Behavioral Intention and Actual Use of Mobile Learning During the COVID-19 Pandemic in the Higher Education System

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Abstract. This study aims to investigate the impact on Behavioral Intention and Actual use of Mobile Learning in the Higher Education (HE). The survey was conducted at Cihan University Erbil, and the data was collected by questionnaire. 207 valid questionnaires have been analyzed by Structural equation modelling (SEM). The results indicated that performance expectancy, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, and Habit had a positive and significant impact on Behavioral Intention to use Mobile learning among the students. On the other hand, Social influence and Price Value had an insignificant impact on Behavioral Intention to use Mobile learning among the students. Besides that, the current study reported that behavioral intention directly impacts user behavior (UB). At the same time, facilitating conditions and Habit had an insignificant impact on user behavior.

Keywords: UTAUT · Use behavior · Mobile learning · Higher education · Behavioral intention

1 Introduction

Nowadays, Mobile learning (ML) has grown in popularity due to the pandemic of COVID 19. Furthermore, the low cost of telecommunications and the high quality of mobile devices (MDs) led to extensive use of ML among learners, particularly in the HE. Education institutions during the COVID-19 pandemic have been more open to the use of mobile learning, offering students and educators a better learning environment during the lockdown and postponed attendance at the university campus. Meanwhile, Due to the unique capabilities of mobile learning has been universally recognized as a valuable educational system [1]. However, integrating educational technology into the teaching and learning process is becoming commonplace in today's curriculum. It has been shown that such innovations can aid in the improvement of learning outcomes and learner expectations [2].

During and after the COVID-19 pandemic, universities are moving away from the hierarchical and regular teaching rule favoring technology-assisted mass teaching

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programs, adaptive learning pathways, and student-centered learning approaches that promote a symbiotic relationship with society [3–5].

Mobile learning, According to Al-Emran et al. [6] can be described from three viewpoints. To begin with, it refers to learning that occurs through the use of smart devices. Furthermore, it is a form of learning originating from the wider term "distance learning." Finally, it reflects the next wave of mobile-based e-learning. Thus, in addition to the intrinsic advantages of MDs, such as accessibility and durability, ML may be a more innovative way of collaboration and information sharing for learners and educators. The Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT2 has been used in different area of information technology. Such as E-learning systems [4], mobile banking [7, 8], and mobile shopping [9, 10].

Many universities Nowadays have incorporated ML into their work environments. However, universities face issues that hinder students from using ML entirely, particularly in the developing world. These barriers may be technological or non-technological, such as system capability, network reach, enabling circumstances, social impact, and so on [11–13]. The sluggish adoption of ML, on the other hand, has been seen as a technological problem rather than an educational problem. As a result, core technical reasons that could inspire learners to use ML systems in their education must be identified. Furthermore, before implementing new technologies, such as m-learning, it is essential to gain community approval.

Following multiple suspensions of academic activities in Iraq due to the COVID-19 epidemic, maintaining public education in Iraq became exceedingly difficult on various levels due to a lack of technology and consistency in the online teaching experience.

Even though students are rapidly using mobile devices [14], there are limited studies has been conducted in Iraqi HE and Arab countries [2, 10, 15].

Nowadays, the use of technology tools such as e-learning and ML has been rising in the Iraqi education system due to the COVID-19 pandemic [16]. As a result, Iraqi universities have shifted their practices in teaching and learning to the portals provided by various educational technology, allowing students to receive learning material at home during the self-isolate and lockdown in the country. These portals include learning management systems (LMSs) such as Moodle platform, and the students efficiently use various electronic devices such as tablets, computers, and smartphones. This study aims to investigate the impact of UTAUT2 dimensions on ML among undergraduate students in the Iraqi HE.

2 Literature Review and Hypotheses Development

2.1 Mobile Learning

ML is described as disseminating teaching resources through mobile devices, allowing students to learn whenever and wherever they are. As a result, m-learning has provided new methods to reach learning materials via mobile devices such as tablets, notebooks, and computers [17, 18]. M-learning is widely regarded as one of the most significant new developments in modern instructional activities [19]. ML refer to the Learners may conduct authentic practices in the sense of their learning because they have access to information at any time and from any location through mobile technologies [1]. Alghazi

et al. [10] described Mobile learning as the transmission of any instructional material created and used by MDs to the user, whether it is basic knowledge or a complete curriculum. Since m-learning enables students to study outside of the university or schools and the students have the advantage to learn at any time and from any place [1, 2]. M-learning is a combination of mobile communication and online learning that allows users to learn whenever and wherever they want and share what they've learned with others [20, 21]. On the other hand, Kim and Rha [22] describe the ML as a tool that incorporates many emerging tools, such as internet networking and MDs. It has a greater degree of complexity and danger in people's minds, which may cause them to deny or defer accepting it. As a result, learner adoption of mobile technology is regarded as critical to optimizing the benefits of M-learning [21, 23, 24]. M-learning enhances the acceptability of the process of education, particularly for younger generations who tend to follow and use new technologies [15]. Furthermore, According to Ng, Lui, and Ngao [25] m-learning enables users to learn autonomously without teachers, increasing the extent of their communication with others and knowledge.

2.2 The UTAUT Theory

Several theories have been developed to identify the elements that may lead to accepting the technology among users. However, when it comes to individual technology acceptance, UTAUT has been recognized as a fully-fledged chain of information system (IS) science, implying a cohesive view of the art of information technology [26, 27] One of the most widely adopted technology is the UTAUT theory. Several previous studies confirmed that UTAUT2 models have significant and more explained the acceptance of technology compared to other technology theories [1, 4].

Venkatesh et al. [26] proposed the UTAUT theory, which consisted of three factors that has a direct impact on "behavioral intention" (BI), namely; ("Performance Expectancy" (PE), "Effort Expectancy" (EE), "Social Influence" (SI)). At the same time, two factors are ("Facilitating Conditions" (FC) and "behavioral Intention" (BI) has a direct impact on "user behavior" (UB).

Later in 2012, Venkatesh, Thong, and Xu [28] extended the UTAUT theory by adding three new factors, namely, "Hedonic Motivation" (HM), "Price Value" (PV), and "Habit" (HA) extended known as UTAUT2. The HM, PV, and HA have a direct impact on BI. Besides, HA, FC and BI has a direct effect on UB.

BI refers to the degree to which user intend to use MDs in learning and execute a certain behavior [29]. Several prior studies reported that BI in the setting of ML had a direct effect on UB [1, 23, 30, 31].

H1: BI Has a Significant Effect on UB Using Mobile Learning Among Students.

2.3 Performance Expectancy

PE Refers to the extent to which a person's use of a device will help them in improving their job performance [26]. To put it another way, PE refers to a student's ability to complete an assignment and duties successfully in the future. It's a measure of a student's belief that using mobile devices can help them perform better. [15] define PE as the extent

to which a student assumes that ML can increase their learning ability. Empirically several prior studies confirmed that PE significantly impacts on BI to use ML [1, 2, 4, 15, 20, 23, 30].

H2: PE Has a Significant Effect on BI to Use Mobile Learning Among Students.

2.4 Effort Expectancy

EE refers to user interpretation of how simple a device is to use [26]. EP refers to the student's impression level of ease of use when using the M-Learning to complete the university tasks and duties.

Venkatesh & Davis [32] Confirmed that conceptions of EE could only be well-constructed after a direct, realistic experience. The degree of comfort with students using mobile devices to study. EE refers to the degree of comfort in which mobile devices can be used in the learning process [15]. The study conducted by Shukla [20] among m-learning users reported that EE can enhance the intention to use ML. However, based on the empirical studies, there is an inconsistency of results. That EE significantly impacts on BI to use ML [1, 2, 4, 15, 20, 23]. On the other hand, Arain et al. [30] reported that EE had an insignificant impact on BI to use of the technology. This inconsistency of results is one of the main motivations to conduct this study to examine the impact of EE on BI in the Iraqi higher education context.

H3: EE Has a Significant Effect on BI to Use Mobile Learning Among Students.

2.5 Social Influence

SI refers to the level of effect from others such as (friends and family) to students to use mobile technology in learning. SI refers to the ability of students' friends and family to persuade them to use ML during university study, particularly nowadays during the pandemic of COVID-19. Furthermore, SI refers to the extent to which a student feels that the essential culture around them supports using mobile learning [15]. Alowayr and Al-Azawei [2] defined SI as the user's decision impacted by social pressures to do a particular action and depending on the behavior in question. Empirically BI to use ML is impacted by SI [1, 20, 23]. On the other hand, BI does not impact by SI [2, 15, 30, 31]. Based on what was mentioned, there is an inconsistency in previous results, and this study tries to solve this inconsistency in the Iraqi context.

H4: SI Has a Significant Effect on BI to Use Mobile Learning Among Students.

2.6 Facilitating Conditions

FC refers to users who believe that systemic and technological infrastructural support is required to maintain device use [26]. In other words, FC refers to the technology infrastructure and support that receive it the students when they use ML. Users' impressions of the resources and assistance accessible to them in order to carry out a behavior

[4]. Alowayr and Al-Azawei [2] define the FC as a user's get from their institutes or organizations assist when using technology.

Statistically, FC examined to impact on BI and BU, and the results showed FC had a significant impact on BI [1, 4, 20] and BU [1, 23]. On the other hand, BI does not impacted by FC [2, 30, 31] and BU [31].

H5: FC Has a Significant Effect on BI to Use Mobile Learning Among Students.
H6: FC Has a Significant Effect on UB to Use Mobile Learning Among Students.

2.7 Hedonic Motivation

HM refers to the enjoyment or gratification gained from using MDs for educational purposes. According to Jameel et al. [4] If the student enjoys utilizing technology, there is a greater possibility that he or she will continue to use that technology. Several previous studies confirmed that using Mobile increased users' joy and pleasure [4, 30]. Empirically BI impacted by HM [1, 7, 30]. While [4] reported HM had an insignificant impact on BI.

H7: HM Has a Positive Effect on BI to Use Mobile Learning Among Students.

2.8 Price Value

The students' perceptual trade-off between the supposed educational gains of mobile apps during the learning process. However, it means that the perceived gain compared to costs from using technology [4]. PV refers to the ueser's perception that the cost of the MD is appropriate in the learning process [15]. Empirically, PV impact on BI to use ML [1, 15]. While other studies reported, PV had an insignificant impact on BI [4].

H8: PV Has a Positive Effect on BI to Use Mobile Learning Among Students.

2.9 Habit

According to Venkatesh, the amount users learn causes them to do things automatically and describes the Habit as a perceptual construct. It applies to the degree to which students tend to naturally learn from using MD. According to Jameel et al. [4], Users who have used similar technology in the past have been demonstrated to be easily affected by new similar technology when adopting it. The habits are a significant predictor of BI, which may redirect BU. It has a statistically significant influence on behavioral intention [30]. Previous studies reported BI impacted by HA [1, 4, 30] and BU [1].

H9: HA Has a Positive Effect on BI to Use Mobile Learning Among Students.
H10: HA Has a Positive Effect on Using UB Among Students.

3 Methodology

The data was collected by a questionnaire, which is considered an appropriate method for data collection—the study was conducted on the Moodle users of Cihan university Erbil. The reasons behind choosing Cihan University; First, the university of Cihan has implemented the Moodle Platform since 2018. Second, Cihan university is one of the best rank universities in the Kurdistan Region and Iraq as a private university. Third, the Authors are academic staff at Cihan university which facilitates the Data collection and communication with students as a respondent. The Constructs items were adapted from prior studies, and the study used a five-point Likert scale because it eliminates cognitive biases and responder confusion [33]. The number of items and Sources for each construct has been depicted in Table 1. The population of the current study is undergraduate students from Cihan University Erbil, Located in Iraq. AMOS has analyzed 207 valid questionnaires after conducting the missing value, outliers and Checking the Normality and Multicollinearity by SPSS.

4 Results

4.1 Measurement Model

The aim of this step is to ensure the validity and reliability of the model the outcomes of the measurement model of the current study are illustrated in Table 1. The composite reliability (CR) for all constructs has exceeded the cut-off level of 0.7 and ranged from 0.818 to 0.960. All the items reflect high internal constancy and are reliable to measure the constructs. Further, the average variance extracted (AVE) indicated that all the constructs exceeded the cut-off level of 0.50 as recommended by [34]. Factor loadings for all the items exceeded the recommended value by Hair et al. [34] 0.60, except EE4 showed poor loadings and was removed to enhance the model fit. As a result, all of the underlying variables obtained an acceptable variability with convergent validity.

Table 1. Results of measurement model assessment

Constructs	Items	FL	CR	AVE	Sources
HA	HA1 HA2 HA3 HA4	.974 .973 .900 .738	0.945	0.813	[4, 9]
HM	HM1 HM2 HM3 HM4 HM5	.789 .918 .897 .813 .716	0.917	0.690	[4, 9]

(*continued*)

Table 1. (*continued*)

Constructs	Items	FL	CR	AVE	Sources
FC	FC1 FC2 FC3 FC4 FC5	.842 .845 .762 .823 .758	0.903	0.652	[2, 31]
BI	BI1 BI2 BI3 BI4 BI5	.690 .855 .845 .836 .750	0.897	0.637	[2, 15]
PE	PE1 PE2 PE3 PE4	.851 .909 .939 .661	0.909	0.718	[15, 31]
SI	SI1 SI2 SI3 SI4 SI5	.886 .966 .879 .887 .930	0.960	0.829	[2, 15]
EE	EE1 EE2 EE3 EE5	.699 .878 .644 .673	0.818	0.533	[2, 15]
PV	PV1 PV2 PV3	.690 .799 .670	0.761	0.517	[15]
UB	UB1 UB2 UB3 UB4 UB5	.766 .946 .844 .745 .691	0.900	0.646	[9, 31]

4.2 Model Fit Indices

The results of indices showed the RMSEA = 0.063, CFI = 0.907, TLI = 0.900, IFI = .908 and ChiSq/df = 1.791. According to Hair et al., [34] the RMSEA value should be ≤ 0.08, CFI, TLI, and IFI should be garter or equal to 0.9, and ChiSq/df should be $1.0 \leq \chi 2 / df \leq 5$. Thus, the proposed model of the current study achieved the model fit (see Fig. 1).

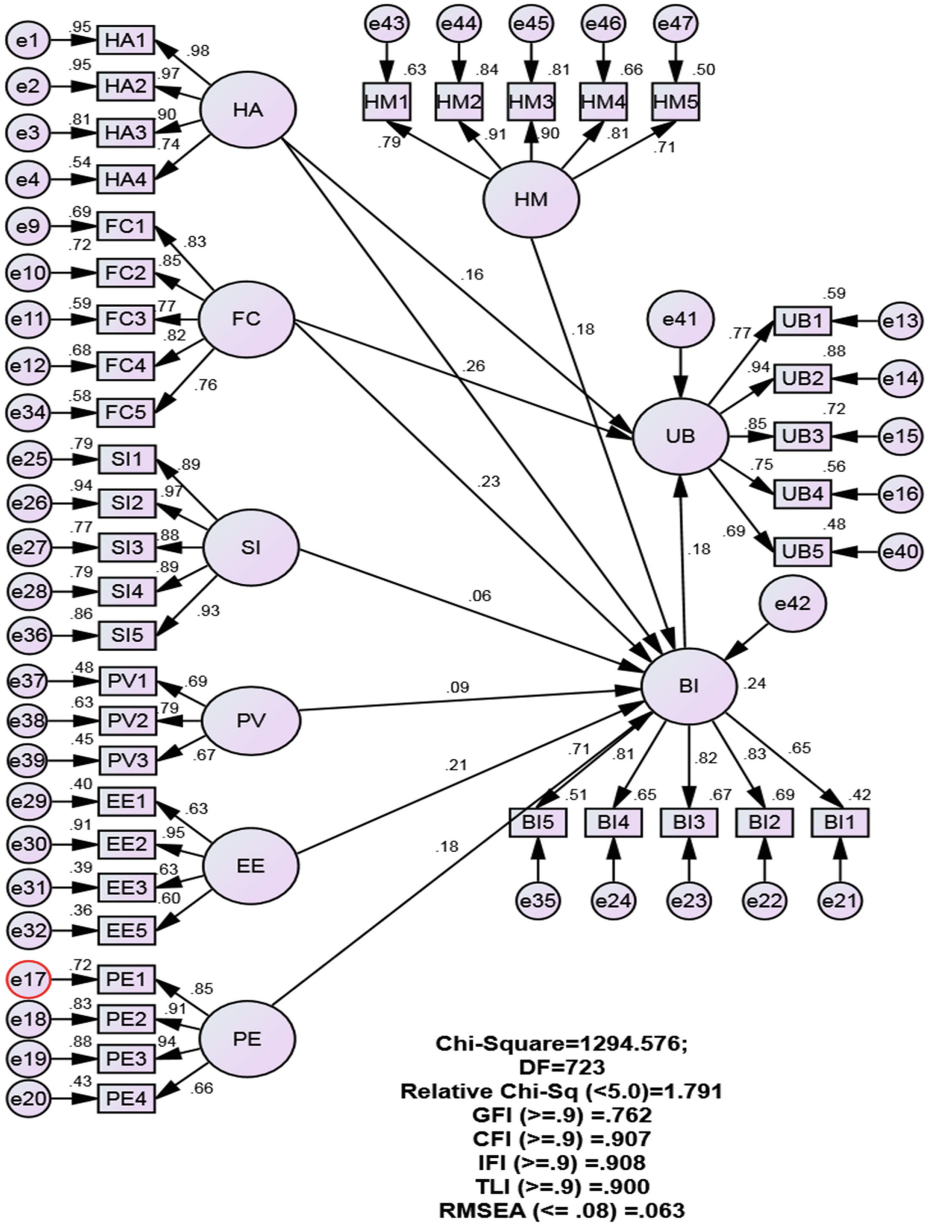

Fig. 1. Structural model

4.3 Structural Model

As depicted in Table 2 and Fig. 1, The results indicated that BI has a positive and significant impact on BI to use the ML among students due to the p-value 0.320 < 0.05 and the T-value 2.143 > 1.96 Thus, H1 is supported. PE, EE, FC, HM and HA has significant impact on BI to use ML among students due to the p-values .0301,.008,.013, .041, .001 < 0.05 respectively and the t-values > 1.96 see Table 2. Thus H2, H3, H5, H7, H9 are supported.

On the other hand, the results reported SI and PV had an insignificant impact on BI to use ML among the students due to the p-values .409 and .235 respectively > 0.05 and the t-values less than 1.96 Thus, H4 and H8 are not supported.

At the same time, FC and HA had an insignificant impact on UB among students due to the p-values .730 and .0508 > 0.05 respectively. Thus, H6 and H10 are not supported.

Table 2. Hypotheses results

Hypotheses		Estimate	S.E	T-value	P-value	Supported
H1	UB ← BI	.247	.115	2.143	.0320	YES
H2	BI ← PE	.119	.054	2.168	.0301	YES
H3	BI ← EE	.212	.080	2.642	.0082	YES
H4	BI ← SI	.042	.052	0.824	.4096	NO
H5	BI ← FC	.217	.087	2.482	.0130	YES
H6	UB ← FC	.037	.108	0.344	.7304	NO
H7	BI ← HM	.181	.089	2.035	.0417	YES
H8	BI ← PV	.204	.171	1.187	.2350	NO
H9	BI ← HA	.139	.043	3.220	.0012	YES
H10	UB ← HA	.116	.059	1.952	.0508	NO

5 Discussion

ML method in teaching and learning is unique. It allows students to view learning resources at any time and in various media, including audio, visual, and textual types, according to their tastes. The provision of the Internet, human capital, and the desire of teachers and students to use it are both factors in the progress of m-learning. As a result, M-learning has the potential to improve self-learning and possibilities tools for practice.

PE and EE significantly predict the IB to use ML this result is consistent with previous results [1, 2, 4, 20, 23]. This means the students believe using the Mobile in the learning process could be helpful and valuable to do their tasks and assignments and increase their knowledge and productivity. This result refers to the student using the Mobile in education easily and free of effort. The interaction with Mobile is understandable and accessible for the students to be skillful when adopting the ML. However, if students believe that universities provide them with the necessary technical assistance, they will put in more effort to do a particular behavior. Furthermore, users' perceptions of a technology's utility may be favorably influenced if they perceive that enacting a specific behavior would not require much effort.

Most of the previous results obtained the SI able to increase BI to use ML [1, 20, 23]. At the same time, the current study's findings revealed that students do not consider SI as a factor that may influence BI to use the ML; this finding in line with [2, 15]. May explain the negligible impact of SI on ML uptake in underdeveloped nations due to the lack of sustaining technology and the expensive cost of Mobile.

FC significantly impacts on BI to use ML among students. Similar results reported by [1, 20]. When students believe their knowledge, abilities, and resources are conducive

to using mobile learning, they are more likely to use mobile technology to study. However, this result indicated the students have the necessary resources, knowledge, and technology to use ML.

HM significantly impact on BI to use ML among students. Similar results reported by [1, 7, 30]. When students' enjoyment of utilizing mobile devices in the classroom grows, so does their desire to utilize these devices. Students find the mobile app entertaining, which may encourage them to participate in ML activities. Thus, students are motivated to join in m-learning activities through fun and pleasure. This result indicates that PV has an insignificant effect on the intention to use ML among students, similar finding reported by Jameel et al. [4]. The insignificant impact may be due to the fact the study was conducted at private universities, and usually, the students who enroll at private universities have a good economic level, and the price does not impact their intention to use ML.

HA reported as a predictor on BI to use ML. Similar findings reported by [1, 4, 30]. Usually, the students utilize mobile devices regularly, and the technology becomes used daily [4]. Thus, students have a more habitual behavior toward utilizing ML technology, and the technology adoption rate is expected to be more significant.

UB does not impacted by FC among students this result inconsistent with most of the previous findings, which reported the FC and HA has a significant impact on UB [1, 4, 23] and consistent with the finding reported by [31] reported FC had an insignificant impact on UB. According to Venkatesh [26] usually, the FC shift to insignificant when the PE and EE are significant.

HA did not lead to an increase in the BU among students and had an insignificant impact on BU consistent with previous findings [4] and inconsistent with the previous finding which is reported HA had a significant impact on BU [1]. This could be due to the students must use the system to be in touch with the instructor and submit tasks and assignments as well as download the materials, particularly during the pandemic of COVID 19 and most of the universities postponed the physically attending or shifted to the blended learning process BI statistically predicted to UB and able to increase the actual use of ML among students, this finding in line with prior findings [1, 23].

6 Conclusion

The study aim has been achieved, and the results demonstrated that PE, EE, FC, HM, and HA are capable of enhancing the BI to use ML among the students. The universities should improve the performance and facilitating at the university to motivate the students to engage with ML, particularly nowadays with the pandemic of COVID19.as well the study reported that SI and PV do not impact students' Intention to use mobile learning. Practitioners and university administrators should clarify to persuade students of the advantages of using ML in university classes. In addition, some students who have a lower level of personal innovation may require motivation during the first stages of m-learning implementation. A mobile learning system's simplicity of use and utility can add value to an existing LMS by improving learning and increasing users' acceptance of ML.

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