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Continued Usage Intention of Mobile Learning (M-Learning) in Iraqi Universities Under an Unstable Environment: Integrating the ECM and UTAUT2 Models

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Abstract

Aim/Purpose	This study examines the adoption and continued use of m-learning in Iraqi universities amidst an unstable environment by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Expectation-Confirmation Model (ECM) models. The primary goal is to address the specific challenges and opportunities in Iraq's higher education institutions (HEIs) due to geopolitical instability and understand their impact on student acceptance, satisfaction, and continued m-learning usage.
Background	The research builds on the growing importance of m-learning, especially in HEIs, and recognizes the unique challenges faced by institutions in Iraq, given the region's instability. It identifies gaps in existing models and proposes

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extensions, introducing the variable “civil conflicts” to account for the volatile context. The study aims to contribute to a deeper understanding of m-learning acceptance in conflict-affected regions and provide insights for improving m-learning initiatives in Iraqi HEIs.

Methodology — To achieve its objectives, this research employed a quantitative survey to collect data from 399 students in five Iraqi universities. PLS-SEM is used for the analysis of quantitative data, testing the extended UTAUT2 and ECM models.

Contribution — The study’s findings are expected to contribute to the development of a nuanced understanding of m-learning adoption and continued usage in conflict-affected regions, particularly in the Iraqi HEI context.

Findings — The study’s findings may inform strategies to enhance the effectiveness of m-learning initiatives in Iraqi HEIs and offer insights into how education can be supported in regions characterized by instability.

Recommendations for Practitioners — Educators and policymakers can benefit from the research by making informed decisions to support education continuity and quality, particularly in conflict-affected areas.

Recommendations for Researchers — Researchers can build upon this study by further exploring the adoption and usage of m-learning in unstable environments and evaluating the effectiveness of the proposed model extensions.

Impact on Society — The research has the potential to positively impact society by improving access to quality education in regions affected by conflict and instability.

Future Research — Future research can expand upon this study by examining the extended model’s applicability in different conflict-affected regions and assessing the long-term impact of m-learning initiatives on students’ educational outcomes.

Keywords — mobile learning (m-learning), higher education institutions (HEIs), unified theory of acceptance and use of technology 2 (UTAUT2), expectation confirmation model (ECM)

INTRODUCTION

Mobile learning (m-learning) has emerged as a transformative force in higher education, offering flexibility and accessibility to learners worldwide (Al-Rahmi et al., 2022). In recent years, its significance has become more pronounced in regions experiencing geopolitical instability, where traditional educational systems face significant disruptions (Chao, 2019). Given the unstable internal conflicts and political turmoil, Iraq is a critical context for implementing and maintaining m-learning (Al-Swidi & Faaeq, 2019). To better understand the dynamics of m-learning adoption in this challenging environment, this research seeks to extend and adapt two influential technology acceptance models: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Expectation-Confirmation Model (ECM) (Rabaa’i & ALMaati, 2021). By contextualizing and expanding these models, this study explores the complex interplay of factors influencing m-learning adoption in Iraqi universities. Through a comprehensive examination of this multifaceted phenomenon, this research provides insights and recommendations that can inform educational policymakers, institutions, and stakeholders, ultimately contributing to the advancement of m-learning in Iraq.

The adoption of m-learning in higher education institutions (HEIs) worldwide has been shaped by various factors, including students’ perceptions of the technology, their satisfaction with the learning experience, and the influence of external factors (J. Chen, 2022). However, these factors may operate differently in regions facing unique challenges, such as political instability and civil conflicts. Understanding the nuanced dynamics of m-learning adoption in such environments requires adapting and extending existing technology acceptance models.

UTAUT2, developed by Venkatesh et al. (2012), provides a comprehensive framework for understanding technology adoption, considering key constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Similarly, the ECM proposed by Oliver (1980) and Bhattacherjee (2001) focuses on users' satisfaction and post-adoption behaviors, which are crucial aspects of m-learning adoption. While these models have been widely applied in various contexts, there is a growing recognition that they may need to be extended and adapted to capture the unique challenges and drivers of m-learning adoption in unstable environments like Iraq.

This research project aims to address this gap by extending UTAUT2 and ECM to fit the Iraqi HEI context better and provide a comprehensive understanding of the factors influencing m-learning adoption. By doing so, it seeks to contribute to the knowledge of technology adoption in challenging contexts and provide actionable insights for HEIs, policymakers, and practitioners looking to enhance the effectiveness of m-learning initiatives in regions affected by instability (Sattarov & Khaitova, 2019).

This research paper is organized as follows. The next section is the literature review, which provides the theoretical background. Then, context-specific issues and challenges in unstable environments are examined, followed by an examination of regional contextual factors in Iraq. The research framework and hypotheses are then presented, establishing the theoretical framework. The data collection and analysis methods are described next, followed by the research findings. The results and their implications are then discussed. Finally, the limitations and study constraints are presented, followed by the implications, future research, and a summary of key findings and insights.

LITERATURE REVIEW

MOBILE LEARNING

Mobile learning (m-learning) refers to the use of mobile devices, such as smartphones and tablets, for educational purposes, enabling learners to access content, interact with instructors, and engage in learning activities anytime and anywhere. M-learning provides flexibility and convenience in learning, making it a prominent component of modern education. Diverse studies, including those by Almaiah et al. (2022) and Alshurideh et al. (2020), have highlighted its potential to transform education by catering to learners' needs for on-the-go, personalized, and ubiquitous learning experiences.

M-learning has been recognized globally as a powerful tool for enhancing education and providing access to learning resources (Al-Azawei & Alowayr, 2020). However, in regions marked by political instability and civil conflicts, such as Iraq, the adoption and effectiveness of m-learning can be significantly influenced by contextual factors unique to these environments. This literature review explores the existing body of knowledge related to m-learning adoption in unstable environments and the applicability of technology acceptance models, particularly UTAUT2 and ECM, in understanding this phenomenon (Al-Hamad et al., 2021). By examining relevant studies and their findings, this review sets the stage for extending these models to better address the challenges faced by m-learning initiatives in Iraqi universities.

Understanding the dynamics of m-learning adoption in regions characterized by instability is crucial. Al-Rahmi et al. (2022) conducted a study on m-learning adoption in open universities, emphasizing the equitable and sustainable use of m-learning, particularly relevant in unstable environments where access to traditional education may be disrupted. Their findings highlight the potential of m-learning to bridge educational gaps under challenging conditions.

UTAUT2 IN TECHNOLOGY ADOPTION

UTAUT2 has been extensively applied to investigate technology adoption across various contexts. The model, introduced by Venkatesh, Thong, et al. (2012), incorporates constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Research conducted by Venkatesh, Morris, et al. (2003) has confirmed the effectiveness of UTAUT2 in comprehending user acceptance of information technology. This makes it a valuable framework for investigating the adoption of m-learning in Iraq's unstable environment.

ECM AND POST-ADOPTION BEHAVIOR

ECM, introduced by Oliver (1980), centers around user satisfaction and behaviors after adopting a product or service. Although it has been extensively utilized in different settings, further investigation is necessary regarding its implementation in m-learning (Bhattacherjee, 2001). Considering the significance of user satisfaction and ongoing usage in m-learning initiatives, this model could provide valuable perspectives, particularly in unstable environments.

CHALLENGES IN UNSTABLE ENVIRONMENTS

Political instability and civil conflicts pose unique challenges to m-learning adoption. These challenges can include limited infrastructure, security concerns, and disruptions to traditional education. Researchers like Al-Hamad et al. (2021) have examined the impact of such challenges on educational technology adoption in conflict-affected areas, shedding light on the need for context-specific models and strategies. In unstable environments, such as regions affected by civil conflicts or natural disasters, m-learning faces unique challenges. Infrastructure disruptions, unreliable connectivity, and limited access to power sources can hinder the effective use of mobile devices and learning platforms (Hamse et al., 2020). Additionally, learners in these settings may experience emotional distress and psychological challenges, so addressing the emotional and psychological support needed to maintain their engagement and motivation in m-learning (Salhab & Daher, 2023). Moreover, in unstable environments, learners often experience significant mobility, displacement, or unpredictable disruptions to their daily routines. This makes it challenging to establish consistent learning habits and engage in structured m-learning activities (Elfeky & Yakoub Masadeh, 2016). The dynamic nature of these environments necessitates adaptable m-learning solutions that cater to learners' ever-changing needs and circumstances. Overall, the challenges of m-learning in unstable environments underscore the importance of designing resilient and flexible educational approaches that can effectively deliver learning resources despite adversity and unpredictability (Al-Hamad et al., 2021).

CONTEXTUAL FACTORS IN IRAQ

To gain a deeper understanding of m-learning adoption in Iraqi universities, it is essential to consider context-specific factors. Research by Mohammadi et al. (2021) explores the challenges and opportunities of e-learning in Iraq, providing insights into the broader educational technology landscape. Contextual factors play a crucial role in shaping the adoption of m-learning in Iraqi universities (Mussa, 2020). Factors such as the political and security situation in Iraq, limited infrastructure, and varying levels of technological accessibility can significantly impact the implementation and success of m-learning initiatives. In a country marked by historical conflicts and ongoing security concerns, these contextual challenges can impede m-learning's consistent and widespread use. The work by Alsswey and Al-Samarraie (2019) highlights the importance of understanding local contexts in m-learning adoption, emphasizing the need to adapt technological solutions to the specific challenges and needs of the region. Consequently, gaining a deeper understanding of these contextual factors is essential for tailoring m-learning interventions to the unique circumstances in Iraqi universities.

Moreover, examining the sociocultural aspects of Iraq is essential for m-learning adoption. Iraq's diverse population, with various ethnicities and languages, presents a unique context that necessitates localized content and multilingual support in m-learning platforms. This complexity is underscored by Mussa and Sazalli (2021), who emphasize the significance of cultural factors in m-learning. Therefore, a comprehensive exploration of contextual factors in Iraq is vital for optimizing m-learning strategies that accommodate the region's distinct sociocultural dynamics, technological limitations, and security considerations, ultimately enhancing the adoption and effectiveness of m-learning in Iraqi universities (Younis et al., 2020, 2023).

This literature review highlights the relevance of studying m-learning adoption in unstable environments like Iraq and the potential applicability of technology acceptance models like UTAUT2 and ECM. While existing research provides valuable insights, there is a need for studies that extend these models to accommodate the unique challenges and drivers of m-learning adoption in such contexts. This review sets the stage for further exploration into this critical area, aiming to contribute to enhancing m-learning initiatives in Iraqi universities and similar environments worldwide.

RESEARCH FRAMEWORK AND HYPOTHESES

Continued usage intention of m-learning in Iraqi universities under an unstable environment poses a unique challenge, necessitating an extension of established technology acceptance models. In this study, we propose a research framework that extends UTAUT2 and ECM to understand better the factors influencing the continued usage intention of m-learning in this context (Figure 1).

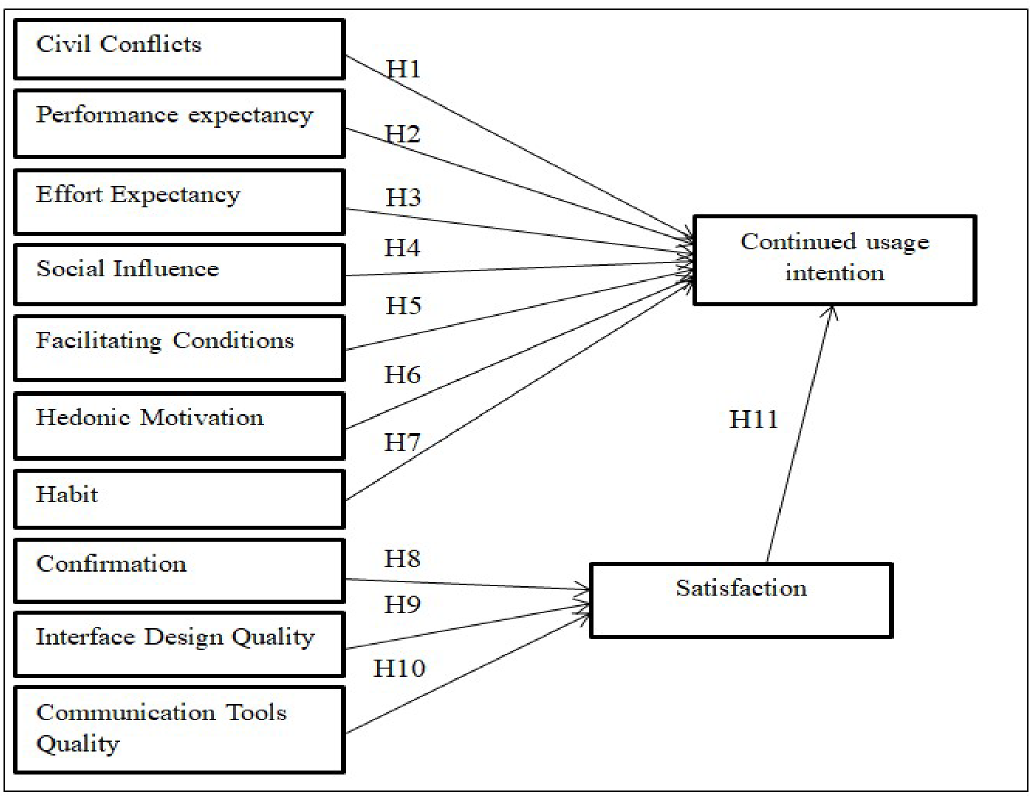

Figure 1. Proposal model

CIVIL CONFLICTS (CC)

The research framework for the factor "civil conflicts" on continued usage intention of m-learning within this study is based on the contextual challenges faced by Iraqi universities due to instability.

This factor is essential to understanding the impact of external disruptions on students' willingness to continue using m-learning platforms (Al Omoush, 2019). This factor represents the influence of political and social unrest on students' perceptions of m-learning. It encapsulates the challenges and uncertainties brought about by civil conflicts in Iraq, affecting the continuity of education through m-learning (Al-Swidi & Faaeq, 2019). This hypothesis provides a critical foundation for the research, highlighting the unique challenges faced by Iraqi universities and their impact on students' intentions to persist with m-learning despite the unstable environment.

> **H1:** Civil conflicts negatively influence the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Performance Expectancy (PE)

We posit that students' expectations regarding the benefits of continued use of m-learning will positively influence their intention to continue using m-learning in Iraqi universities in an unstable environment (Lutfi et al., 2022). The study suggests the following to explain performance expectancy (PE) towards employing the m-learning system.

> **H2:** Performance expectancy (PE) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Effort Expectancy (EE)

Perceptions of the ease of continued use are critical, especially in challenging contexts. Students' perceived ease of continued m-learning use will significantly impact their intention to persist (Al-Abdullatif & Alsubaie, 2022). The researchers suggest the following as a result of this.

> **H3:** Effort expectancy (EE) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Social Influence (SI)

The influence of peers and educators plays a crucial role in technology acceptance (Perera & Abeysekera, 2022). We anticipate that social factors, such as recommendations from peers and educators, will influence students' decisions to continue using m-learning. The researchers suggest the following as a result of this.

> **H4:** Social influence (SI) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Facilitating Conditions (FC)

Adequate infrastructure and support are essential for continued usage (Miraz et al., 2022). Students' access to necessary resources and institutional support will positively affect their intention to continue using m-learning. The researchers suggest the following as a result of this.

> **H5:** Facilitating conditions (FC) positively influence the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Hedonic Motivation (HM)

Beyond academic benefits, the enjoyment and satisfaction derived from m-learning may encourage its continued use (Al-Azawei & Alowayr, 2020). Hedonic motivation, associated with enjoying the learning experience, will positively impact the continued usage intention. The researchers suggest the following as a result of this.

> **H6:** Hedonic motivation (HM) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Habit (H)

Habit formation is likely to play a significant role in the continued usage of m-learning tools, especially as students become accustomed to using them in response to disruptions caused by instability (Yang et al., 2022). The researchers suggest the following as a result of this.

> **H7**: Habit (H) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Confirmation (CON)

We extend the ECM to include confirmation as a factor influencing the continued usage intention. Confirmation, which measures the congruence between users' expectations and post-adoption experiences, may affect the decision to persist with m-learning (Tian & Wu, 2022). The researchers suggest the following as a result of this.

> **H8**: Confirmation (CON) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Interface Design Quality (IDQ)

The quality of the m-learning interface is vital for user satisfaction. Interface design quality will positively influence students' continued usage intention (Al-Zu'bi & Al-Gasawneh, 2022). The researchers suggest the following as a result of this.

> **H9:** Interface design quality (IDQ) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Communication Tool Quality (CTQ)

Effective communication tools enhance the m-learning experience. The quality of communication tools will positively impact the continued usage intention (Almaiah et al., 2022). The researchers suggest the following as a result of this.

> **H10:** Communication tool quality (CTQ) positively influences the continued usage intention of m-learning in Iraqi universities under an unstable environment.

Satisfaction (SAT)

According to the extant literature, satisfaction has been identified as a crucial determinant for technology's sustained adoption and usage. In the present context, the level of satisfaction plays a crucial role in influencing students' choices to persist with the utilization of m-learning, particularly within the demanding and uncertain setting of Iraqi universities. This research framework offers a comprehensive understanding of the influence of satisfaction with the m-learning experience on students' ongoing intentions by integrating the ECM and UTAUT2 models. This contributes to the existing knowledge of technology adoption in higher education settings.

The "satisfaction with continued usage intention" construct holds significant importance within the research framework. The foundation of this relationship lies in the notion that when students perceive the m-learning system as fulfilling and addressing their educational requirements, they are inclined to exhibit a heightened intention to continue utilizing it. Based on the information mentioned earlier, the subsequent hypothesis was formulated.

> **H11:** The level of satisfaction with m-learning systems significantly impacts students' intention to continue using m-learning in universities in Iraq.

This research framework and hypotheses provide a structured approach to understanding the factors influencing the continued usage intention of m-learning in the unique context of Iraqi universities facing instability. By extending established models and considering additional variables, this study aims to contribute valuable insights for enhancing the effectiveness of m-learning initiatives in similarly challenging environments.

MEDIATING ROLE OF SATISFACTION

The mediating role of satisfaction plays a pivotal role in understanding students' intentions to continue using m-learning platforms. This mediation hypothesis suggests that students' satisfaction with various aspects of the m-learning experience, such as system confirmation, interface design quality, and communication tool quality, can serve as an intermediary mechanism that bridges the relationship between these factors and their continued usage intention. In essence, satisfaction acts as a key driver that translates students' perceptions and experiences into a commitment to persist in using m-learning despite the challenges posed by an unstable environment (X. Chen et al., 2022; Ma et al., 2022).

Previous research has highlighted the significance of satisfaction as a mediating variable in technology adoption and continued usage models. When students perceive m-learning systems as effective, user-friendly, and equipped with high-quality communication tools, they are more likely to feel satisfied with their learning experiences. This satisfaction, in turn, reinforces their intention to continue using the technology (Arshad Khan & Alhumoudi, 2022; Hwang et al., 2022). By integrating this mediating role into the research framework, this study aims to shed light on the intricate dynamics between students' perceptions, satisfaction, and their determination to persist in utilizing m-learning solutions within the unique context of Iraqi universities facing an unstable environment.

To provide a more structured understanding of the mediating role of satisfaction, an indirect relationship was formulated:

> Satisfaction plays a mediating role in the relationship between confirmation (CON), interface design quality (IDQ), communication tools quality (CTQ), and the continued usage intention of m-learning systems among students in Iraqi universities.

This hypothesis-driven approach aims to provide a comprehensive analysis of the mediating role of satisfaction in the context of continued usage intention within m-learning, offering valuable insights into the factors influencing students' intentions in an unstable environment.

METHODOLOGY

The present study aims to elucidate the research methodology employed in this research project. This section provides an overview of the data collection process, the measurement scale development, the survey methodology employed, the sample population used in the research, and the data analysis methods employed.

DATA COLLECTION AND PARTICIPANTS

The data collection period spanned from April to October 2023. Empirical data was obtained through an electronic cross-sectional survey distributed online. The researchers employed a convenient sampling method in which 700 individuals were invited to participate in the study. Of these, 399 responses were considered suitable for constructing a robust model using partial least squares structural equation modeling (PLS-SEM) (Hair et al., 2017). The study recruited participants from five prominent higher education institutions in the country, namely two situated in Baghdad, one in Basra, another in Al-Anbar, and the fifth in Al-Najaf. The researchers employed a research assistant to facilitate the electronic dissemination of the survey and the recruitment of participants, which was carried out through personal networking methods. The introduction of the survey presented a succinct overview of the subject matter and objectives. It also emphasized the importance of maintaining the confidentiality and anonymity of the respondents, ensuring that the gathered data would be utilized solely for research purposes.

All participants in the study willingly and without any financial inducements chose to participate. Completing the questionnaire required a time frame of approximately 10 to 15 minutes.

DEVELOPMENT OF SCALE

A survey was designed to include two main sections: demographic items and latent construct items. The demographic part included seven questions on gender, age, marital status, educational stage, the university of study, device(s) owned, and experience with the usage of m-learning (Table 1).

Table 1. Profile of respondents (N = 399)

		Frequency	Percent
Age	>27 years old	128	31.5
	18-20 years old	37	9.1
	21-23 years old	178	43.8
	24-26 years old	63	15.5
Gender	Female	165	40.6
	Male	241	59.4
Marital status	Married	164	40.4
	Single	242	59.6
Educational stage	Fourth stage	221	54.4
	Third stage	185	45.6
The university of study	Al-Mustansiriya University	90	22.2
	University of Anbar	49	12.1
	University of Baghdad	120	29.6
	University of Basrah	99	24.4
	University of Kufa	48	11.8
Device(s) owned by respondents	Hand phone	101	24.9
	I-pad	45	11.1
	Laptop	142	35.0
	Smartphone	240	59.1
	Others	40	9.9
Experience using m-learning	1-3 years	210	51.7
	4-6 years	63	15.5
	Less than 1 year	46	11.3
	More than 6 years	87	21.4

The second section comprised 61 items measuring the seven constructs of the research model. The instruments (i.e., CC, PE, EE, SI, FC, HM, HB, CON, IDQ, CTQ, SAT, and CUI) were developed after a thorough review of studies exploring m-learning usage based on the UTAUT2 theory with adjustments according to the study context and ECM model as in the Appendix.

The questionnaire responses were scored using a 5-point Likert scale, with multiple items measured within each dimension. The Likert scale consisted of five response options ranging from "strongly disagree" (coded as 1) to "strongly agree" (coded as 5). The initial administration of the survey aimed to evaluate and confirm the dependability of the items through empirical means, ensuring the accuracy and precision of all measurement items (Hair et al., 2017).

Cronbach's alpha values were computed to assess the reliability of each dimension, with a predetermined cutoff score of 0.7, as recommended by Hair et al. (2017). The reliability scores ranged from 0.842 for FC to 0.947 for EE. Once the necessary level of reliability had been established for all measurement items, it was determined that the final questionnaire was reliable and suitable for use.

The reliability coefficients for the following measures were calculated: CC (α=0.899), CON (α=0.930), CTQ (α=0.917), CUI (α=0.940), EE (α=0.947), FC (α=0.842), HB (α=0.916), HM (α=0.915), IDQ (α=0.918), PE (α=0.920), SAT (α=0.932), and SI (α=0.885).

Technique of Statistical Analysis

PLS-SEM was utilized with Smart PLS software to analyze the significance of the hypothesized paths and the amount of variance in the dependent variables attributed to the explanatory variables using bootstrapping Hair, Risher, et al. (2019). PLS-SEM is considered adequate and valuable in exploring areas pertinent to a technology acceptance model, such as the UTAUT (Hair, Sarstedt, et al., 2016).

PLS-SEM encompasses measurement and structural models, making it a versatile statistical analysis technique for assessing relationships and latent constructs. The measurement model establishes the relationships between latent constructs and their observed indicators. It enables researchers to assess the reliability and validity of the measures used and understand how well the observed variables represent the underlying latent constructs. PLS-SEM allows for incorporating reflective (effect indicators loading on the construct) and formative (construct determined by its indicators) measurement models, making it adaptable to various research contexts and facilitating a more comprehensive assessment of the measurement model. This approach enables researchers to refine their measurement instruments and enhance the accuracy of their findings. Becker et al. (2013) provide comprehensive guidance on the intricacies of developing and evaluating measurement models in PLS-SEM, emphasizing its practical applications in research.

The structural model in PLS-SEM focuses on uncovering the relationships between latent constructs and understanding the patterns of influence among them. This stage examines the causal pathways and interactions between latent constructs, offering insights into the complex relationships that exist in the research model. Researchers can use PLS-SEM to test hypotheses, validate theoretical frameworks, and assess the strength and direction of relationships within the structural model. This technique provides robust results, especially when dealing with small sample sizes and data that may not conform to the assumptions of traditional SEM. Henseler and Sarstedt (2013) and Hair et al. (2017) offer guidance on constructing and analyzing the structural model in PLS-SEM, ensuring the practical application of this method in various research domains.

Results

Model of Measurement

The measurement model is a statistical framework used to assess and quantify the relationship between observed variables and latent constructs in a research study. The convergence validity assessment was conducted to evaluate the degree of agreement between various measures of the same construct. According to the study conducted by Hair, Page, et al. (2019),D the assessment of convergent validity involved the evaluation of factor loading, average variance extracted, and composite reliability values. Confirmatory factor analysis (CFA) was employed to assess the reliability and validity of the measures derived from existing literature. The findings are displayed in Table 2. According to the findings, the factor loadings of all the measured items exhibited a range of 0.655 to 0.920, surpassing the recommended threshold of 0.5, as proposed by Hair, Risher, et al. (2019).

The average variance extracted, which represents the overall variance in the indicators of the latent construct, ranged from 0.609 to 0.806, surpassing the recommended threshold of 0.5 (Hair et al., 2017). The indicators' construct reliability was found to range from 0.864 to 0.948, surpassing the recommended threshold of 0.6, as proposed by Hair et al. (2017). The Cronbach alpha test was employed to assess the reliability of the constructs. The values exhibited a range from 0.842 to 0.947, surpassing the recommended threshold of 0.7, as proposed by Nunnally and Bernstein (1994).

Table 2 displays the means, standard deviations, correlations between constructs, and the results of discriminant validity analysis, which indicate the extent to which each construct is distinct from the others (Fornell & Larcker, 1981; Hair, Sarstedt, et al., 2016).

Table 2. Means, standard deviations, and correlations between constructs and the discriminant validity findings

Construct	Indicator	Loading	Composite reliability	Cronbach alpha	Ave
CC	CC1	0.655	0.946	0.899	0.664
	CC2	0.805			
	CC3	0.808			
	CC4	0.879			
	CC5	0.882			
	CC6	0.840			
CON	CON1	0.908	0.931	0.930	0.782
	CON2	0.874			
	CON3	0.882			
	CON4	0.859			
	CON5	0.898			
CTQ	CTQ1	0.861	0.918	0.917	0.750
	CTQ2	0.865			
	CTQ3	0.878			
	CTQ4	0.864			
	CTQ5	0.861			
CUI	CUI1	0.896	0.940	0.940	0.806
	CUI2	0.911			
	CUI3	0.890			
	CUI4	0.898			
	CUI5	0.894			
EE	EE1	0.867	0.948	0.947	0.792
	EE2	0.894			
	EE3	0.898			
	EE4	0.882			
	EE5	0.902			
	EE6	0.896			
FC	FC1	0.776	0.864	0.842	0.609
	FC2	0.852			
	FC3	0.836			
	FC4	0.708			
	FC5	0.719			
HB	HB1	0.851	0.919	0.916	0.748
	HB2	0.831			
	HB3	0.885			
	HB4	0.871			
	HB5	0.886			
HM	HM1	0.900	0.918	0.915	0.798
	HM2	0.920			
	HM3	0.898			
	HM4	0.854			

Construct	Indicator	Loading	Composite reliability	Cronbach alpha	Ave
IDQ	IDQ1	0.914	0.919	0.918	0.803
	IDQ2	0.919			
	IDQ3	0.849			
	IDQ4	0.900			
PE	PE1	0.867	0.923	0.920	0.759
	PE2	0.896			
	PE3	0.899			
	PE4	0.870			
	PE5	0.823			
SAT	SAT1	0.876	0.932	0.932	0.786
	SAT2	0.901			
	SAT3	0.899			
	SAT4	0.874			
	SAT5	0.883			
SI	SI1	0.788	0.886	0.885	0.685
	SI2	0.854			
	SI3	0.812			
	SI4	0.851			
	SI5	0.829			

The square root of the average variance extracted for each construct exceeds the correlations between that construct and other constructs, as documented by Hair et al. (2017). The descriptive statistics of all the constructs, including the mean and standard deviation, are presented in Table 3. The SI group exhibited the lowest mean value (mean = 3.198), whereas the IDQ group displayed the highest mean value (mean = 3.779). The sequence variable (IDQ) exhibited the lowest standard deviation (SD = 0.912), while the mean squared error variable (CC) had the highest standard deviation (SD = 1.280).

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
CC	3.323	1.280	**0.815**											
CON	3.617	0.917	0.080	**0.884**										
CTQ	3.534	0.928	0.017	0.749	**0.866**									
CUI	3.704	0.923	0.108	0.788	0.770	**0.898**								
EE	3.571	0.958	0.040	0.796	0.752	0.787	**0.890**							
FC	3.516	0.976	0.020	0.713	0.679	0.691	0.784	**0.780**						
HB	3.561	0.950	0.091	0.846	0.726	0.787	0.780	0.706	**0.865**					
HM	3.669	0.937	0.025	0.790	0.732	0.762	0.869	0.765	0.762	**0.893**				
IDQ	3.779	0.912	0.009	0.755	0.767	0.728	0.802	0.700	0.712	0.752	**0.896**			
PE	3.702	0.971	-0.014	0.726	0.670	0.728	0.797	0.716	0.710	0.760	0.717	**0.871**		
SAT	3.654	0.922	0.077	0.814	0.780	0.865	0.781	0.712	0.787	0.786	0.736	0.725	**0.886**	
SI	3.198	1.007	-0.006	0.718	0.672	0.719	0.766	0.783	0.723	0.723	0.666	0.762	0.683	**0.827**

Note. Values displayed in diagonal bold represent the square root of the average variance extracted-PLS-SEM.

Table 3. Descriptive statistics, correlations & AVE

Structural Model

The structural model is a theoretical framework used to analyze and understand the relationships between different components or elements within a system. The structural model was subsequently assessed after satisfactory results in the measurement model were obtained. The model's predictive power was assessed using R2 values, which measure the proportion of variance accounted for by the latent variables. The results indicate that the model explains 80% of the variance in continued usage intention (CUI) and 73% in satisfaction (SAT), as depicted in Figure 2. In order to ascertain the potential impact of other variables on continued usage intention (CUI), this study employed a control mechanism by accounting for factors such as student age, gender, marital status, education level, and experience with m-learning. There was no observed statistical significance in the impact of any of the control variables on academic performance. Consequently, the model exhibited a high level of predictive accuracy, as indicated by the proportion of variance explained (R-square). Table 4 presents the path coefficients and the outcomes obtained from the analysis of hypothesized direct effects.

According to the findings presented in Table 4, it can be observed that the paths from CC, EE, SI, and HB on CUI, as well as CON, IDQ, and CTQ on SAT and SAT on CUI, all exhibited statistical significance. This is evident because the p-values associated with these paths were all below the conventional significance threshold, typically set at 0.05. All paths exhibited a positive direction, indicating that an increase in each independent variable also corresponded to an increase in the dependent variables. The findings provided support for Hypotheses H1, H3, H4, H7, H8, H9, H10, and H11. The results showed that there was no significant importance for the following paths: PE, FC, and HM on CUI. However, performance expectancy (PE) did not directly affect CUI, suggesting that students' expectations regarding m-learning performance may not be the primary driver of their continued usage intention. Facilitating conditions (FC) and hedonic motivation (HM) did not directly impact CUI, indicating that the availability of resources and the pleasure derived from m-learning might not be direct drivers of continued usage intention.

Table 4. Discriminant validity, correlations, and descriptive statistics

No.	Path	Path coefficient	T-value	P-value	Hypothesis result
Direct Effects					
H1	CC->CUI	0.050	2.057	0.040	Supported
H2	PE->CUI	0.052	1.058	0.290	Not Supported
H3	EE->CUI	0.142	2.051	0.040	Supported
H4	SI->CUI	0.138	2.589	0.010	Supported
H5	FC->CUI	-0.061	1.267	0.205	Not Supported
H6	HM->CUI	0.011	0.167	0.867	Not Supported
H7	HB->CUI	0.144	2.509	0.012	Supported
H8	CON->SAT	0.470	8.347	0.000	Supported
H9	IDQ->SAT	0.128	2.194	0.028	Supported
H10	CTQ->SAT	0.330	5.605	0.000	Supported
H11	SAT->CUI	0.540	9.613	0.000	Supported
Indirect Effects – The mediating role of Satisfaction (SAT)					
	CON->SAT->CUI	0.254	6.032	0.000	Supported
	IDQ->SAT->CUI	0.069	2.178	0.029	Supported
	CTQ->SAT->CUI	0.178	4.813	0.000	Supported

The results refer to the effect of satisfaction as a mediator between confirmation (CON), interface design quality (IDQ), communication tool quality (CTQ), and continued usage intention. All exhibited statistical significance. This is evident from the fact that the p-values associated with these paths were all below the conventional threshold of significance, which is typically set at 0.05. All paths exhibited a positive direction, indicating that an increase in each independent variable also corresponded to an increase in the dependent variables.

The study's findings revealed that satisfaction (SAT) demonstrated the most substantial influence on continued usage intention (CUI), as evidenced by a path coefficient of 0.540. This relationship was found to be statistically significant at the 0.001 level. The confirmation (CON) variable was determined to have the most significant impact on satisfaction (SAT), as evidenced by a path coefficient of 0.470. This relationship was found to be statistically significant at the 0.001 level.

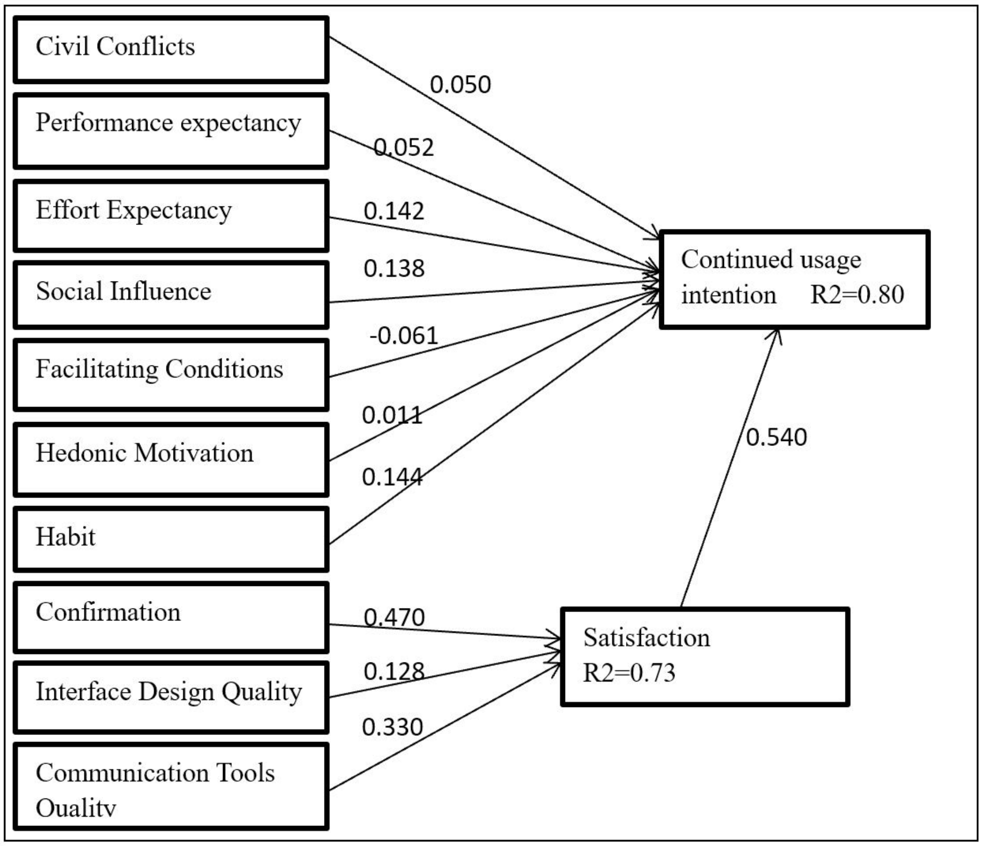

Figure 2. Detailed results of the structural model to examine the research hypotheses

DISCUSSION

Information and communication technologies bring many opportunities to higher educational settings (Al-Musawi & Ali, 2022; Shaya et al., 2023). M-learning can be viewed as a logical progression of e-learning, with enhanced communication and tailored processes, or as a new platform for distance learning. It enables students of all ages to study and access learning resources from any location and time, especially during unstable circumstances such as conflicts, wars, and epidemics (Al-Swidi & Faaeq, 2019). This article draws on the literature on IT integration in general and UTAUT2, ECM, and m-learning research to better understand students' relative attitudes and intentions in utilizing m-learning instead of conventional classroom environments.

Fourteen hypotheses were examined. The hypothesis posits that factors such as CC (H1), EE (H3), SI (H4), and HB (H7) will exert a positive influence on CUI, while CON (H8), IDQ (H9), and CTQ (H10) will have a positive impact on SAT. Furthermore, it is hypothesized that SAT (H11) will positively contribute to the use of m-learning by enhancing CUI . The results of this study show that all of these hypotheses are supported. On the contrary, hypotheses PE (H2), FC (H5), and HM (H6) do not affect CUI.

The mediating role of satisfaction (SAT) signifies that confirmation (CON), interface design quality (IDQ), and communication tool quality (CTQ) influence continued usage intention (CUI). The supported hypotheses suggest that when users confirm their expectations, the interface and communication tool quality are positively perceived, leading to higher user satisfaction. This elevated satisfaction encourages their continued intention to use m-learning in Iraqi universities. These findings underscore the pivotal role of user satisfaction in sustaining the use of technology. When users have their initial expectations confirmed, encounter a well-designed interface, and experience effective communication tools, their satisfaction is a crucial link between these elements and their intention to persist in using the m-learning platform. Ensuring these favorable factors can positively impact students' continued engagement with m-learning in the challenging context of Iraqi universities.

Although the outcome of this study is consistent with previous studies investigating the fostering of m-learning systems in higher education, such as Almaiah et al. (2022) and Qashou (2021), the results of this study are distinct from prior studies. Unlike previous studies, which strictly explored UTAUT2 and ECM-related components and other precursors to the adoption of m-learning systems, in this study, the researchers further modified the model to add the new construct of CC, which was then empirically tested with the non-conventional constructs such as the variables of CON, IDQ, and CTQ. This study contributes to the literature on technology acceptance by testing the UTAUT2 and ECM modules on m-learning. The suggested model contains many constructs from the most widely used theoretical frameworks (Roslan et al., 2023). Direct routes from students' CC, PE, EE, SI, FC, HM, and HB for UTAUT2 and the ECM variables, CON and SAT, with new variables such as IDQ and CTQ, were postulated in the structural model to users.

Consistent with the UTAUT2 and previous research, results show that antecedents such as CC, EE, SI, and HB substantially influence CUI. This lends credence to hypotheses H1, H3, H4, and H7 (Almaiah & Alismaiel, 2019; Chao, 2019; Lutfi et al., 2022; Waleed, 2022). In addition, CON, IDQ, and CTQ have an indirect effect on continued usage intention of m-learning through user SAT, as well as the direct effect of SAT on CUI, which supports hypotheses H8, H9, H10 and H11 (Alshurideh et al., 2020; Alzaidi & Shehawy, 2022; Roslan et al., 2023). This implies that learner SAT is the primary antecedent and plays a key role in mediating the effects of CON, IDQ, and CTQ on CUI. With a path coefficient of 0.540, which is significant at the 0.001 level, results identified user SAT as the most important driver of CUI, validating hypotheses. Students' CUI to use m-learning was found to be directly affected by SAT (Waleed, 2022).

According to ECM and UTAUT2, student adoption and utilization of m-learning is heavily influenced by user SAT and how simple an m-learning system is to use (Al-Emran et al., 2020; Almaiah & Alismaiel, 2019). Further, SAT was shown to have the greatest impact on CUI, with a path coefficient of 0.540 and significance at the 0.001 level. HB is a powerful predictor of future behavior; this was in line with previous research that found a link between the use of technology and greater academic achievement (Arshad Khan & Alhumoudi, 2022; Hwang et al., 2022).

Results revealed a strong positive correlation between variables, indicating that when each of the independent factors grew, so did the dependent variables. According to the findings, PE, EE, SI, FC, HM, and HB are key variables in effective m-learning (UTAUT2) and enabling factors that impact students' CUI to use m-learning. In addition, behavioral desire to use m-learning modulates the link between technological acceptability features and actual student m-learning utilization (Al-Musawi & Ali, 2022; Shaya et al., 2023).

LIMITATIONS

It is imperative to acknowledge the limitations inherent in this study, which encompass potential sample bias and the particular context of Iraqi universities. The existing models may need to capture the unique influencing factors in an unstable environment fully. Furthermore, the study's cross-sectional design precludes the establishment of causal relationships. To address the limitations mentioned earlier and to gain a more comprehensive understanding of the adoption of m-learning in unstable environments, it is recommended that future research incorporate longitudinal designs and diverse samples. This approach will enable researchers to examine the phenomenon over an extended period and gather data from a wide range of participants, thereby enhancing the depth and complexity of the findings.

IMPLICATIONS

The results of this study hold practical implications for educators, policymakers, and institutions operating in Iraq and other comparable settings. Gaining a comprehensive comprehension of the significance of user satisfaction and the precise determinants that impact it can facilitate the development and execution of efficacious m-learning strategies. In order to increase students' satisfaction and subsequent intention to continue using educational institutions, these institutions should prioritize the improvement of performance expectancy, effort expectancy, and hedonic motivation. Furthermore, it is imperative to make endeavors towards the provision of facilitating conditions and the promotion of habit formation, as these factors can significantly enhance the likelihood of achieving success in m-learning.

FUTURE RESEARCH

Subsequent investigations in this particular field of study may delve into the influence of individual variances, such as cultural elements and prior experiences, on the behavioral patterns of students when it comes to adopting m-learning. Furthermore, a thorough examination of the influence exerted on adopting m-learning by external variables, such as the caliber of internet connectivity and digital infrastructure, could yield a more holistic comprehension of the obstacles encountered in volatile contexts. Conducting longitudinal studies that monitor the m-learning behavior of students over an extended period has the potential to provide valuable insights into the long-term sustainability of their intentions.

CONCLUSION

This research on continued usage intention to use m-learning in Iraqi universities amidst an unstable environment, integrating the ECM and UTAUT2 models using PLS-SEM, has produced valuable findings with noteworthy implications and opportunities for further investigation, albeit within its inherent constraints. The research findings offer a comprehensive comprehension of the factors that influence students' intention to continue using m-learning in the particular context of Iraqi universities grappling with instability.

Significantly, the determinants of continued usage intention were identified as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. The significance of satisfaction in bridging the gap between technology adoption and user intentions is highlighted by its mediating role in linking these factors to continued usage intention. Moreover, the present study expanded upon the UTAUT2 and ECM frameworks to accommodate the unique context of Iraqi universities, thus making a valuable contribution to the theoretical comprehension of m-learning adoption.

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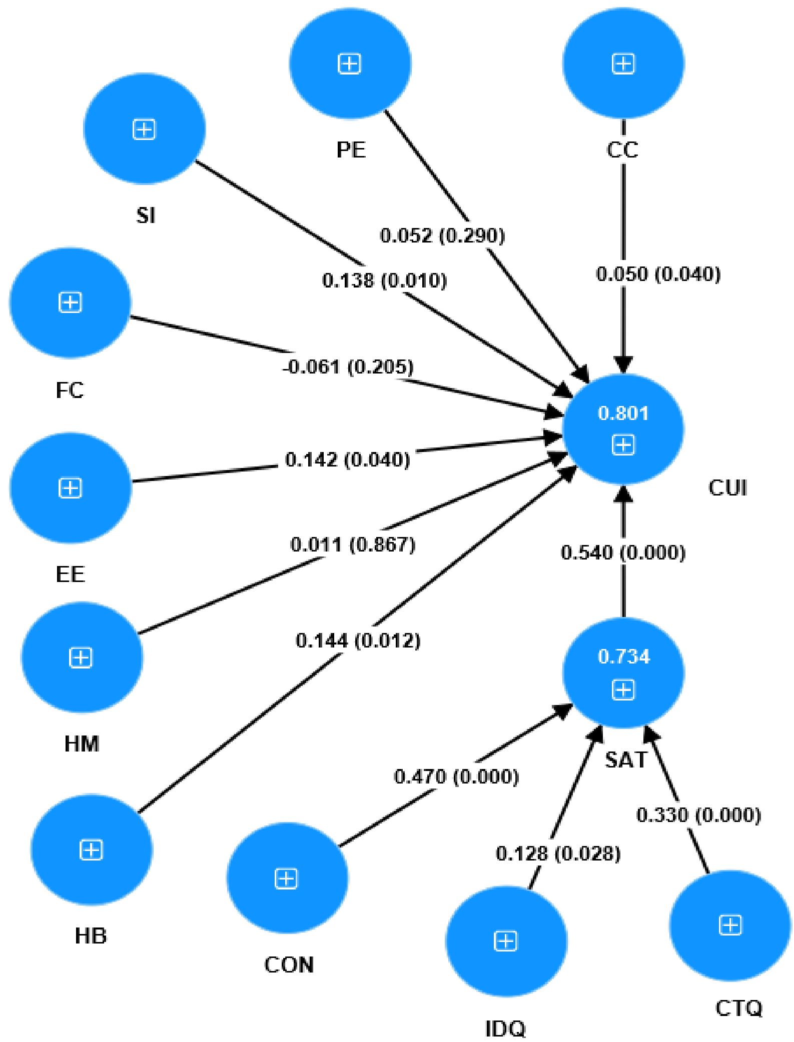
APPENDIX: STRUCTURAL MODEL ACCORDING TO PLS-SEM



Note: (CC) civil conflicts; (PE) performance expectancy; (SI) social influence; (FC) facilitating conditions; (EE) effort expectancy; (HM) hedonic motivation; (HB) habit; (CON) confirmation; (IDQ) interface design quality; (CTQ) communication tools quality; (SAT) satisfaction; (CUI) continued usage intention.

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