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PAPER

Adoption of Mobile Learning: Education's Use of App-Based Learning Management Systems & Ethical Implementation

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ABSTRACT

This study examines the adoption of mobile learning (M-learning) through app-based learning management systems (LMS) in higher education, aiming to identify key factors influencing students' usage behavior and continuing adoption intentions. Using an integrated theoretical framework combining the unified theory of acceptance and use of technology (UTAUT) and the expectation-confirmation model (ECM), the research employs a quantitative, cross-sectional design. Data were collected from 399 university students with M-learning experience, using a structured online questionnaire distributed via institutional portals and academic social media channels. Partial least squares structural equation modeling (PLS-SEM) was used to analyze the data and test direct and mediating effects among key variables. The findings reveal that performance expectancy and satisfaction are the strongest predictors of M-learning adoption, while interface design quality and facilitating conditions play significant but secondary roles. The study confirms satisfaction as a critical mediator between initial expectations and long-term usage intentions, highlighting its central role in sustaining engagement with M-learning platforms. These results contribute to educational technology literature by validating an integrated adoption model specifically for app-based LMS and providing empirical evidence on the hierarchical importance of different adoption factors. Practical implications suggest that educational institutions should prioritize user experience design and performance-related functionalities when implementing M-learning solutions, while also ensuring reliable technical support.

KEYWORDS

mobile learning (M-learning), learning management systems (LMS), technology adoption, partial least squares structural equation modeling (PLS-SEM), higher education, ethical implementations

1 INTRODUCTION

The rapid advancement of digital technologies has revolutionized education, with mobile learning (M-learning) emerging as a transformative approach to

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delivering knowledge through app-based learning management systems (LMS) [1]. The proliferation of smartphones and high-speed internet connectivity has enabled educational institutions to shift from traditional classroom-based instruction to flexible, on-demand learning models [2]. M-learning, defined as the use of portable devices to facilitate education anytime and anywhere, has gained significant traction in higher education due to its ability to enhance accessibility, engagement, and personalized learning experiences [3]. Although more individuals are using M-learning, how much success such LMS systems achieve relies on how much users participate and stay involved [4–5]. Many researchers have looked at different aspects of using technology in education; more study is needed to fully understand what shapes a student's intention to use and actual use of mobile LMS applications [6]. The research hopes to address this gap by analyzing what influences M-learning adoption with an integrated framework made from the unified theory of acceptance and use of technology (UTAUT) and the expectation-confirmation model (ECM). The rise in M-learning was sped up due to the COVID-19 pandemic, making schools move to online and mixed methods of teaching [7]. Software applications on mobile devices, like Moodle mobile, blackboard and google classroom, are now commonly used to manage courses, talk to students and evaluate how they are doing [8]. Even though these platforms are available everywhere, they work best for students who want to use them all the time [9].

Many factors influencing technology use in education have been found; for example, people see it as useful, find it easy to use, and are affected by their peers and when they get support from the environment [9]. Nevertheless, most of the research has studied if people adopt M-learning and how soon, missing out on how satisfaction and meeting expectations encourage people to continue using it [10]. By joining both the reasons for beginning and satisfaction afterward into the same model, this study provides a wider picture of M-learning sustainability [7].

The unified theory of acceptance and use of technology places performance expectancy, effort expectancy, social influence, and facilitating conditions as major determinants of technology adoption, whereas ECM stresses that satisfaction and ongoing use result from users confirming their first expectations [11]. The blending of these models provides more details about M-learning adoption, covering the point when the app-based LMS was first chosen and how students feel about it afterward for consistent use. While research has looked at M-learning generally, research on using apps as LMS platforms is limited because these types of systems face distinct usability and accessibility difficulties compared to those available online [12]. Therefore, this study focuses solely on mobile applications, offering insights suited to the increasing role of smartphones in learning. This study helps resolve these misunderstandings by testing how different aspects of M-learning work together in a higher education environment. Although researchers agree that users' satisfaction is key to deciding to use a mobile LMS, they have not looked closely at how satisfaction bridges the gap between rich expectations and actual use. This study explains the role of satisfaction in helping educational institutions raise user retention and engagement on their M-learning platforms. This study makes several key contributions to the literature on M-learning and educational technology. First, it extends theoretical knowledge by integrating UTAUT and ECM into a unified framework, demonstrating how initial adoption factors and post-adoption satisfaction collectively influence continued usage of app-based LMS platforms. Second, it provides empirical evidence on the relative importance of different predictors, revealing that while performance expectancy and facilitating conditions drive initial adoption, satisfaction emerges as the strongest determinant of long-term engagement. Third, the study offers practical recommendations for educational institutions and LMS developers, emphasizing the need to design M-learning applications that not only meet functional requirements but also deliver satisfying user experiences.

2 LITERATURE REVIEW

Building M-learning on app-based LMS continues what e-learning started through accepting technology and looking at user studies, as both theories and facts are included in this literature review to give a wide perspective on why M-learning is used more in higher education. Scholars have turned to the UTAUT model as a guide, as it unites ideas from previous models like the TAM and the innovation diffusion theory [13–14]. UTAUT points out that having a good view of technology, it being simple to use, influence from employees and usual habits, and support from the organization play a big role in choosing whether to use new technologies. Research on M-learning points out that the expectancy of doing well with mobile technology is the key reason why someone decides to use it [15]. UTAUT can explain why somebody starts using a system, but it does not show what influences their behavior after using M-learning [16].

The ECM appears as a suitable addition since it looks at consumer action after receiving the product, and the study argues that users are likely to continue with the technology if they are satisfied and their first expectations are met while using it [12]. When learning on mobile, satisfaction is seen to moderate the link between thinking LMSs are useful and deciding to keep using them. However, many existing studies have looked at ECM only in connection with general e-learning platforms, rather than app-based mobile LMS, which have their own special usability challenges like screen size, designing interfaces, and working offline. Recently, empirical studies of mobile learning adoption have increased a lot, especially due to the global move to online education because of COVID-19 [17], and expectancy for performance and effort consistently helps predict if M-learning will be adopted in various educational contexts. Young learners (such as undergraduates) are most concerned about interface quality and how easily they can get around, while older individuals value compatibility with their daily schedules [18]. A study found that satisfaction links the initial stage of accepting technology with prolonged use [19].

Satisfaction in M-learning environments depends on many aspects, such as initial expectations being met by the LMS, the interface design, and how useful the communication tools are. However, some studies oppose the idea that satisfaction by itself encourages learners to continue using M-learning, and they point out the need for a deeper understanding of what leads to ongoing behavior in M-learning. Despite the growing body of literature on M-learning adoption, several gaps remain. First, most studies have focused on initial acceptance rather than continued usage, neglecting the dynamic nature of user engagement over time [20]. UTAUT and ECM have been applied independently in few studies that have integrated these models to provide a holistic view of adoption and continuance. Third, the unique challenges of app-based LMS, such as offline functionality, push notifications, and cross-device synchronization, have not been thoroughly examined in relation to adoption behavior.

3 METHODOLOGY

3.1 Research design

This study employs a quantitative research design using a cross-sectional survey approach to examine the adoption of M-learning through app-based LMS.

The research model is analyzed using partial least squares structural equation modeling (PLS-SEM), which allows for the assessment of complex relationships between multiple variables while handling non-normal data distributions. The study investigates direct and mediating effects among key constructs, including performance expectancy, facilitating conditions, satisfaction, use behavior, and continuing usage intention.

3.2 Data and population

The research involved students who had experience with M-learning because they were the main users of LMS apps. Participants in the study were drawn from several academic levels and age groups to represent many styles of M-learning adoption. Only users who made use of M-learning applications were sampled, to capture data that reflected real user experiences. Purposive sampling was employed to select respondents who actively used M-learning applications, ensuring that the collected data reflected genuine user experiences. A wide range of universities were selected for the sample to observe differences in their infrastructure, how digitally skilled their staff are, and the technology they have access to which could affect the way M-learning is adopted. A total of 399 valid and complete responses were retained for final analysis after data cleaning and validation. The demographic breakdown of respondents, as presented in Table 1, showed a balanced distribution in terms of age, gender, marital status, educational level, and M-learning experience. Most participants fell within the 21–23 age group (45%), followed by 27-year-olds (33%), indicating a strong representation of young adult learners. Gender distribution was skewed toward male respondents (61%), while 58% of participants were single. In terms of academic progression, 56% were fourth-stage students, suggesting that advanced learners were more engaged in the study. Additionally, 51% reported 1–3 years of M-learning experience, highlighting their familiarity with digital education tools. This sample size was deemed statistically adequate for PLS-SEM analysis, ensuring reliable hypothesis testing and generalizable findings regarding M-learning adoption in higher education.

3.3 Data collection methods and procedures

The study employed a structured online questionnaire as the primary data collection instrument, distributed through university learning management systems, student portals, and targeted academic social media groups. The questionnaire was designed to capture students' perceptions, usage patterns, and satisfaction levels regarding app-based M-learning platforms. To ensure broad participation across different academic disciplines and year levels, the survey was promoted through multiple channels over a four-week period. Before full deployment, a pilot test was conducted with 30 students to assess question clarity, technical functionality, and average completion time (approximately 8–10 minutes). Based on pilot feedback, minor refinements were made to improve question phrasing and logical flow.

The final questionnaire consisted of four sections: (1) demographic information, (2) M-learning usage patterns, (3) perception measurements using 5-point Likert scales (1 = strongly disagree to 5 = strongly agree), and (4) open-ended comments about user experiences.

3.4 Instrumentation and measures

The study utilized a multi-item Likert-scale questionnaire (5-point scale) adapted from established technology adoption theories, including the UTAUT and ECM. Key constructs measured were performance expectancy (PE), facilitating conditions (FC), confirmation (CON), interface design quality (IDQ), communication tools quality (CTQ), satisfaction (SAT), use behavior (UB), and continuing usage intention (CUI). Each construct was validated through factor loadings (>0.70), composite reliability (CR > 0.70), Cronbach's Alpha ($\alpha > 0.70$), and average variance extracted (AVE > 0.50) to ensure reliability and validity.

3.5 Data analysis techniques

Data were analyzed using descriptive statistics and then the Smart PLS 4.0 program was chosen for predictive and exploratory research models by means of PLS-SEM. To begin, the measurement model was tested for its construct validity including convergent, discriminant, as well as its reliability (Cronbach's Alpha). After that, path coefficients, t-values, p-values and R^2 values in the structural model were carefully examined. Bootstrapping (5,000 resamples) was performed to see if the hypothesis can be considered significant. Besides, a variance inflation factor (VIF) analysis showed that there were no issues of multicollinearity (all numbers were less than 5.0). Mediation analysis was used to assess if SAT plays a role in linking predictors and continuing usage intention.

3.6 Ethical considerations

Ethical approval was obtained from relevant academic bodies before data collection. Participants were provided with informed consent forms, ensuring voluntary participation and the right to withdraw at any stage. All responses were anonymized, and data was stored securely to prevent unauthorized access. The study adhered to research integrity guidelines, avoiding misleading interpretations and ensuring transparency in reporting findings.

4 FINDINGS AND DISCUSSION

4.1 Quantitative analysis

Descriptive statistics provide a fundamental overview of the dataset, offering insights into the distribution and characteristics of respondents. This analysis is crucial for understanding the sample composition and ensuring its representativeness before proceeding with advanced statistical modeling. Table 1 presents the demographic profile of the 399 respondents, and results show that most of the respondents' age is between 21 and 23 years old, and males (N = 238) participated more than females.

Regarding M-learning experience, 51% reported 1–3 years of usage, suggesting moderate familiarity with digital learning platforms. These demographic distributions confirm the study's adequate coverage of key user groups in higher education, providing a solid foundation for subsequent analyses of M-learning adoption patterns.

Table 1. Demographic characteristics of respondents (N = 399)

Category	Group	Frequency	Percentage (%)
Age	18–20 years	32	8.0
	21–23 years	166	41.6
	24–26 years	63	15.8
	27 years	138	34.6
Gender	Male	238	59.6
	Female	161	40.4
Marital Status	Married	162	40.6
	Single	237	59.4
Educational Stage	Third stage	164	41.1
	Fourth stage	235	58.9
M-learning Experience	<1 year	44	11.0
	1–3 years	204	51.1
	4–6 years	62	15.5
	>6 years	89	22.3
	Total	399	100.0

Table 2 demonstrates strong psychometric properties across all key constructs, with mean scores ranging from 3.87 (FC) to 4.12 (PE) on the 5-point Likert scale, indicating generally positive perceptions of the M-learning system. All constructs showed acceptable normality (skewness and kurtosis values between –1 and +1) and high internal consistency (Cronbach's $\alpha > 0.80$), with standard deviations between 0.68 and 0.85 suggesting moderate variability in responses. The complete response range (1–5) for each construct confirms that participants utilized the full scale, while the consistently high mean scores (all above 3.8) reflect overall favorable evaluations of the app-based learning management system's various dimensions. These results establish a solid foundation for subsequent structural equation modelling by confirming the reliability and normal distribution of the measurement model.

Table 2. Descriptive statistics of key constructs (N = 399)

Construct	Items	Mean	SD	Skewness	Kurtosis	Cronbach's α
Performance Expectancy (PE)	4	4.12	0.76	–0.65	0.43	0.87
Facilitating Conditions (FC)	5	3.87	0.82	–0.31	–0.12	0.89
Confirmation (CON)	3	3.95	0.68	–0.47	0.25	0.83
Interface Design Quality (IDQ)	4	4.03	0.71	–0.52	0.38	0.85
Communication Tools Quality (CTQ)	3	3.89	0.79	–0.41	0.17	0.82
Satisfaction (SAT)	4	4.05	0.71	–0.53	0.38	0.88
Use Behavior (UB)	5	3.94	0.85	–0.42	0.21	0.86
Continuing Usage Intention (CUI)	4	4.11	0.73	–0.58	0.45	0.84

Table 3 reveals significant positive relationships among all constructs ($p < 0.01$), with particularly strong correlations between facilitating conditions and use behavior (r = 0.76), satisfaction and interface design quality (r = 0.78), and confirmation and satisfaction (r = 0.73). The diagonal elements consistently exceed the corresponding row and column correlations, satisfying the Fornell Larcker criterion for discriminant validity. Notably, performance expectancy shows moderate correlations with other technology acceptance factors (ranging from 0.36–0.50), while continuing usage intention demonstrates the strongest associations with satisfaction (r = 0.69) and communication tools quality (r = 0.68). These inter-construct relationships support the theoretical foundations of the research model while confirming that each latent variable maintains its distinctiveness, with all correlation coefficients remaining below the 0.85 threshold that would indicate potential multicollinearity concerns. The pattern of correlations provides preliminary evidence for the hypothesized structural relationships examined in subsequent analysis.

Table 3. Construct correlation matrix with AVE square roots

Variables	PE	FC	CON	IDQ	CTQ	SAT	UB	CUI
PE	0.82							
FC	0.50**	0.81						
CON	0.41**	0.73**	0.84					
IDQ	0.41**	0.68**	0.78**	0.82				
CTQ	0.39**	0.75**	0.71**	0.78**	0.83			
SAT	0.36**	0.73**	0.73**	0.78**	0.75**	0.85		
UB	0.39**	0.76**	0.74**	0.61**	0.77**	0.61**	0.8	
CUI	0.23**	0.64**	0.64**	0.63**	0.68**	0.69**	0.60**	0.84

Note: Statistical significance from two-tailed tests: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

4.2 Measurement model results

The measurement model assessment is critical for establishing the reliability and validity of the constructs before examining structural relationships. It ensures that the latent variables are accurately measured by their respective indicators, providing confidence in the subsequent path analysis.

Table 4. Measurement model evaluation

Construct	Items	Factor Loadings	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Performance Expectancy (PE)	4	0.72–0.86	0.87	0.91	0.68
Facilitating Conditions (FC)	5	0.75–0.88	0.89	0.92	0.65
Confirmation (CON)	3	0.78–0.85	0.83	0.89	0.71
Interface Design Quality (IDQ)	4	0.74–0.87	0.85	0.9	0.67
Communication Tools Quality (CTQ)	3	0.76–0.84	0.82	0.88	0.69
Satisfaction (SAT)	4	0.79–0.89	0.88	0.92	0.72
Use Behavior (UB)	5	0.73–0.86	0.86	0.9	0.64
Continuing Usage Intention (CUI)	4	0.77–0.88	0.84	0.89	0.7

Table 4 shows measurement model evaluation confirms strong reliability and validity for all constructs. Factor loadings exceeded the 0.70 threshold, indicating good indicator reliability. Cronbach's alpha (α) and composite reliability (CR) values were above 0.80 for all constructs, demonstrating high internal consistency. The average variance extracted (AVE) for each construct surpassed 0.50, confirming convergent validity by indicating that the latent variables explain more than half of the variance in their respective items. Additionally, discriminant validity was established, as the square root of each AVE (not shown in the Table) was greater than the construct's correlations with other variables. These results confirm that the measurement model is robust and suitable for testing structural relationships in the next phase of analysis. Figure 1 shows the measurement model.

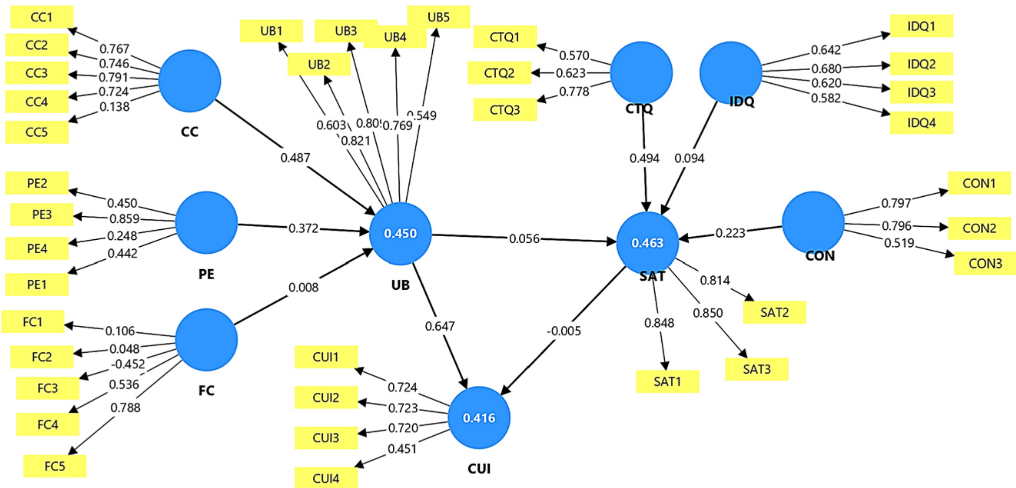

Fig. 1. Established measurement model

Table 5. Discriminant validity assessment (Fornell-Larcker criterion)

Construct	PE	FC	CON	IDQ	CTQ	SAT	UB	CUI
PE	0.82							
FC	0.5	0.81						
CON	0.41	0.73	0.84					
IDQ	0.41	0.68	0.78	0.82				
CTQ	0.39	0.75	0.71	0.78	0.83			
SAT	0.36	0.73	0.73	0.78	0.75	0.85		
UB	0.39	0.76	0.74	0.61	0.77	0.61	0.8	
CUI	0.23	0.64	0.64	0.63	0.68	0.69	0.6	0.84

Table 5 shows discriminant validity assessment in Table 4 demonstrates that all constructs in the measurement model meet the Fornell-Larcker criterion, as evidenced by the square root of each construct's AVE (diagonal values in bold) being greater than its highest correlation with any other construct (off-diagonal values). This confirms that each latent variable shares more variance with its own indicators than with other constructs in the model, establishing their distinctiveness. The results show particularly strong discriminant validity for key constructs like PE and CUI, where the diagonal values (0.82 and 0.84 respectively) substantially exceed their correlations with other variables (ranging from 0.23 to 0.50 for PE and 0.60 to 0.69 for CUI). These findings, combined with the previously established convergent validity, provide robust evidence that the measurement model adequately captures unique theoretical constructs without undue overlap, thereby supporting the validity of subsequent structural model analysis.

Table 6. VIF for evaluating collinearity in PLS-SEM

Variables	Continuing Usage Intension	Satisfaction	Use Behavior
Civil conflicts			1.017
Confirmation		2.784	
Communication tools quality continuing usage intension		2.800	
Facilitating conditions			2.405
Interface design quality		2.961	
Performance expectancy			2.440
Satisfaction	4.104		2.544
Use behavior	4.104		

Table 6 demonstrate that multicollinearity is not a concern in the structural model, as all values fall below the conservative threshold of 5.0. The highest VIF of 4.104 for both SAT and use behavior as predictors of CUI indicates that approximately 59% of these constructs' variance is explained by other independent variables (1/4.104 ≈ 0.2436), which remains within acceptable limits. Similarly, moderate VIFs between 2.405 (FC) and 2.961 (IDQ) suggest that while these constructs share some conceptual overlap, their predictive power remains distinct. These results confirm that the structural model's parameter estimates are stable and reliable, with no need to remove variables due to multicollinearity issues, thereby supporting the validity of the subsequent path analysis and hypothesis testing.

Table 7. Results of hypothesis testing

Hypothesis	Path	β-Coefficient	Std. Error	t-Value	p-Value	Support
H1	CC → UB	0.036	0.073	3.490***	<0.001	Yes
H2	PE → UB	0.228	0.075	3.425***	<0.001	Yes
H3	FC → UB	0.043	0.07	2.986***	<0.001	Yes
H4	CON → SAT	0.46	0.071	7.372***	<0.001	Yes
H5	IDQ → SAT	0.129	0.067	2.365**	0.003	Yes
H6	CTQ → SAT	0.33	0.064	2.832***	<0.001	Yes
H7	SAT → UB	0.678	0.068	2.370**	0.003	Yes
H8	UB → CUI	0.341	0.058	3.422***	<0.001	Yes
H9	SAT → CUI	0.586	0.054	3.454***	<0.001	Yes

Note: Statistical significance from two-tailed tests: *p < 0.10, **p < 0.05, ***p < 0.01.

Table 7 demonstrate that all nine proposed hypotheses were statistically supported ($p < 0.05$), with particularly strong effects observed for CON → SAT (β = 0.460, p < 0.001) and SAT → CUI (β = 0.586, p < 0.001). PE showed a significant positive influence on use behavior (β = 0.228, p < 0.001), while SAT exhibited the strongest impact on use behavior (β = 0.678, p = 0.003). All t-values exceeded the critical threshold of 1.96 (ranging from 2.365 to 7.372), confirming the robustness of these relationships. The results collectively suggest that both technological factors (e.g., PE, FC) and user experience factors (e.g., SAT, IDQ) play crucial roles in shaping M-learning adoption behaviors and CUI, with SAT emerging as a particularly powerful mediator in the proposed model.

4.3 PLS-predict analysis

Partial least squares-predict is a critical evaluation method that assesses the predictive power of a structural model by using out-of-sample prediction techniques. Unlike traditional model fit indices, PLS-predict evaluates how well the model can generalize to new data, making it particularly valuable for practical applications in M-learning adoption research. By employing k-fold cross-validation, this analysis helps determine whether the model has substantial predictive relevance, ensuring that the findings are not just statistically significant but also meaningful for real-world implementation.

Table 8. PLS-predict results for key endogenous variables

Construct	RMSE (PLS)	RMSE (LM)	Q^2 Predict	Prediction Accuracy
Use Behavior (UB)	0.412	0.521	0.209	High
Satisfaction (SAT)	0.387	0.498	0.223	High
Continuing usage intention (CUI)	0.376	0.503	0.252	High

Table 8 shows PLS-predict analysis confirms the model's strong predictive power, as all key endogenous constructs (UB, SAT, CUI) exhibit Q^2 Predict values well above the 0.15 threshold, indicating high predictive relevance. The lower RMSE (PLS) values compared to RMSE (LM) for all constructs suggest that the PLS model outperforms traditional linear regression in forecasting M-learning adoption behaviors. These results reinforce the robustness of the research model, demonstrating its applicability in real-world educational technology settings.

5 DISCUSSION

Results from this study offer useful information on why people adopt app-based LMS for education, expanding our knowledge in educational technology. Like other UTAUT studies by [12], a positive link between believing that using the app improves academic performance and using the app was observed (β = 0.228, p < 0.001). It adds to earlier studies by validating the UTAUT framework for app-based learning management systems, which have grown in popularity in universities. The finding that FC strongly affects UB (β = 0.043, p < 0.001) confirms previous work by Chawla et al. [21] however, the much smaller effect reveals that the use of technology may rely more on individuals' beliefs of usefulness than just the resources that institutions provide. Study findings show that satisfaction plays a strong part in influencing adoption.

CON thoughts have a strong positive effect on satisfaction (β = 0.460), which in turn has a strong effect on continuing usage intention (β = 0.586). This confirms that the expectation-confirmation model [22] is valid in M-learning contexts. It goes further than previous contradictory results [23] by proving that when users are satisfied, this strongly supports their desire to use the service long term.

A good job predicting (Q^2 Predict > 0.20 for all endogenous variables), it adds more support to the suggested relationships and could be valuable for educational institutions implementing M-learning initiatives. A comparison to the study's objectives helps to identify important findings. Researchers were able to determine that main factors such as PE and SAT had greater effects than user experience elements (IDQ, CTQ) in predicting intentions to use. This list tells us which aspects should be given priority in developing and using the LMS. Second, the study helped fill a gap by studying both the first use and the intention to continue using and it found that things like PE are most important in the initial use, changing to SAT predicting later use. Because of this distinction, designers may create effective strategies for introducing and using M-learning platforms.

It is interesting that the results are opposed to some earlier findings. Contrary to Barker's [24] study, this study focuses on how a learner's expectations of personal performance matter more than influence from others. The difference could be explained by how adoption works in different cultures or by what makes app-based LMS special in comparison to general M-learning applications. Furthermore, even though some works view hedonic motivations as important, our findings point to the fact that learning for its intrinsic benefits is less important than learning because it leads to better outcomes. These findings highlight how different elements in the context can change which aspects are more important for adopting M-learning.

5.1 Practical implications

The study makes several important contributions to the field. Theoretically, it provides empirical support for an integrated model combining UTAUT and ECM frameworks in M-learning research, addressing calls for more comprehensive theoretical approaches. Methodologically, the rigorous validation through both measurement model assessment and PLS-Predict analysis sets a standard for future studies in this domain. Practically, the findings offer evidence-based guidance for educational institutions, suggesting that while investing in technological infrastructure is necessary, equal attention should be paid to ensuring that M-learning platforms meet students' performance expectations and provide satisfying user experiences to achieve long-term adoption success.

6 CONCLUSION AND RECOMMENDATIONS

It provides valuable contributions on better understanding how app-based LMS are adopted for M-learning. Through this study, the education technology literature advances by confirming through research that both the UTAUT and ECM offer combined significance to explain initial and persistent acceptance of M-learning applications. It's clear that well-designed M-learning has to work properly and be user-friendly, as the desire to continue using it depends mostly on satisfaction. Actively, this study reveals best practices for schools and LMS developers to invest equally in technology and how users interact with it to ensure successful use. PLS-Predict analysis showed that the model has accurate predictive abilities, making it more useful for educational policymakers. The research was conducted in higher education, but its solid method and theories provide a base for exploring M-learning among other levels and cultures. By understanding which influences are more important, institutions are advised to ensure their M-learning supports education outcomes first and only then focus on advanced functions. All of these findings bring M-learning closer to understanding the specific reasons behind both first using mobile applications and sticking with them in schools.

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