pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 - 868x © 2021 AU-GSB e-Journal.
https://assumptionjournal.au.edu/index.php/AU-GSB

Determining Factors of Behavioral Intention to Use Mobile Learning Among Information Engineering Students in Higher Vocational Colleges in Chengdu, China

Deng Haiying*

Received: August 9, 2024. Revised: September 16, 2024. Accepted: February 22, 2025.

Abstract

Purpose: This research aimed to study performance expectancy (PE), effort expectancy (EE), trust (TR), attitude towards behavior (ATB), intrinsic motivation (IM) and mobile-learning self-efficacy (MLSE) with the influence of behavioral intention (BI) on one dependent variable, and significant differences between variables before and after IDI were verified. **Research design, data, and methodology:** The statistical tool performed the initial Item Objective Congruence (IOC) test and Cronbach's Alpha preliminary experimental measurement. Multiple linear equation regression (MLR) was used to analyze the influencing factors of mobile learning behavior intention of a higher vocational college student in Chengdu, and the influence results of independent and dependent variables were verified. The Intervention Design Implementation (IDI) was then conducted for 14 weeks with 30 selected students. Finally, the quantitative results of Pre-IDI and Post-IDI were compared by paired sample T-test. **Results:** All had significant effects on behavioral intention, while intrinsic motivation had no significant effects on behavioral intention. The comparison results of the paired sample T-test showed that all variables had significant differences in the post-IDI stage and pre-IDI stage. **Conclusion:** This study aims to effectively improve students' behavioral intention using mobile learning in information engineering higher vocational colleges in Chengdu, China, through various intervention measures.

Keywords: Behavioral Intention, Mobile Learning, Intervention Design Implementation

JEL Classification Code: I23, J28, L2

1. Introduction

Being a teacher is a tremendous vocation, as art The 52nd Statistical Report on China's Internet Development released by the China Internet Network Information Center (CNNIC) shows that mobile Internet applications have developed rapidly, and the network has become the mainstream way for Chinese netizens to work and study. Many studies show that in higher education, students are no longer limited to traditional classroom learning but have access to rich learning resources through the Internet and mobile devices (Shan, 2024).

In China's education field, especially in higher vocational colleges, mobile learning is gradually changing the traditional learning mode with its unique portability, real-time and interactive, and has attracted wide attention. Mobile learning provides college students with unprecedented learning experiences and diversified learning resources. However, compared with traditional face-to-face learning, mobile learning has problems, such as difficulty in supervising students and low learning efficiency (Martin & Ertzberger, 2013).

As an important base for training technical talents, studying students' learning behavior intention helps improve the teaching level and help students achieve their learning goals. This study uses a higher vocational college in Chengdu to explore the factors that affect the behavioral intention of higher vocational students in mobile learning. Based on the actual situation of Chinese college students, this study constructs and verifies the models and variables that

1* Deng Haiying, Sichuan Post and Telecommunication College, China. Email: 19831709@qq.com

affect students' behavioral intention in the mobile learning environment, including intrinsic motivation, mobile learning self-efficacy, performance expectation, effort expectation, attitude towards behavior, trust, and behavioral intention. The model is developed by combining different research theories and previous literature, aiming to provide a reference for relevant research and promote the construction of a learning society.

2. Literature Review

2.1 Behavioral Intention

Behavioral intention refers to an individual's expectation to carry out a certain behavior in a certain situation (Conner & Armitage, 1998), and it represents an individual's purposeful action strategy rooted in their attitude and perceived social pressure (Sheeran & Webb, 2016). Chang et al. (2016) believes that in the context of mobile learning, students' behavioral intention pays more attention to the degree of use of mobile technology. Hamidi and Chavoshi (2018) studied the implementation of mobile learning in higher education. Buabeng-Andoh (2018) predicted the tendency of college students to adopt mobile learning in the educational environment and (Huang et al., 2021) further confirmed this prediction tendency. Prieto et al. (2015) research confirms that students' attitude towards mobile learning is generally positive. Students' active learning behavior significantly impacts their behavioral willingness to participate in mobile courses. The more actively students participate in learning, the more likely they are to continue participating and achieve good learning results (Abdullah et al., 2022).

2.2 Performance Expectancy

Venkatesh et al. (2003) defined PE as an individual's belief that technology can improve their work performance when completing a certain activity. Alowayr (2022) believes technology can help a person achieve effective job expectations. In the context of mobile learning, performance expectation refers to students' belief that using mobile learning can improve their academic performance and overall performance (Wang et al., 2009). Research by (Reyes Mercado et al., 2023) shows that the use of mobile and e-learning systems positively impacts the expected performance of undergraduate and graduate students. Personal learning styles and perceived pleasure also influence the use of mobile learning in all learning contexts (Karimi, 2016). Students' behavioral intention to use technology in the classroom is strongly influenced by their performance expectations (Šumak & Šorgo, 2016). The study of (Kang et al., 2015) and (Ahmed et al., 2023) further confirmed the important role of performance expectation in influencing behavioral intention. Performance expectation significantly impacts college students' behavioral willingness to use mobile learning (Kang et al., 2015).

Therefore, based on these studies, the author proposes the following hypothesis:
H1: Performance expectancy has a significant impact on behavioral intention to use mobile learning.

2.3 Effort Expectancy

EE is defined as the degree of ease or simplicity users feel when using a particular system or application (Venkatesh et al., 2003). Users who try to complete a job expect to achieve the learning outcome with only a small effort (Sang et al., 2023). This is also related to the ease of using the learning system (Taamneh et al., 2023), and (Srikanth, 2018) found that striving for anticipation has a positive impact on young students' use of mobile learning systems and is strongly correlated with their willingness to use them (Fianu et al., 2020). EE plays a prominent role in both voluntary and involuntary situations, but with continuous use, its importance will gradually diminish (Venkatesh, 2000). Venkatesh et al. (2016) found that when users think that the less effort required to use a certain technology, the more willing they are to use it. If the platform can reduce the learning cost and operational difficulty for users, users will be more likely to continue using the platform. Lowenthal (2010) and Rofiah and Suhermin (2022) explored the factors influencing students' behavioral willingness to use mobile learning technologies and found a statistically significant relationship between expected effort and intention to use mobile learning strategies. Prasetya and Harnadi (2019) study the use of smartphones in learning, arguing that there is a significant correlation between the expectation of effort and the tendency to engage in certain behaviors.

Based on the survey, the author proposes the following hypothesis:
H2: Effort expectancy has a significant impact on behavioral intention to use mobile learning.

2.4 Trust

Trust in mobile learning refers to students' confidence and dependence on the mobile learning environment (Noh et al., 2021). Aljazzaf et al. (2010) define the core of trust as the degree of matching the trusting party's expectation and the trusted object's reliability. Edwards et al. (2018) further defined trust as students' respect and guarantee for the security of personal privacy data, which is crucial in the mobile learning environment, and (Booth, 2012) believed that trust relationship is one of the important motivations for users to participate in activities. From the technical perspective of mobile learning, Almaiah et al. (2020) outlined the intention of users to use mobile phones as learning tools. He et al. (2020) studied network trust from the technical level, believing that trust formed through social relationships can encourage users to share resources. McKnight et al. (1998) proposed that trust plays a key role in shaping an individual's willingness to engage in activities in a new relationship, and (Riegelsberger et al., 2005) introduced a framework outlining the mechanisms of trust. Wang and Emurian (2005) conducted an in-depth discussion on the concept and elements of trust in the network environment, which enriched the understanding of how trust affects individuals' behavioral intentions when they participate in network activities. Chao (2019) showed that empirical research significantly correlates behavioral intention with trust.

Given the above research, the author proposes the following hypothesis:
H3: Trust has a significant impact on behavioral intention to use mobile learning.

2.5 Attitude Towards Behavior

According to research (Bohner & Dickel, 2011), attitude is a long-term framework. Wicker (1969) definition of attitude emphasizes the relationship between attitude and behavior, and it is generally believed that attitude directly affects behavior. Venkatesh et al. (2003) defined the behavioral attitude in mobile learning as the learner's tendency to accept and use mobile technology for education. Zhang et al. (2004) argued that behavioral attitude in mobile learning refers to learners' thoughts, emotions, and intentions regarding using mobile technology to improve their learning experience. Suner et al. (2019)pointed out that undergraduates hold a positive and optimistic attitude toward mobile learning. Koole and Parchoma (2013) and Liaw & Huang, 2013) believe that behavioral attitudes in mobile learning cover learners' perceptions, values, and assessments of the impact of mobile technology on their learning outcomes and academic performance. Kumar et al. (2020) found that mobile learning attitude significantly impacts behavioral intention. Anditiarina et al. (2021) show that learning attitude directly impacts online learning behavior. Liaw et al. (2007) show that behavioral attitudes positively correlate with learners' tendency to use mobile learning.

Based on the above investigations, the author proposes the following hypotheses:
H4: Attitude towards behavior has a significant impact on behavioral intention to use mobile learning.

2.6 Intrinsic Motivation

Deci and Ryan (2008) define intrinsic motivation as an underlying drive or desire that is interesting or enjoyable rather than for external rewards or pressure (Reeve, 2012). Hidi and Renninger (2006) proposed that intrinsic motivation refers to the inner driving force generated by the satisfaction and happiness brought by the activity when an individual engages in an activity or task. According to(Sharples, 2013), the intrinsic motivation of mobile learning refers to students' intrinsic motivation and enthusiasm for learning. Kim (2015) proposed that intrinsic motivation is the intrinsic desire and pleasure students experience when learning activities through mobile devices. Giunchiglia et al. (2018) highlighted the intrinsic interest and enjoyment of learning through mobile devices. Sun and Gao (2020) explored the relationship between intrinsic motivation and technology adoption, paid attention to the impact of intrinsic motivation on students' behavioral intention, and found a significant positive correlation between intrinsic motivation and technology adoption and behavioral intention. Senaratne and Samarasinghe (2019) argue that intrinsic motivation substantially impacts the desire to use mobile learning. Research by (Nikou & Economides, 2016) found that more interactive and personalized learning can improve learning motivation using mobile devices. Tri Minh Cao (2022) shows that intrinsic motivation is an important factor affecting the behavioral willingness of smartphones in mobile learning.

Therefore, the author proposes the following hypothesis:
H5: Intrinsic motivation has a significant impact on behavioral intention to use mobile learning.

2.7 Mobile-Learning Self-Efficacy

According to research Alqurashi (2016), MLSE is defined as the learner's ability and confidence to effectively utilize mobile applications and digital resources in a mobile learning environment. Menekse et al. (2018) pointed out that mobile self-efficacy plays an important role in learners' success in mobile learning. Wang et al. (2023) also emphasize the importance of learners' confidence in their ability to achieve mobile learning goals. Hidayah (2020) confirmed that students' self-efficacy significantly impacts mobile learning, and (Dahri et al., 2023) supported this conclusion. The theoretical framework (Senaratne & Samarasinghe, 2019) shows that mobile self-efficacy significantly impacts higher education students' tendency to accept mobile learning. Therefore, improving learners' sense of self-efficacy can significantly improve their willingness to use mobile learning. The (Kumar et al., 2020) and (Chao, 2019) research also support this view.

Based on the above research, the author proposes the following hypothesis:
H6: Mobile-learning self-efficacy has a significant impact on behavioral intention to use mobile learning.

3. Research Methods and Materials

3.1 Research Framework

Using three key theories: Learning style theory (LST), Technology Acceptance Model (TAM) and Unified Theory of Technology Acceptance and Use (UTAUT), Four basic theoretical frameworks (Marikyan & Papagiannidis, 2021),(Chao, 2019),(Afandi, 2022)and (Alowayr, 2022)are combined to support and improve the conceptual framework, as shown in Figure 1.

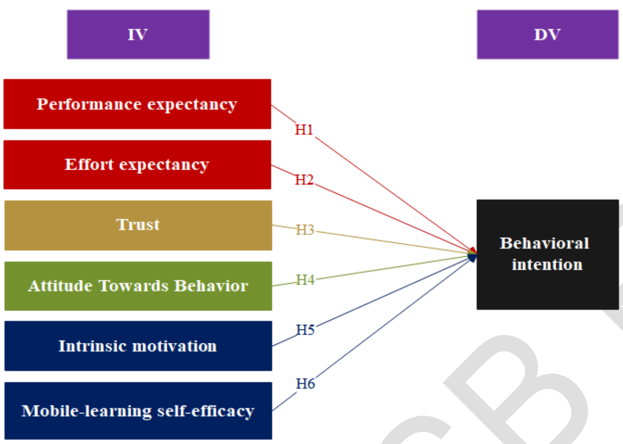

Figure 1: Conceptual Framework

H1: Performance expectancy has a significant impact on behavioral intention to use mobile learning.
H2: Effort expectancy has a significant impact on behavioral intention to use mobile learning.
H3: Trust has a significant impact on behavioral intention to use mobile learning.
H4: Attitude towards behavior has a significant impact on behavioral intention to use mobile learning.
H5: Intrinsic motivation has a significant impact on behavioral intention to use mobile learning.
H6: Mobile-learning self-efficacy has a significant impact on behavioral intention to use mobile learning.

3.2 Research Methodology

This research is mainly divided into three stages: the first stage is pre-IDI, the second stage is IDI, and the third stage is post-IDI. A method of combining qualitative and quantitative research is adopted.

The first stage focuses on the diagnosis of the current situation. In the qualitative research part, the author conducted a SWOT analysis and interviewed 15 students to collect data. In the quantitative part, the author applied the project-goal consistency (IOC) technique to confirm the validity of the questionnaire designed in this study. The second step is to conduct a small-scale pilot study of 30 valid questionnaires to verify the reliability of the questionnaire design. In the third step, the whole study population (N=439) was investigated, and a strict MLR was conducted to test the hypothesis, and the significance of P value <0.05 was determined. Supported hypotheses were retained, and unsupported hypotheses were eliminated. In the fourth step, the author selected 30 information engineering students as intervention objects collected data, and built the final intervention design and implementation model.

The second stage involved a series of interventions over 14 weeks for a selected group of 30 students.

In the third stage, 30 students were surveyed by questionnaire, and 15 were interviewed. Relevant data were collected, and the paired sample T-test was used to verify whether there were significant differences in intervention variables, such as pre-IDI and post-IDI.

3.3 Research Population, Sample Size, and Sampling Procedures

3.3.1 Research Population

The author conducted a preliminary investigation of the School of Information Engineering (SIE) of Sichuan Post and Telecommunications College (SPTC). According to the data of 2022, SIE has a total of 6 information engineering majors. The author chooses 3 of them as the research object, which is as follows: Computer network technology, there are 611 students; Digital media application technology, there are 366 students; information security and management, there are 259 students, a total of 1236 students in these three majors, a total of 490 students submitted questionnaires, after the author checked, there are 439 valid questionnaires.

3.3.2 Sample size

In the initial diagnostic stage, the author interviewed 15 selected samples and conducted pilot tests on 30 random samples to verify reliability. Then, 490 students were given questionnaires, and 439 valid questionnaire data were tested by multiple linear regression to determine the relationship between independent and dependent variables. Finally, 30 students are selected as participants in the implementation of IDI. These 30 students use the same research method in the post-IDI and pre-IDI stages, and the differences before and after IDI are tested by paired sample T. The same 15 students previously selected will also be interviewed again.

3.3.3 Sampling Procedures

The researchers will use the convenient sampling method in the non-probability sampling method and the stratified sampling method in the probability sampling method. Among the 340 people surveyed, 30 will be selected at the undergraduate level, 60 will be selected at the language training level, and a total of 90 people will be sampled.

The judgment sampling method is adopted when making the strategic plan. According to the results of the questionnaire survey, representative samples are purposefully selected, and in-depth interviews are conducted to provide a reference for the strategic plan.

Researchers will collect student information through offline questionnaires, online Wenjuanxing apps, and social software.

This study adopts multi-stage, probability, and non-probability sampling for quantitative analysis.

Step 1: Sample with purpose. The non-probability sampling method is called objective sampling. The author selected 3 out of the six majors in the SIE of SPTC because they are the backbone of Information Engineering Technology (IET) majors.

Step 2: Stratified random sampling. Stratified random sampling was used to determine the appropriate sample size for each major, and finally, 439 valid responses were confirmed. Multiple linear regression analysis was carried out on the questionnaire data, and the analysis results are valuable for formulating the final research strategy.

Step 3: Easy sampling. A non-probabilistic sampling method, i.e., purpose-based and convenient sampling, was adopted to ensure respondents were willing to answer the questionnaire. Thirty students majoring in digital media application technology were selected as participants to voluntarily register and fill out the questionnaire twice, once pre-IDI. Once post-IDI, the effect of IDI was evaluated through quantitative data analysis.

3.4. Research Instruments

3.4.1 Design of Questionnaire

The author adopts the following method to design the questionnaire, which consists of three steps.

Step 1: The questionnaire for this study was determined from the questionnaires provided in the published articles of the three investigators (Alowayr, 2022), (Chao, 2019) and (Afandi, 2022).

Step 2: Translate the questionnaire professionally into a context suitable for Chinese vocational college students and appropriately adjust and present it.

Step 3: The IOC technique was applied to confirm the validity of the questionnaire designed in this study.

3.4.2 Components of Questionnaire

The questionnaire consists of three parts.

Part I: Contains three screening questions designed to determine that the respondent meets the study requirements.

Part II: Demographic information of the respondents, including gender, age, and other information.

Part III: Investigate the factors that affect behavioral intention, with 27 questions, to identify the variables that affect students' propensity to use mobile learning.

3.4.3 IOC Results

Three experts were invited to implement IOC. All three experts are from China; all of them have doctoral degrees, are professional vocational education teachers, have rich experience in vocational education teaching, and use mobile teaching platforms. +1 means Congruent, 0 means Questionable, and -1 means Incongruent. All 27 items evaluated by IOC scored higher than 0.67 and were passed. No items were discarded. Therefore, the author retained all questionnaire items.

3.4.4 Pilot survey and Pilot test results

After IOC processing, the author sent the questionnaire to 30 respondents for a reliability test. All items passed the Jamovi tool test. All items in this questionnaire passed the reliability test (Clark & Watson, 2016), and scores of 0.6 or above were obtained (Nunnally, 1994). Table 1 shows the test results of each variable.

Table 1: Pilot Test Result

Variable	Reference	Cronbach's Alpha (α)	Strength of Association
Behavioral intention (BI)	Alowayr (2022)	0.870	Good
Performance expectancy (PE)	Alowayr (2022)	0.982	Excellent
Effort expectancy (EE)	Alowayr (2022)	0.943	Excellent
Trust (TR)	Chao (2019)	0.961	Excellent
Attitude Towards Behavior (ATB)	Afandi (2022)	0.960	Excellent
Intrinsic motivation (IM)	Alowayr (2022)	0.965	Excellent
Mobile-learning self-efficacy (MLSE)	Alowayr (2022)	0.945	Excellent

4. Results and Discussion

4.1 Results

4.1.1 Demographic Profile

The author analyzed the demographic characteristics of the study population (n=439) and then analyzed the students majoring in digital media application technolog y who participated in IDI (n=30). The results are show n in Table 2 and Table 3.

Table 2: Demographic Profile

Entire Research Population (n=439)		Frequency	Percent
Gender	Male	210	47.84%
	Female	229	52.16%
Age	18-19 years old	105	23.92%
	20-21 years old	321	73.12%
	22-24 years old	12	2.73%
	Over 24 years old	1	0.23%
Major	Computer network technology	217	49.43%
	Digital media application technology	130	29.61%
	Information security and management	92	20.96%
Total		**439**	**100%**
Strategic Plan Participants (n=30)		**Frequency**	**Percent**
Gender	Male	17	56.67%
	Female	13	43.33%
Age	18-19 years old	2	6.67%
	20-21 years old	25	83.33%
	22-24 years old	3	10.00%
	Over 24 years old	0	0.00%
Total		**30**	**100%**

4.1.2 Results of multiple linear regression

The author performed multiple linear regression (MLR) on the results of 439 questionnaires to test whether each hypothesis was supported. The value of the independent variable's volatility index function (VIF) is between 1.54 and 4.0, lower than 5.00, so there is no problem with multicollinearity (Ringle et al., 2015). After multiple linear regression analyses of the six hypotheses proposed at the diagnostic stage, the results showed that the six predictors explained 69.0% of the variance of behavioral intent (R2=0.690, F (6,432) =160, p<.001). Table 4, Table 5and Table 6 show the MLR results.

Table 3: The multiple linear regression of five independent variables on behavioral intention

Variables	Standardized Coefficient Beta	T-value	P-value	R	R^2
Performance expectancy (PE)	0.0455	11.559**	< .001	0.831	0.69
Effort expectancy (EE)	0.0313	-2.952*	0.003		
Trust (TR)	0.0561	-3.399**	< .001		
Attitude Towards Behavior (ATB)	0.0677	2.411*	0.016		
Intrinsic motivation (IM)	0.0578	0.432	0.666		
Mobile-learning self-efficacy (MLSE)	0.0485	8.421**	< .001		
Dependent variable: Student satisfaction					

Note: p-value <0.05*, p-value <0.001**

The MLR results support five hypotheses: H1, H2, H3, H4, and H6. However, H5 is not supported (note: p-value <=0.05, supporting hypothesis), PE, EE, TR, ATB, and MLSE have a significant impact on BI, and IM has no significant impact on BI. Therefore, the author deleted the independent variable IM and made relevant adjustments. Based on the result analysis of MLR, a new hypothesis was developed, which will be analyzed by the following assumptions in IDI:

H7: There is a significant mean difference in PE between the pre-IDI and post-IDI phases.

H8: There are significant mean differences in EE between the pre-IDI and post-IDI phases.

H9: There is a significant mean difference in TR between the pre-IDI and post-IDI phases.

H10: ATB has significant mean differences between the pre-IDI and post-IDI phases.

H11: There are significant mean differences in MLSE between the pre-and post-IDI phases.

H12: There are significant mean differences in BI between the pre-IDI and post-IDI phases.

4.2 IDI Intervention Stage

The detailed design of the IDI stage lasted for 14 weeks, and the overall goal of the intervention implementation was to improve the behavioral intention of higher vocational students using mobile learning. Therefore, this study conducted the intervention design from the procedural perspective of task-driven teaching mode. The author designed the model according to the intervention stage by collecting quantitative and qualitative data for analysis, as shown in Figure 2.

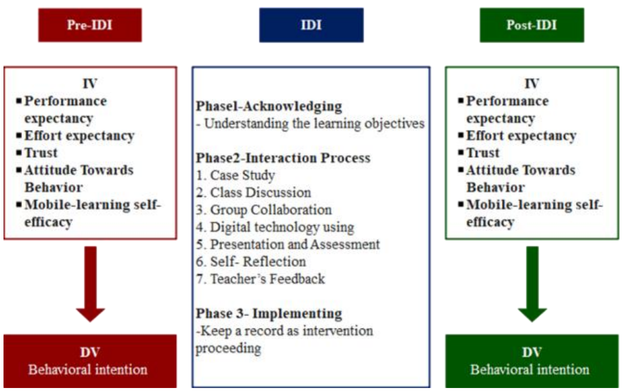

Figure2: IDI Activities

4.3 Results Comparison between Pre-IDI and Post-IDI

The author conducted a paired sample T-test analysis for all six variables to detect whether the intervention was effective to determine whether there were differences in the behavioral intentions of students in the pre-IDI and post-IDI stages regarding the use of mobile learning. Table 7 shows the paired sample T-test analysis of 6 variables as follows:

Table 5: Paired-Sample T-Test Results

Variables	Mean	SD	SE	t-value	p-value
Performance expectancy					
Pre-Strategic Plan	3.53	0.798	0.1457	-2.80	0.009
Post-Strategic Plan	4.19	0.700	0.1278		
Effort expectancy					
Pre-Strategic Plan	3.50	0.701	0.1280	-4.09	<0.001
Post-Strategic Plan	4.28	0.762	0.1390		
Trust					
Pre-Strategic Plan	3.88	0.535	0.0976	-2.95	0.006
Post-Strategic Plan	4.25	0.478	0.0872		
Attitude Towards Behavior					
Pre-Strategic Plan	3.90	0.473	0.0863	-2.13	0.042
Post-Strategic Plan	4.17	0.572	0.1045		
Mobile-learning self-efficacy					
Pre-Strategic Plan	3.42	0.711	0.1297	-2.15	0.040
Post-Strategic Plan	3.96	0.780	0.1424		
Behavioral intention					
Pre-Strategic Plan	3.81	0.730	0.1333	-2.35	0.026
Post-Strategic Plan	4.29	0.602	0.1099		

Table 5 shows the T-test results of paired samples compared to pre- and post-IDI. The test analysis of each variable before and after intervention is as follows:

There was a significant difference between PE Pre-IDI (M=3.53, SD=0.798) and post-IDI (M=4.19, SD=0.700), with T (29) =-2.80, P=0.009 (P<0.05) and a mean difference of -0.658, so H7 is supported.

There was a significant difference in EE between pre-IDI (M=3.50, SD=0.701) and post-IDI (M=4.28, SD=0.762). T (29) =-4.09, P<0.001 (P<0.05), the mean difference is -0.783, therefore, H8 is supported.

There was a significant difference between TR pre-IDI (M=3.88, SD=0.535) and TR post-IDI (M=4.25, SD=0.478). T (29) =-2.95, P=0.006 (P<0.05), the mean difference is -0.367, therefore, H9 is supported.

ATB was significantly different between pre-IDI (M=3.90, SD=0.473) and post-IDI (M=4.17, SD=0.572). T (29) =-2.13, P=0.042 (P<0.05), and the mean difference is -0.267, so H10 is supported.

There were significant differences in MLSE pre-IDI (M=3.42, SD=0.711) and post-IDI (M=3.96, SD=0.780). T (29) =-2.15, P=0.040 (P<0.05), and the mean difference is -0.533, so H11 is supported.

There were significant differences in BI between pre-IDI (M=3.81, SD=0.730) and post-IDI (M=4.29, SD=0.602). T (29) =-2.35, P=0.026 (P<0.05), the mean difference is -0.483, therefore, H12 is supported.

5. Conclusions, Recommendations and Limitations

5.1 Conclusions & Discussions

Individualized intervention is an effective teaching strategy to improve students' behavioral intention to adopt mobile learning (Crompton et al., 2016). Through explicit feedback and guidance, the intervention effect is significant.

Individualized intervention for students can pay attention to the uniqueness of students, provide tailored teaching resources and guidance, and improve their academic performance and learning motivation. The flexible implementation of individualized mobile learning intervention helps improve students' scientific literacy and academic performance. However, this requires a significant investment of resources and the experience and skills of teachers. Teachers must stimulate students' interest, explore innovative teaching methods, and form diversified models to enhance learning intentions.

Group intervention significantly positively affects the mobile learning environment (Chu et al., 2009). Group intervention can enhance students' participation and initiative through group learning and communication and cultivate team cooperation and communication skills. Effective group intervention needs to understand the needs of students, formulate reasonable plans, group reasonably, and encourage students' active participation. Process supervision and guidance must also be strengthened to form a good learning atmosphere. At the same time, this will increase the workload of teachers. Teachers need to have a clear division of labor, pay attention to students' emotions and learning attitudes and have a high level of professional literacy to ensure that the whole intervention process is healthy and effective.

Autonomous learning through mobile devices can improve students' learning enthusiasm and behavioral willingness (Traxler, 2010). The intervention of students' interactive strategies can stimulate their interest in learning, enhance their participation, cultivate their autonomous learning ability and cooperative spirit, and help students establish good learning habits and positive attitudes. Through frequent interaction, teachers can promptly understand the students' situation and provide personalized guidance. Therefore, the design of interactive intervention strategies must consider students' differences, and teachers must possess high-level professional literacy and practical experience. Platform stability and security are also key to developing an effective engagement strategy.

Becker et al. (2018) believe integrating interactive content in the mobile learning environment can positively affect students' learning. Course design intervention can enhance students' interest in and participation in learning. Optimizing course content and integrating mobile learning elements can help stimulate students' independent learning and innovation ability, as well as enhance students' behavioral intention to adopt mobile learning. However, it also requires teachers to constantly update their teaching concepts and skills, adapt to the mobile learning trend, pay attention to students' differences, and needs, and combine offline teaching to improve students' willingness to learn on mobile effectively.

5.2 Recommendations

The results of this study show that it is necessary to take various measures in teaching intervention to improve the behavioral intention of vocational students to use mobile learning, and these intervention measures are effective. However, there are some suggestions for future researchers:

First, it is suggested that the mobile learning needs of vocational college students be fully collected and analyzed. This can not only help researchers develop a series of targeted teaching intervention strategies but also meet the personalized learning needs of vocational college students.

Second, it is suggested that students be provided with a more convenient, efficient, and interesting mobile learning experience by strengthening the platform's development and maintenance and enriching the learning content and form so as to promote their overall development.

Third, it is suggested that by holding lectures, setting up training courses, and establishing mobile learning communities, more students can understand and try to use mobile learning, better master knowledge, and skills in the digital era, and realize the development of personal mobile learning.

Fourth, cultivating students' independent learning abilities and habits is suggested to be strengthened, a long-term and arduous task. To further improve students' mobile learning ability, it is suggested to set independent learning tasks and challenges in teaching, guide students to form good learning habits, and constantly explore and improve training strategies through empirical research.

Fifth, more evidence and data can be used to more convincingly propose targeted teaching intervention strategies.

Sixth, it is suggested to strengthen the training of teachers' information-based teaching ability, which is also very important.

5.3 Limitations for Future Research

There are still some research limitations in this study, which need further research and exploration:

1. Improve measurement tools: Although the mobile learning measurement scale developed by research and development has high reliability and validity, due to the limitations of sample size and the distribution of students' majors, the scale's adaptability needs to be measured in more disciplines and majors in a wider range to further improve its reliability and validity.

2. Optimization of research model: Due to the limitations of samples, the model of influencing factors of mobile learning behavior intention needs to be further improved. Variables such as student behavior, social influence, environmental impact, and other possible influencing factors

need to be analyzed. Follow-up studies need to improve and verify the model further.

3. Strengthen empirical research: In intervention practice research, the analysis based on existing data needs to be more comprehensive, especially since the data on deep learning needs to be more comprehensive. At the same time, implementing intervention strategies puts higher requirements on teachers' digital literacy and data analysis ability, especially in large-scale courses. The follow-up research should focus on the intelligent analysis of mobile learning, use data mining and learning analysis technology to establish intelligent learning intervention mechanisms, and conduct more empirical research in multiple disciplines and professions to obtain more abundant teaching intervention data and cases.

4. Application of promotion results: Only one course, "Photography and Post-Photoshop Technology," was selected for practical and quasi-experimental research to verify the effectiveness of the intervention strategy. Follow-up research will continue to be applied in different professional courses to improve further and optimize the intervention strategy, making it an effective tool to enhance students' behavioral intention in mobile learning.

References

Abdullah, I., Parveen, S., & Haq, S. U. (2022). Forced online experiment and its acceptance among the University students during pandemic in Pakistan. *foresight, 24*(3/4), 392-407. https://doi.org/10.1108/FS-01-2021-0026

Afandi, W. (2022). Saudi higher education student acceptance of mobile learning. *International Journal of Information and Education Technology, 12*(6), 500-506.

Ahmed, S. A. M., Suliman, M. A. E., Al-Qadri, A. H., & Zhang, W. (2023). Exploring the intention to use mobile learning applications among international students for Chinese language learning during the COVID-19 pandemic. *Journal of Applied Research in Higher Education, 16*(4), 1093-1116. https://doi.org/10.1108/JARHE-01-2023-0012

Aljazzaf, Z. M., Perry, M., & Capretz, M. A. M. (2010). *Online Trust: Definition and Principles* (1st ed.). 2010 Fifth International Multi-conference on Computing in the Global Information Technology

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. M. (2020). Analysis the Effect of Different Factors on the Development of Mobile Learning Applications at Different Stages of Usage. *IEEE Access, 8*, 16139-16154. https://doi.org/10.1109/ACCESS.2019.2963333

Alowayr, A. (2022). Determinants of mobile learning adoption: extending the unified theory of acceptance and use of technology (UTAUT). *The International Journal of Information and Learning Technology, 39*(1), 1-12. https://doi.org/10.1108/IJILT-05-2021-0070

Alqurashi, E. (2016). Self-efficacy in online learning environments: A literature review. *Contemporary Issues in Education Research (CIER), 9*(1), 45-52. https://doi.org/https://doi.org/10.19030/cier.v9i1.9549

Anditiarina, D., Duarsa, A. B. S., & Anulus, A. (2021). *Knowledge, Attitude, Gender and Their Association Towards Online Learning Behavior Among Medical Students During Covid-19 Pandemic* (1st ed.). International Conference on Medical Education (ICME 2021)

Becker, S. A., Brown, M., Dahlstrom, E., Davis, A., DePaul, K., Diaz, V., & Pomerantz, J. (2018). *NMC horizon report: 2018 higher education edition.* Educause.

Bohner, G., & Dickel, N. (2011). Attitudes and Attitude Change. *Annual review of psychology, 62*(1), 391-417. https://doi.org/10.1146/annurev.psych.121208.131609

Booth, S. E. (2012). Cultivating Knowledge Sharing and Trust in Online Communities for Educators. *Journal of Educational Computing Research, 47*(1), 1-31. https://doi.org/10.2190/EC.47.1.a

Buabeng-Andoh, C. (2018). Predicting students’ intention to adopt mobile learning. *Journal of Research in Innovative Teaching & Learning, 11*(2), 178-191. https://doi.org/10.1108/JRIT-03-2017-0004

Chang, C. Y., Tseng, K. H., Lou, S. J., & Chen, W. H. (2016). Exploring behavioral intention of using mobile learning. *Journal of Educational Technology & Society, 19*(3), 84-96.

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model [Original research]. *Frontiers in Psychology, 10*, 1652. https://doi.org/10.3389/fpsyg.2019.01652

Chu, H.-C., Hwang, G.-J., Tsai, C.-C., & Chen, N.-S. (2009). An innovative approach for promoting information exchanges and sharing in a Web 2.0-based learning environment. *Interactive Learning Environments, 17*(4), 311-323. https://doi.org/10.1080/10494820903195173

Clark, L. A., & Watson, D. (2016). *Constructing validity: Basic issues in objective scale development.* American Psychological Association. https://doi.org/10.1037/14805-012

Conner, M., & Armitage, C. J. (1998). Extending the Theory of Planned Behavior: A Review and Avenues for Further Research. *Journal of Applied Social Psychology, 28*(15), 1429-1464. https://doi.org/https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Crompton, H., Burke, D., Gregory, K. H., & Gräbe, C. (2016). The Use of Mobile Learning in Science: A Systematic Review. *Journal of Science Education and Technology, 25*(2), 149-160. https://doi.org/10.1007/s10956-015-9597-x

Dahri, N. A., Al-Rahmi, W. M., Almogren, A. S., Yahaya, N., Vighio, M. S., Al-maatuok, Q., Al-Rahmi, A. M., & Al-Adwan, A. S. (2023). Acceptance of Mobile Learning Technology by Teachers: Influencing Mobile Self-Efficacy and 21st-Century Skills-Based Training. *Sustainability, 15*(11), 8514.

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macro theory of human motivation, development, and health. *Psychologies Canadienne, 49*(3), 182-185. https://doi.org/10.1037/a0012801

Edwards, C., Whitelock, D., Okada, A., & Holmes, W. (2018). *Trust in online authentication tools for online assessment in both formal and informal contexts* (1st ed.). ICERI 2018 Proceedings.

Fianu, E., Blewett, C., & Ampong, G. O. (2020). Toward the development of a model of student usage of MOOCs. *Education + Training, 62*(5), 521-541. https://doi.org/10.1108/ET-11-2019-0262

Giunchiglia, F., Zeni, M., Gobbi, E., Bignotti, E., & Bison, I. (2018). Mobile social media usage and academic performance. *Computers in Human Behavior, 82,* 177-185. https://doi.org/https://doi.org/10.1016/j.chb.2017.12.041

Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics, 35*(4), 1053-1070. https://doi.org/https://doi.org/10.1016/j.tele.2017.09.016

He, Y., Liang, C., Yu, F. R., & Han, Z. (2020). Trust-Based Social Networks with Computing, Caching and Communications: A Deep Reinforcement Learning Approach. *IEEE Transactions on Network Science and Engineering, 7*(1), 66-79. https://doi.org/10.1109/TNSE.2018.2865183

Hidayah, N. (2020). MOBILE-LEARNING FEEDBACK AND STUDENTS'SELF-EFFICACY IN NEW NORMAL POST COVID-19. *Journal Of Educational Experts (JEE), 3*(2), 39-45. https://doi.org/10.30740/jee.v3i2p39-45

Hidi, S., & Renninger, K. A. (2006). The Four-Phase Model of Interest Development. *Educational Psychologist, 41*(2), 111-127. https://doi.org/10.1207/s15326985ep4102_4

Huang, R., Liu, D., Tlili, A., Yang, J. F., & Wang, H. H. (2021). Toward an integrated model for measuring behavioral intention in mobile learning: Integration of extrinsic and intrinsic motivations. *Sustainability, 13*(3), 1151.

Kang, M., Liew, B. Y. T., Lim, H., Jang, J., & Lee, S. (2015). Investigating the determinants of mobile learning acceptance in Korea using UTAUT2. In G. Chen, V. Kumar, Kinshuk, R. Huang, & S. C. Kong (Eds.), *Emerging issues in smart learning* (pp. 23-48). Berlin, Heidelberg: Springer.

Karimi, S. (2016). Do learners' characteristics matter? An exploration of mobile-learning adoption in self-directed learning. *Computers in Human Behavior, 63,* 769-776. https://doi.org/https://doi.org/10.1016/j.chb.2016.06.014

Kim, Y. (2015). Investigating Factors that Influence TPACK and Technology Integration for in-service Science Teachers. *Computers & Education, 91,* 74-85.

Koole, M. L., & Parchoma, G. (2013). *The web of identity: A model of digital identity formation in networked learning environments.* IGI Global. https://doi.org/10.4018/978-1-4666-1915-9.ch002

Kumar, J. A., Bervell, B., Annamalai, N., & Osman, S. (2020). Behavioral Intention to Use Mobile Learning: Evaluating the Role of Self-Efficacy, Subjective Norm, and WhatsApp Use Habit. *IEEE Access, 8,* 208058-208074. https://doi.org/10.1109/ACCESS.2020.3037925

Liaw, S.-S., & Huang, H.-M. (2013). Perceived satisfaction, perceived usefulness, and interactive learning environments as predictors to self-regulation in e-learning environments. *Computers & Education, 60*(1), 14-24. https://doi.org/https://doi.org/10.1016/j.compedu.2012.07.015

Liaw, S.-S., Huang, H.-M., & Chen, G.-D. (2007). An activity-theoretical approach to investigate learners' factors toward e-learning systems. *Computers in Human Behavior, 23*(4), 1906-1920. https://doi.org/https://doi.org/10.1016/j.chb.2006.02.002

Lowenthal, J. N. (2010). Using Mobile Learning: Determinates Impacting Behavioral Intention. *American Journal of Distance Education, 24*(4), 195-206. https://doi.org/10.1080/08923647.2010.519947

Marikyan, M., & Papagiannidis, P. (2021). *Unified theory of acceptance and use of technology* (1st ed.) Theory Hub book.

Martin, F., & Ertzberger, J. (2013). Here and now mobile learning: An experimental study on the use of mobile technology. *Computers & Education, 68,* 76-85. https://doi.org/10.1016/j.compedu.2013.04.021

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial Trust Formation in New Organizational Relationships. *Academy of Management Review, 23*(3), 473-490. https://doi.org/10.5465/amr.1998.926622

Menekse, M., Anwar, S., & Purzer, S. (2018). Self-Efficacy and Mobile Learning Technologies: A Case Study of Course MIRROR. In C. B. Hodges (Ed.), *Self-Efficacy in Instructional Technology Contexts* (pp. 57-74). Springer International Publishing. https://doi.org/10.1007/978-3-319-99858-9_4

Nikou, S. A., & Economides, A. A. (2016). An Outdoor Mobile-Based Assessment Activity: Measuring Students' Motivation and Acceptance. *International Journal of Interactive Mobile Technologies (iJIM), 10*(4), 11-17. https://doi.org/10.3991/ijim.v10i4.5541

Noh, J. S., Jang, H. Y., & Jeon, S. S. (2021). The influence of e-WOM information characteristics on learning trust and e-WOM intention among online learning. *Journal of Logistics, Informatics and Service Science, 8*(2), 17-33. https://doi.org/10.33168/liss.2021.0208

Nunnally, J. C. (1994). *Psychometric Theory 3E* (1st ed.). Tata McGraw-Hill Education.

Prasetya, F. H., & Harnadi, B. (2019). Investigation of adoption of smartphone technology for learning. In *Proceedings of the 2019 23rd International Computer Science and Engineering Conference (ICSEC)* (pp. 23-67). IEEE. https://doi.org/10.xxxx/ICSEC.2019.xxxx

Prieto, J. C. S., Migueláñez, S. O., & García-Peñalvo, F. J. (2015). *Behavioral intention of use of mobile technologies among pre-service teachers: Implementation of a technology adoption model based on TAM with the constructs of compatibility and resistance to* change (1st ed.). 2015 International Symposium on Computers in Education (SIIE).

Reeve, J. (2012). A Self-determination Theory Perspective on Student Engagement. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of Research on Student Engagement* (pp. 149-172). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_7

Reyes Mercado, P., Barajas-Portas, K., Kasuma, J., Almonacid-Duran, M., & Zamacona-Aboumrad, G. A. (2023). Adoption of digital learning environments during the COVID-19 pandemic: merging technology readiness index and UTAUT model. *Journal of International Education in Business, 16*(1), 91-114. https://doi.org/10.1108/JIEB-10-2021-0097

Riegelsberger, J., Sasse, M. A., & McCarthy, J. D. (2005). The mechanics of trust: A framework for research and design. *International Journal of Human-Computer Studies, 62*(3), 381-422. https://doi.org/https://doi.org/10.1016/j.ijhcs.2005.01.001

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. SmartPLS GmbH, Boenningstedt. *Journal of Service Science and Management, 10*(3), 32-49.

Rofiah, C., & Suhermin, S. (2022). Importance of performance expectancy, effort expectancy, and social influence on behavioral intention and actual usage of e-healthcare applications in Indonesia. *International Journal of Research and Analytical Reviews (IJR), 9*(2), 123-134. https://doi.org/10.6084/m9.figshare.19780460

Sang, G., Wang, K., Li, S., Xi, J., & Yang, D. (2023). Effort expectancy mediate the relationship between instructors' digital competence and their work engagement: evidence from universities in China. *Educational technology research and development, 71*(1), 99-115.

Senaratne, S. I., & Samarasinghe, S. M. (2019). Factors affecting the intention to adopt m-learning. *International Business Research, 12*(4), 1-11. https://doi.org/10.5539/ibr.v12n4p1

Shan, X. (2024). Reflection on the development of Chinese cultural psychology through short video communication. *Communications in Humanities Research, 34*(1), 36-41. https://doi.org/10.54254/2753-7064/34/20240097

Sharples, M. (2013). Mobile learning: research, practice and challenges. *Distance education in China, 3*(5), 5-11.

Sheeran, P., & Webb, T. L. (2016). The Intention–Behavior Gap. *Social and Personality Psychology Compass, 10*(9), 503-518. https://doi.org/https://doi.org/10.1111/spc3.12265

Srikanth, V. J. B. R. (2018). Modified UTAUT2 model for m-learning among students in India. *International Journal of Learning and Change, 10*(1), 5-20. https://doi.org/10.1504/ijlc.2018.089532

Šumak, B., & Šorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behavior, 64*, 602-620. https://doi.org/https://doi.org/10.1016/j.chb.2016.07.037

Sun, Y., & Gao, F. (2020). An investigation of the influence of intrinsic motivation on students' intention to use mobile devices in language learning. *Educational technology research and development, 68*(3), 1181-1198. https://doi.org/10.1007/s11423-019-09733-9

Suner, A., Yilmaz, Y., & Pişkin, B. (2019). Mobile learning in dentistry: usage habits, attitudes, and perceptions of undergraduate students. *PeerJ, 7*, e7391. https://doi.org/10.7717/peerj.7391

Taamneh, A., Alsaad, A., Elrehail, H., Al-Okaily, M., Lutfi, A., & Sergio, R. P. (2023). University lecturers' acceptance of moodle platform in the context of the COVID-19 pandemic. Global Knowledge, *Memory and Communication, 72*(6/7), 666-684. https://doi.org/10.1108/GKMC-05-2021-0087

Traxler, J. (2010). Students and mobile devices. *Research in Learning Technology, 18*, Article 10759. https://doi.org/10.3402/rlt.v18i2.10759

Tri Minh Cao, N. P. N. (2022). Factors Affecting Students in Vietnam's Intention on Using Smartphones for Learning on the Mobile Learning Platforms. *Journal of Educational and Social Research, 12*(2), 113. https://doi.org/10.36941/jesr-2022-0038

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research, 11*(4), 343.

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), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association of Information Systems, 17*(5), 328-376.

Wang, J. C., Hsieh, C.-Y., & Kung, S.-H. (2023). The impact of smartphone uses on learning effectiveness: A case study of primary school students. *Education and Information Technologies, 28*(6), 6287-6320. https://doi.org/10.1007/s10639-022-11430-9

Wang, Y. D., & Emurian, H. H. (2005). An overview of online trust: Concepts, elements, and implications. *Computers in Human Behavior, 21*(1), 105-125. https://doi.org/https://doi.org/10.1016/j.chb.2003.11.008

Wang, Y.-S., Wu, M.-C., & Wang, H.-Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology, 40*(1), 92-118. https://doi.org/https://doi.org/10.1111/j.1467-8535.2007.00809.x

Wicker, A. W. (1969). Attitudes versus Actions: The Relationship of Verbal and Overt Behavioral Responses to Attitude Objects. *JOURNAL OF SOCIAL ISSUES, 25*(4). https://doi.org/10.1111/j.1540-4560.1969.tb00619.x

Zhang, D., Zhao, J. L., Zhou, L., & Nunamaker, J. F. (2004). Can e-learning replace classroom learning? *Communications of the ACM, 47*(5), 75-79. https://doi.org/10.1145/986213.986216