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Factors influencing students' behavioral intention to use mobile learning: a study of E-commerce majors in private higher vocational colleges

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Abstract: In today's world of rapid advances in information technology, mobile learning provides learners with a new way of acquiring knowledge, enabling them to access information anywhere according to their schedule. Mobile learning expands the scope of electronic and distance education, which makes modern technology and globalization possible. The purpose of this study is to explore the factors influencing the willingness of e-commerce students to use M-learning in private higher vocational colleges and universities based on the integration model of expectancy confirmation model (ECM) and unified theory of acceptance and use of technology (UTAUT). Data were collected from 219 students majoring in e-commerce in Guangzhou City Construction College through questionnaires. SPSS 26.0 and Smart-PLS 3.3.9 were used to analyze the data. The results showed that perceived usefulness, facilitating conditions, social influence, perceived enjoyment and satisfaction had a significant effect on students' willingness to use mobile learning. This study developed and validated a new mobile learning model. We encourage future researchers to investigate other predictors of M-learning intentions not found in this study.

Key words: mobile learning; private higher vocational colleges; ECM; UTAUT

1 Introduction

The fast expansion of the information technology sector affects every aspect of our lives. The pervasiveness of mobile devices in modern life has drastically changed traditional methods of communication and education. By enabling uniform learning activities to be accessed by a variety of mobile and smart devices, the convergence of mobile devices with current educational technologies gives students more flexibility [1]. Due to the widespread use of M-learning, smartphones are becoming increasingly popular as teaching aids worldwide due to their unique features (portability, low weight, simple connectivity, and affordability). The term "mobile learning" or "M-learning" refers to e-learning procedures carried out using personal mobile devices, including laptops, tablets, smartphones, and digital notebooks [2]. Mobile learning is an extension of e-learning that facilitates educational purposes through wireless mobile devices and communication [3]. M-learning fills in a gap, like the wireless feature, and is a logical progression of e-learning.

M-learning is a crucial component of education and higher learning. One of the newest technologies to improve teaching and learning is m-learning, which is a vital tool for both teachers and students. Traditional teaching and learning paradigms have been altered by the introduction of mobile technology into higher education, giving teachers new chances to improve their methods and classroom management [4]. Students can access university services and real-time learning utilizing M-learning devices such cellphones [5]. Mobile technology makes it easy for students to participate in learning environments [6]. Therefore, recognizing M-learning is crucial and imperative for faculty and students in this age of high technology [7].

This study focuses on an integrated model that reveals vocational college students' intention to use mobile learning by combining social influences and facilitating conditions components (from UTAUT) with perceived usefulness and satisfaction (from ECM). In addition, this study also explores the relationship between perceived enjoyment and students' intention to use mobile learning.

The conceptual framework, literature review, and development of hypotheses will be covered in the following section of this paper. The research methodology is then covered, along with the empirical findings and a discussion of the theoretical and practical ramifications. Lastly, limitations and directions for future research are discussed in the paper's conclusion.

2 Literature review and hypothesis

2.1 Expectancy confirmation model (ECM)

ECM was proposed by Bhattacherjee. ECM investigates people's desire to keep using an information system by employing the frameworks of satisfaction, perceived usefulness, and confirmation. Satisfaction (SAT) is influenced by both perceived usefulness and confirmation. Perceived usefulness, which affects continuing intention, is determined by confirmation [8].

2.2 Perceived usefulness (PU)

According to Davis et al, the PU is based on how much a person believes he may increase his work performance by employing a specific system [9]. The perceived usefulness of M-learning is the degree to which a person believes it can be a motivator for reaching learning objectives [10]. The study found a substantial link between PU and SAT [11]. PU is an effective predictor of both student satisfaction and intent to use. Therefore, we offered the following hypotheses:

Hypothesis 1 (H1): Perceived usefulness positively affect students' satisfaction.

Hypothesis 2 (H2): Perceived usefulness positively affect students' intentions to use M-learning.

2.3 Satisfaction (SAT)

The findings of Sánchez-Prieto et al. showed that user satisfaction has a positive impact on their willingness to utilize e-learning services [12]. Students who are satisfied with the M-learning system will continue to use the system and recommend it to others [13]. Satisfaction has a significant effect on students' intention to adopt mobile learning [14]. Thus, this research hypothesizes:

Hypothesis 3 (H3): Satisfaction positively affect students' intentions to use M-learning.

2.4 Unified theory of acceptance and use of technology (UTAUT)

Venkatesh et al. developed the UTAUT technology acceptance model by combining the key elements of behavioral intentions models applied in many technology acceptance scenarios [15]. The UTAUT model hypothesized and identified performance expectation (PE), effort expectancy (EE), social influence (SI), and facilitating circumstances (FC) as direct drivers of behavioral intention (BI) and technology usage.

2.5 Facilitating conditions (FC)

Facilitating conditions refer to how much a person believes their company's available infrastructure supports their use of technology. In M-learning contexts, technical support teams may be viewed as an enabling condition that makes users feel at ease while engaging, enhancing their behavioral intention [16]. Hence, this study hypothesizes:

Hypothesis 4 (H4): Facilitating conditions positively affect students' intentions to use M-learning.

2.6 Social influence (SI)

Alraja defines social influence as "the degree to which others (family, friends, peers, etc.) believe (either this believes are positive or negative) will affect someone to use the new system" [17]. Lutfi argued that those close to the individual may affect their final judgment [18]. The social influence had the most significant impact and was one of the strongest predictors of behavioral intention to utilize M-learning. Thus, this study suggests the following hypothesis to test:

Hypothesis 5 (H5): Social influence positively affect students' intentions to use M-learning.

2.7 Perceived enjoyment (PE)

"Perceived enjoyment" refers to "the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" [19]. Perceived enjoyment refers to how enjoyable the activity of using M-learning is perceived to be in addition to the technology's instrumental value. Perceived enjoyment is an example of intrinsic motivation that has been shown to impact users' acceptance of new technology [20]. Therefore, this study suggests the following hypothesis:

Hypothesis 6 (H6): Perceived enjoyment positively affect the students' intentions to use M-learning.

Based on the extended ECM and UTAUT models (Figure 1), this study explores the factors that influence students' behavioral intention to utilize mobile learning. The structural relationships among perceived usefulness, facilitating conditions, social influence, perceived enjoyment, satisfaction, and BI were examined.

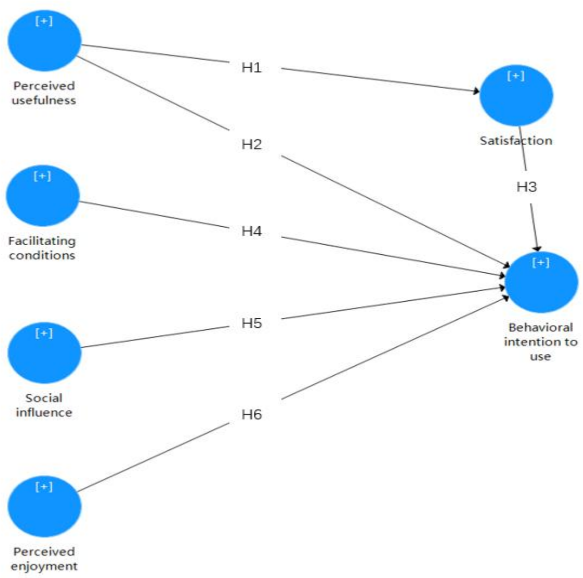

Figure 1. Research model

3 Methodology

This study used a questionnaire, which was divided into three parts. The first part is the definition of M-learning. The second part has several questions about the respondents' profile, such as gender, age, grade level, and length of time using M-learning. The third part had several questions about the variables in the research model, and a 7-point Likert scale ranging from "strongly agree" to "strongly disagree" was used to assess these structures. In order to conduct the study, 243 questionnaires were distributed to the students of Guangzhou City Construction College and 219 questionnaires were valid with a recovery rate of 90.12%. In the introductory section, the researcher clarified the academic purpose of the study and ensured confidentiality and informed consent of the respondents. Data were analyzed using IBM SPSS 26.0 and Smart-PLS 3.3.9.

Table 1 shows the information of the respondents. There were 125 (57.08%) males and 94 (42.92%) females. In terms of age, the main focus was on 20-21 years and 22-23 years with 78 (35.62%) and 86 (39.27%) respectively. In terms of grades, there were 80 (36.53%) in the first grade, 84 (38.36%) in the second grade, and 55 (25.11%) in the third grade. In terms of devices used, 189 (86.30%) used mobile cell phones. In terms of how much time was spent on mobile learning per day, it was concentrated on 1-2 hours and 3-5 hours, totaling 75.34%.

Table 1. Demographic profile

Items	Description	N	%
Gender	Male	125	57.08%
	Female	94	42.92%
Age	Below 20	32	14.61%
	20-21	78	35.62%
	22-23	86	39.27%
	Above 23	23	10.50%
Grade	1st year	80	36.53%
	2nd Year	84	38.36%
	3rd year	55	25.11%
Devices of usually use	Mobile phones	189	86.30%
	Labtop	65	29.68%
	Tablets	21	9.59%
	Others	19	8.68%
How much time spend on mobile learning each day	<1 hour	33	15.07%
	1-2 hours	112	51.14%
	3-5 hours	53	24.20%
	Above 5 hours	21	9.59%

4 Results and analysis

4.1 Measurement model analysis

According to the criteria of Hair et al, Cronbach's alpha value and composite reliability value (CR) are greater than 0.7, and the extracted mean variance (AVE) value is greater than 0.50, indicating that the model has good reliability and convergence validity [21]. Table 2 shows that the outside loading numbers are much more than 0.7, indicating item dependability. Composite reliability (CR), Rho_A, and Cronbach's Alpha values are more than 0.7. The AVE (average variance extracted) figures are more than 0.5, indicating convergence validity (Table 2).

A concept's AVE should be higher than its shared variance with other concepts, according the Fornell-Larcker criterion [22]. Table 3 demonstrates that all squared roots of AVE were found to be higher on the diagonal line than correlation coefficients between components, indicating construct-level discriminant validity.

Table 4 shows the heterotrait-monotrait correlation ratio (HTMT). HTMT values were all less than 0.85, which met the criterion of discriminant effectiveness proposed by Henseler et al [23]. The results show that the model has good validity and reliability.

Table 2. Validity and reliability

Variables	Item	Factor loadings	Cronbach's Alpha	rho_A	CR	AVE
	PU1	0.847				
	PU2	0.871				
PU	PU3	0.889	0.920	0.920	0.940	0.757
	PU4	0.878				
	PU5	0.863				
	FC1	0.835				
	FC2	0.860				
FC	FC3	0.828	0.899	0.900	0.925	0.712
	FC4	0.834				
	FC5	0.861				
	SI1	0.856				
	SI2	0.869				
SI	SI3	0.883	0.915	0.917	0.937	0.747
	SI4	0.865				
	SI5	0.848				
	PE1	0.908				
	PE2	0.883				
PE	PE3	0.855	0.930	0.933	0.947	0.782
	PE4	0.893				
	PE5	0.880				
	SAT1	0.887				
	SAT2	0.884				
SAT	SAT3	0.864	0.929	0.929	0.946	0.778
	SAT4	0.881				
	SAT5	0.894				
	BI1	0.911				
	BI2	0.861				
BI	BI3	0.884	0.930	0.931	0.947	0.783
	BI4	0.871				
	BI5	0.895				

Table 3. Fornell-Larcker discriminant validity correlation matrix (AVE square root)

Variables	BI	FC	PE	PU	SAT	SI
BI	0.885					
FC	0.577	0.844				
PE	0.728	0.511	0.884			
PU	0.712	0.440	0.587	0.870		
SAT	0.681	0.523	0.574	0.659	0.882	
SI	0.627	0.437	0.570	0.596	0.466	0.864

Table 4. HTMT ratio of the studies

Variables	BI	FC	PE	PU	SAT	SI
BI	-					
FC	0.631	-				
PE	0.779	0.558	-			
PU	0.769	0.483	0.631	-		
SAT	0.732	0.571	0.615	0.712	-	
SI	0.679	0.480	0.616	0.648	0.505	-

4.2 Structural model

The path coefficients, t-statistics, and p-value were used to determine the significance of each direct impact or hypothesis in the structural model. Table 5 and Figure 2 show the results of the bootstrapping computation for all factors. Figure 3 displays the results of the bootstrapping computation. Table 5 summarizes the study's findings for all factors. The hypothesis regarding the association between PU and SAT (H1) was supported ($\beta = 0.659$; $t = 15.185$, $p < 0.001$). The hypothesis regarding the link between PU and BI (H2) was supported ($\beta = 0.251$; $t = 4.391$, $p < 0.001$). The association between SAT -> BI (H3) ($\beta = 0.193$; $t = 4.108$; $p < 0.001$) suggests that the hypothesis was validated. The correlation between FC and BI (H4) ($\beta = 0.141$; $t = 3.212$, $p < 0.01$) suggests the hypothesis was validated. Moreover, SI is also a significant predictor for BI, H5 ($\beta = 0.147$; $t = 2.782$; $p < 0.01$), so the hypothesis was supported. Finally, PE is a significant predictor for BI, H6 ($\beta = 0.314$; $t = 6.474$; $p < 0.001$), supporting the prediction.

Table 5. Hypotheses testing

Hypotheses	Relationship	Path (β)	Stdev	t-Value	p Values	Results
H1	PU -> SAT	0.659	0.043	15.185	0.000	Supported
H2	PU -> BI	0.251	0.057	4.391	0.000	Supported
H3	SAT -> BI	0.193	0.047	4.108	0.000	Supported
H4	FC -> BI	0.141	0.044	3.212	0.001	Supported
H5	SI -> BI	0.147	0.053	2.782	0.006	Supported
H6	PE -> BI	0.314	0.049	6.474	0.000	Supported

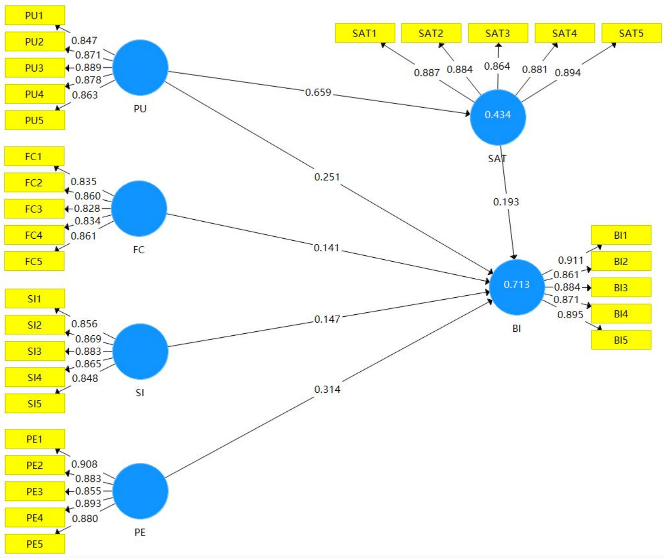

Figure 2. Path coefficient findings

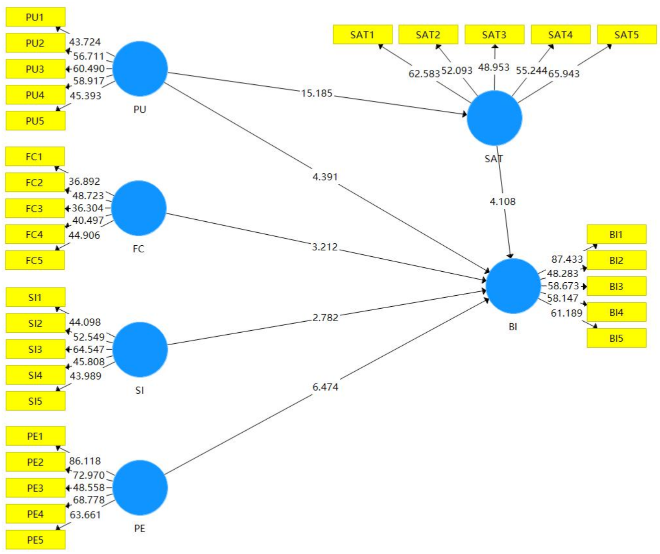

Figure 3. Path (T-values) findings

5 Discussions

The purpose of this study is to explore the factors that influence the adoption of mobile learning by e-commerce majors in Guangzhou City Construction College. Path coefficient analysis shows that all hypotheses are supported.

Hypothesis 1 and Hypothesis 2 indicate that PU has a positive effect on SAT and BI. When students believe that mobile learning is useful to them and can help them achieve their learning goals, their satisfaction is also higher, which further promotes students' willingness to use it, similar to the findings of Alturki and Aldraiweesh as weill as Lutfi et al, Khadija [24].

The study shows that user satisfaction has a positive effect on the intention to use M-learning. This result supports the findings of Su and Chao and Lutfi et al.

Students' behavioral desire to use M-learning was significantly impacted by facilitating conditions, which may indicate how much they use M-learning resources related to mobile and information and communication technologies. These results validated the findings of Alowayr and Al-Azawei and Afandi [25][26].

Social influence has a positive impact on mobile learning usage intention. Students will be influenced by people they value and will take advantage of mobile learning systems if they think it is beneficial. This is consistent with the research results of Su and Chao, as well as Shaya, Sabri, Shukla [27][28][29].

Perceived enjoyment positively influences students' willingness to use mobile learning. When students perceive using mobile learning as enjoyable and fun, they are more likely to use them. This finding is consistent with previous findings [30].

6 Managerial implication

This study adequately validates the factors influencing students' willingness to use M-learning in private higher education institutions. The findings have important contributions and insights for both management and practice. First, although there are many studies on the influencing factors of students' use of M-learning, fewer studies have been conducted on students in private higher education institutions. The results of this study may provide valuable suggestions for educational administrators to develop appropriate policies that are suitable for the individual characteristics of students in private higher education institutions.

Second, this study helps software developers to gain a deeper understanding of the acceptance and behavioral drivers affecting the use of M-learning by students in private institutions of higher education, and better target students' needs in designing apps and systems that better meet pedagogical requirements for the effective use of M-learning. In addition, perceived enjoyment is also an important factor influencing students' use of M-learning. Consideration can be given to choose a more convenient and engaging user interface so that M-learning can integrate various video, text and multimedia resource applications to attract students' curiosity and stimulate their critical thinking. Teachers should pay attention to students' perceptions when designing instruction, design attractive content, enhance real-time interaction between teachers and students, and realize the deep integration of online and offline learning.

7 Conclusion, limitations and recommendations

This study is based on a comprehensive extended theoretical model (ECM and UTAUT). According to the results of the study, the important factors affecting students' use of M-learning are perceived usefulness, social influence, facilitating conditions, perceived enjoyment and satisfaction. Therefore, the integrated model used in this study can be considered an important contribution. However, there are some limitations of the study. First, the study was conducted with only e-commerce students, and in the future, the perceptions of more students from different majors on the use of M-learning should be considered. Second, in addition to the variables described in the study, future research should consider more other factors that may have an impact.

Conflicts of interest

The author declares no conflicts of interest regarding the publication of this paper.

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