2007)	0.858
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.821
NFI	≥0.80 (Wu & Wang, 2006)	0.832
CFI	≥0.80 (Bentler, 1990)	0.869
TLI	≥0.80 (Sharma et al., 2005)	0.847
RMSEA	<0.08 (Pedroso et al., 2016)	0.078
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, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

As the measured conclusions of testing results shown in Table 7, there are two constructs that had a significant direct influence on the dependent variable, behavioral intention to use. Perceived usefulness had the highest culminating in a standardized path coefficient, presented by β, which was 0.280, of which the t-value was 5.492***; the other second was quality of service, β was 0.308, and the t-value was 4.061***. Moreover, for this dependent variable, perceived enjoyment had a certain direct influence with β was 0.152 and t-value was 2.921**, And facilitating conditions had the least significant direct influence with β was 0.150 and t-value was 2.085*. In addition, the strongest direct influence on the mediator's perceived usefulness, which the perceived ease of use had with β was 0.719, and the t-value was 11.236***.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.719	11.236***	Supported
H2: PU→BI	0.280	5.492***	Supported
H3: PE→BI	0.152	2.921**	Supported
H4: FC→BI	0.150	2.085*	Supported
H5: SI→BI	0.058	1.047	Not Supported
H6: QOS→BI	0.308	4.061***	Supported

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

The regression weights and R2 variances evaluated could indicate the significance of the relationship between variables in this structural model. Five independent variables, one mediator, and one dependent variable were investigated in this conceptual framework. According to the presentation of results, except H5, the rest of the proposed hypotheses were supported. Among all the measured values, the strongest significant influence was perceived ease of use, which was towards the mediator's perceived usefulness. This mediator variable was the second close-knit predictor of behavioral intention to use, and more significant than the second close rank was the quality of service.

The analysis and diagram of the structural path that could reveal the relationships among the variables are summarized respectively in Table 7 and Figure 2 below:

H1: Based on coefficient value 0.719 for this structural approach that meets the standardized path parameter threshold, H1 verified that independent perceived ease of use is considered a strong determinant for mediator perceived usefulness. That corresponded to the idea when the TAM model proposed that these two constructs should have an influence (Davis, 1989) or was stated as a dominant factor explaining perceived usefulness (Almaiah et al., 2016). Moreover, in the context of mobile learning, this independent variable had a positive influence on this mediator (Chang et al., 2012; Cheng, 2015; Chin & Ahmad, 2015; Huang et al., 2007; Park et al., 2012; Sabah, 2016; Shukla, 2021; Tan et al., 2012; Yadegaridehkordi et al., 2013), especially in the high education text (Agudo-Peregrina et al., 2014; Al-Emran et al., 2018; Althunibat, 2015; Qashou, 2021).

H2: According to the coefficient value of 0.280 in the standardized path, H2 also confirmed that perceived usefulness was the most significant factor directly influencing behavioral intention to use. Perceived usefulness was an important predictor of behavior intention to use technology (Abu-Al-Aish & Love, 2013; Adejo et al., 2018), including mobile learning technology (Han & Shin, 2016; Hu & Lai, 2019; Joo et al., 2016; Teo et al., 2019).

H3: Cause coefficient value 0.152 in another standardized path, the third hypothesis verified perceived enjoyment had a level significant factor influencing behavioral intention to use. Moreover, this observed variable has been pointed to as having a significant influence on users' perceived usefulness (Sukı & Sukı, 2011).

H4: In addition, the coefficient value of 0.150 in the standardized path gave evidence to support that H4-indicated facilitating conditions had the lowest level of significant factor influencing behavioral intention to use. However, this observed variable has been pointed to having a significant influence on users' perceived usefulness (Iqbal & Qureshi, 2012) Or fitted with the view that technical and organizational facilitators could help individuals use technology more conveniently and efficiently (Al-Adwan et al., 2018).

H5: However, the coefficient value of 0.058 indicated that the statistical finding for H5 showed the hypothesis that social influence had almost no influence on the dependent variable. However, it has been indicated as an influence, it has even had a significant influence on the same path (Iqbal & Qureshi, 2012; Mohammadi, 2015).

H6: The coefficient value of 0.308 in the standardized path explained the last hypothesis presented. The observed variable, quality of service, had a significant relationship with the dependent variable, behavioral intention to use. Research has shown that this independent variable could be a significant factor influencing the dependent variable while the technology was mobile learning (Abu-Al-Aish & Love, 2013).

Furthermore, this dependent variable behavior intention to use, with R2 of 0.496, indicated that all the independent variables plus the mediator variable accounted for 49.6% of the variance in the dependent variable. That was to indicate that on behavioral intention to use, with influence effect points 0.308*** and 0.280*** corresponding respectively to quality of service and perceived usefulness that had direct significant influence and with 0.152** and 0.150* respectively to perceived enjoyment and facilitating conditions had different degrees of direct influence. Moreover, perceived ease of use indirectly influenced the dependent variable with influence effect points 0.201***.

Eventually, the mediator variable with an R2 of 0.517 reflected that perceived ease of use attributed 5.17% of the variance to perceived usefulness. Additionally, there was a 0.719*** direct considerable correlation between these two constructs.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study focused on whether to use mobile learning and took undergraduates in Sichuan, China, as the research object; there was an exploration of the influencing degree from factors on behavioral intention had been completed. The constructed conceptual framework included six hypotheses intended to explore the response among seven variables. The questionnaire was randomly distributed online and offline to Chinese undergraduates of four grades majoring in computer-related majors. Four hundred sixty-seven valid questionnaires were sorted out from collected a total of 529 feedback. CFA was used to verify the validity and reliability of the created conceptual framework; then, SEM was used to test the hypotheses of this framework and to explore the influencing effects of the provided observed factors of behavioral intention to use.

The statistical results of the study revealed several key findings. These findings, which are detailed in the following paragraphs, provide valuable insights into the factors influencing undergraduates' behavioral intention to use mobile learning.

For Chinese undergraduates who use mobile learning, the strongest direct effect on one's behavioral intention was the quality of service. This result agrees with the view that quality of service is suggested as a significant factor toward the same object in the same technology (Abu-Al-Aish & Love, 2013). Ozdamli and Cavus (2011) also indicated that carefully preparing each element of mobile learning should urge the effective implementation of mobile learning. Those elements were the implementation measures of quality of service.

The second most significant observed variable is perceived usefulness, which presented an identical positive effect on behavioral intention to use. This direct effect corresponds to a critical factor proved in TAM (Davis, 1989) and UTAUT. Plus, perceived ease of use had the most significant effect, reflected in the direct path of perceived usefulness. Therefore, perceived ease of use is an indirect significant factor influencing behavioral intention to use. This conclusion was also consistent with the viewpoint put forward by Davis (1989) in TAM.

Secondly, for Chinese undergraduates using mobile learning, perceived enjoyment positively influenced one's behavioral intention. This conclusion also echoesed a suggestion with the same mobile learning technology, that perceived enjoyment was a key facilitating behavioral intention (Al-Adwan et al., 2018). Facilitating conditions were an influencing factor of behavioral intention that had been verified, although not as significant as the variables above. It also verified the argument that identifying the quality of services for meeting students' needs in mobile learning could enhance behavioral willingness to use (Almaiah et al., 2016).

However, social influence in this presentation of results showed almost no significance on behavioral intention to use. However, a positive correlation between these two variables has been demonstrated in the context of mobile learning. (Hassan et al., 2015).

5.2 Recommendation

From the point of theoretical recommendations, a created conceptual framework worth studying could be constructed by combining TAM and UTAUT, or even more, their descendant theories. The result explored the factors influencing learners' behavioral intention to use technology. This study confirmed that quality of service and perceived usefulness both positively affected undergraduates' behavioral intention when using mobile learning. And the same target dependent variable, there was an indirect positive effect provided by perceived ease of use. Moreover, in the same technology context and towards one's behavioral intention, the perceived enjoyment construct was found to have a good direct effect, just better than the facilitating conditions construct. However, in this study, under the same background conditions and environmental context, the effect of social influence showed almost no associations. This was in contrast with some research findings based on UTAUT.

The result of this quantitative research provided some practical recommendations for mobile learning in universities.

Firstly, for the students' behavioral intention to use the technology, mobile learning, quality of service was a significant factor, and facilitating conditions were a factor to a certain degree. For this technology, besides the more versatile devices of individuals, the units of universities should improve the following three aspects: Primarily in daily teaching while ensuring students recognize functions, mobile learning platforms, or systems applied in teaching. For example, popular superstar platforms, MOOC resources, or online exercises and examinations of various subjects are now more popular. In addition, ensure the smooth operations of mobile learning over the network on campus, including both wired and wireless environments. At the same time, it creates an active atmosphere of using mobile learning.

Secondly, in view of the fact that perceived usefulness also significantly influences behavioral intention to use, to provide students with necessary guidance, assistance, positive interaction, and more learning resources or assignments, students could use mobile learning to improve their performance or expand their knowledge effectively. In this way, undergraduates' further understanding of the usefulness of mobile learning can be raised.

Thirdly, as intrinsic motivation, perceived enjoyment was pointed to positively influencing behavior intention. Therefore, in daily teaching, the right amount of reward and interaction while using mobile learning should motivate students' hedonic motivation. For example, the points are submitted in the usual assignments in mobile ways, and the teachers answer questions immediately while the undergraduates use mobile learning, etc.

Furthermore, from the aspect of perceived ease of use, software and platforms should be selected with better compatibility for more devices, such as laptops, iPads, mobile phones, or other mobile devices with portability, so that knowledge and learning can be harvested from the usefulness of mobile learning in a more labor-saving way, leading to making it easier and more convenient for students to use mobile learning during.

5.3 Limitation and Further Study

In order to improve the use experience and cultural identity and ensure the volunteers' willingness, this research selected population and sample were limited to three computer science-related majors at one university, and the number of potential variables for exploring in this created conceptual framework was only seven. Therefore, in the subsequent research, more theories or proven relations should be referred to as the basis for constructing the conceptual framework, such as Rational Behavior theory (TRA), Planning Behavior theory (TPB), or more direct correlations between variables. Furthermore, in higher education, due to the development and popularity of mobile learning, which has increased day by day, the object of the questionnaire could be extended to multiple majors of more universities.

References

Abachi, H. R., & Muhammad, G. (2014). The impact of m-learning technology on students and educators. *Computers in Human Behavior, 30*, 491-496. https://doi.org/https://doi.org/10.1016/j.chb.2013.06.018

Abu-Al-Aish, A., & Love, S. (2013). Factors Influencing Students' Acceptance of M-Learning: An Investigation in Higher Education. *International Review of Research in Open and Distributed Learning, 14*(5), 82-107. https://doi.org/https://doi.org/10.19173/irrodl.v14i5.1631

Adejo, O. W., Ewuzie, I., Usoro, A., & Connolly, T. (2018). E-learning to m-learning: Framework for data protection and security in cloud infrastructure. *International Journal of Information Technology and Computer Science, 10*(4), 1-9. https://doi.org/10.5815/ijitcs.2018.04.01

Agudo-Peregrina, Á. F., Hernández-García, Á., & Pascual-Miguel, F. J. (2014). Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning. *Computers in Human Behavior, 34*, 301-314. https://doi.org/https://doi.org/10.1016/j.chb.2013.10.035

Akbar, F. (2013). What affects students' acceptance and use of technology. *Dietrich College of Humanities and Social Sciences, 15*(1), 1-10.

Al-Adwan, A. S., Al-Madadha, A., & Zvirzdinaite, Z. (2018). Modeling students' readiness to adopt mobile learning in higher education: An empirical study. *International Review of Research in Open and Distributed Learning, 19*(1), 221-241. https://doi.org/10.19173/irrodl.v19i1.3256

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education, 125*, 389-412. https://doi.org/https://doi.org/10.1016/j.compedu.2018.06.008

Almaiah, M. A., Al-Otaibi, S., Shishakly, R., Hassan, L., Lutfi, A., Alrawad, M., & Qatawneh, M. (2023). Investigating the role of perceived risk, web perceived security and perceived trust on smart m-banking application using SEM. *Sustainability, 15*(13), 9908. https://doi.org/10.3390/su15139908

Almaiah, M. A., Jalil, M. M. A., & Man, M. (2016). Empirical investigation to explore factors that achieve high quality of mobile learning system based on students' perspectives. *Engineering Science and Technology, an International Journal, 19*(3), 1314-1320. https://doi.org/10.1016/j.jestch.2016.03.004

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 268. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Education and Information Technologies, 27*(6), 7805-7826. https://doi.org/10.1007/s10639-022-10934-8

Althunibat, A. (2015). Determining the factors influencing students' intention to use m-learning in Jordan higher education. *Computers in Human Behavior, 52*, 65-71. https://doi.org/https://doi.org/10.1016/j.chb.2015.05.046

Awang, Z. (2012). *Structural equation modeling using AMOS graphic*. Penerbit Universiti Teknologi MARA.

Badwelan, A., Drew, S., & Bahaddad, A. A. (2016). Towards acceptance m-learning approach in higher education in Saudi Arabia. *International Journal of Business and Management, 11*(8), 12. https://doi.org/10.5539/ijbm.v11n8p12

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science, 16*, 74-94. https://doi.org/10.1177/009207038801600107

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Chang, C.-C., Yan, C.-F., & Tseng, J.-S. (2012). Perceived convenience in an extended technology acceptance model: Mobile technology and English learning for college students. *Australasian Journal of Educational Technology, 28*(5). https://doi.org/10.14742/ajet.818

Cheng, Y.-M. (2015). Towards an understanding of the factors affecting m-learning acceptance: Roles of technological characteristics and compatibility. *Asia Pacific Management Review, 20*(3), 109-119. https://doi.org/https://doi.org/10.1016/j.apmrv.2014.12.011

Chin, L. P., & Ahmad, Z. A. (2015). Perceived enjoyment and Malaysian consumers' intention to use a single platform e-payment. *SHS Web of Conferences, 18*, 01009. https://doi.org/10.1051/shsconf/20151801009

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, a nd user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of applied social psychology, 22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information systems research, 3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60

Dikko, M. (2016). Establishing construct validity and reliability: Pilot testing of a qualitative interview for research in Takaful (Islamic insurance). *The qualitative report, 21*(3), 521-528. https://doi.org/10.46743/2160-3715/2016.2243

Efiloğlu Kurt, Ö. (2023). Learning with smartphones: the acceptance of m-learning in higher education. *Online Information Review, 47*(5), 862-879. https://doi.org/10.1108/OIR-10-2021-0516

Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning Acceptance Among University Students: An Integrated Model of TPB and TAM. *International Review of Research in Open and Distributed Learning, 20*(3). https://doi.org/https://doi.org/10.19173/irrodl.v20i4.4061

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. Multivariate data analysis.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Pearson Prentice Hall.

Han, I., & Shin, W. S. (2016). The use of a mobile learning management system and academic achievement of online students. *Computers & Education, 102*, 79-89. https://doi.org/10.1016/j.compedu.2016.07.003

Hassan, W., Nawaz, M., Syed, T., Arfeen, M., Naseem, A., & Noor, S. (2015). Investigating Students' Behavioral Intention Towards Adoption of Mobile Learning in Higher Education Institutions of Pakistan. *Technical Journal of University of Engineering & Technology Taxila, 20*(3), 1-10.

Hassanzadeh, A., Kanaani, F., & Elahi, S. (2012). A model for measuring e-learning systems success in universities. *Expert Systems with Applications, 39*(12), 10959-10966. https://doi.org/10.1016/j.eswa.2012.03.028

Hu, X., & Lai, C. (2019). Comparing factors that influence learning management systems use on computers and on mobile. *Information and Learning Sciences, 120*(7/8), 468-488. https://doi.org/10.1108/ils-12-2018-0127

Huang, J. H., Lin, Y. R., & Chuang, S. T. (2007). Elucidating user behavior of mobile learning. *The Electronic Library, 25*(5), 585-598. https://doi.org/10.1108/02640470710829569

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal, 20*(2), 195-204. https://doi.org/10.1002/(sici)1097-0266(199902)20:2<195::aid-smj13>3.3.co;2-z

Iqbal, S., & Qureshi, I. A. (2012). M-Learning Adoption: A Perspective from a Developing Country. *International Review of Research in Open and Distributed Learning, 13*(3), 147-164. https://doi.org/10.19173/irrodl.v13i3.1152

Israel, G. D. (1992). *Determining sample size*. University of Florida.

Joo, Y. J., Kim, N., & Kim, N. H. (2016). Factors predicting online university students’ use of a mobile learning management system (m-LMS). *Educational Technology Research and Development, 64*(4), 611-630. https://doi.org/10.1007/s11423-016-9436-7

Kukulska-Hulme, A. (2010). Mobile learning as a catalyst for change. *Open Learning: The Journal of Open, Distance and e-Learning, 25*(3), 181-185. https://doi.org/10.1080/02680513.2010.511945

Mohammadi, H. (2015). Social and individual antecedents of m-learning adoption in Iran. *Computers in Human Behavior, 49*, 191-207. https://doi.org/10.1016/j.chb.2015.03.006

Ozdamli, F., & Cavus, N. (2011). Basic elements and characteristics of mobile learning. *Procedia - Social and Behavioral Sciences, 28*, 937-942. https://doi.org/https://doi.org/10.1016/j.sbspro.2011.11.173

Park, S. Y., Nam, M. W., & Cha, S. B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British journal of educational technology, 43*(4), 592-605. https://doi.org/10.1111/j.1467-8535.2011.01229.x

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry (São Paulo), 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Peters, K. (2007). m-Learning: Positioning educators for a mobile, connected future. *International Review of Research in Open and Distributed Learning, 8*(2). https://doi.org/https://doi.org/10.19173/irrodl.v8i2.350

Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. *Education and Information Technologies, 26*(2), 1755-1785. https://doi.org/10.1007/s10639-020-10323-z

Rattanaburi, K., & Vongurai, R. (2021). Factors influencing actual usage of mobile shopping applications: Generation Y in Thailand. *The Journal of Asian Finance, Economics and Business, 8*(1), 901-913.

Rui-Ting, H. (2014). Exploring the Moderating Role of Self-Management of Learning in Mobile English Learning. *Journal of educational technology & society, 17*(4), 255-267. http://www.jstor.org/stable/jeductechsoci.17.4.255

Sabah, N. M. (2016). Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. Computers in Human Behavior, 65, 522-533. https://doi.org/10.1016/j.chb.2016.09.009

Sánchez Prieto, J. C., Olmos Migueláñez, S., & García-Peñalvo, F. J. (2016). *Las tabletas digitales en educación formal: Características principales y posibilidades pedagógicas*.

Sarmento, R., & Costa, V. (2017). *Comparative approaches to using R and Python for statistical data analysis* (1st ed.). IGI Global. https://doi.org/10.4018/978-1-68318-016-6

Sarrab, M., Elgamel, L., & Aldabbas, H. (2012). Mobile learning (m-learning) and educational environments. *International journal of distributed and parallel systems, 3*(4), 31-38. https://doi.org/10.5121/ijdps.2012.340

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students* (5th ed.). Pearson Education.

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Sharples, M., Taylor, J., & Vavoula, G. (2010). A Theory of Learning for the Mobile Age. In B. Bachmair (Ed.), *Medienbildung in neuen Kulturräumen: Die deutschprachige und britische Diskussion* (pp. 87-99). VS Verlag für Sozialwissenschaften. https://doi.org/10.1007/978-3-531-92133-4_6

Shorfuzzaman, M., & Alhussein, M. (2016). Modeling learners’ readiness to adopt mobile learning: A perspective from a GCC higher education institution. *Mobile Information Systems, 2016*(1), 1-10. https://doi.org/10.1155/2016/6982824

Shukla, S. (2021). M-learning adoption of management students’: A case of India. *Education and Information Technologies, 26*(1), 279-310. https://doi.org/10.1007/s10639-020-10271-8

Sica, C., & Ghisi, M. (2007). *The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power*. Leading-Edge Psychological Tests and Testing Research.

Su, C. H., & Cheng, C. H. (2015). A mobile gamification learning system for improving the learning motivation and achievements. *Journal of Computer Assisted Learning, 31*(3), 268-286. https://doi.org/10.1111/jcal.12088

Sukı, N. M., & Sukı, N. M. (2011, September). Users’ Behavior Towards Ubiquitous M-Learning. *Turkish Online Journal of Distance Education, 12*(3), 118-129.

Tan, G. W.-H., Ooi, K.-B., Sim, J.-J., & Phusavat, K. (2012). Determinants of Mobile Learning Adoption: An Empirical Analysis. *Journal of Computer Information Systems, 52*(3), 82-91.

Teo, T., Zhou, M., Fan, A. C. W., & Huang, F. (2019). Factors that influence university students' intention to use Moodle: a study in Macau. *Educational Technology Research and Development, 67*(3), 749-766. https://doi.org/10.1007/s11423-019-09650-x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-428. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Wu, J.-H., & Wang, Y.-M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yadegaridehkordi, E., Iahad, N. A., & Baloch, H. Z. (2013). Success factors influencing the adoption of M-learning. *International Journal of Continuing Engineering Education and Life Long Learning, 23*(2), 167-178. https://doi.org/10.1504/ijceell.2013.054290

Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing, 52*(3), 2-22. https://doi.org/10.1177/002224298805200302