INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES

Vol 14, Issue 7, (2024) E-ISSN: 2222-6990

Unearthing the Intention to Use Mobile Learning among Students in Online Flexible Distance Learning Higher Education Institutions

Zahir Osman, Nadzurah Kasbun, Ratna Khuzaimah Mohamad

Open University Malaysia

Email: zahir_osman@oum.edu.my, nadzurahkasbun@oum.edu.my, Ratna_mohamad@oum.edu.my

To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v14-i7/22007 DOI:10.6007/IJARBSS/v14-i7/22007

Published Date: 16 July 2024

Abstract

This study delves into the intricate factors influencing the intention to use mobile learning among students in online flexible distance learning higher education institutions, with self-efficacy serving as a pivotal mediator. The primary objective is to comprehensively assess the direct and indirect impacts of performance expectancy, facilitating conditions, effort expectancy, and self-management learning on the intention to engage with mobile learning platforms. Through a meticulous survey methodology, questionnaires were disseminated via email using purposive sampling, yielding a commendable response rate. Out of the 544 surveys distributed, 431 were successfully collected, and 403 clean datasets were meticulously analyzed. Employing advanced Structural Equation Modeling (SEM) techniques with the aid of Smartpls4 software, the study rigorously examined the relationships between key variables. The empirical findings unveiled compelling insights, showcasing the significant positive relationships between effort expectancy, self-management learning, and self-efficacy to utilize mobile learning. Moreover, facilitating conditions and self-efficacy emerged as influential factors, with self-efficacy playing a crucial mediating role in shaping students' intentions. The study's theoretical implications extend beyond conventional technology acceptance models, shedding light on the intricate interplay of cognitive, motivational, and contextual factors in mobile learning usage. These findings offer a robust foundation for advancing existing technology acceptance frameworks and provide a nuanced understanding of the multifaceted dynamics influencing students' intentions toward mobile learning adoption. Furthermore, the practical implications underscore the importance of enhancing mobile learning initiatives by prioritizing usability, accessibility, technical support, and fostering learners' self-efficacy. This holistic approach aims to optimize the educational experience and promote effective utilization of mobile learning technologies in online flexible distance learning environments.

Keywords: Effort Expectancy, Performance Expectancy, Facilitating Conditions, Self-Management Learning, Self-Efficacy, Intention to Use.

Introduction

The trend and latest development of mobile learning globally have witnessed a remarkable surge in the utilization of mobile devices and applications for educational purposes (Shaya et al., 2023). Mobile learning, or m-learning, has emerged as an innovative approach to language learning, offering a diverse array of functions and activities that enrich multisensory learning experiences (Voicu & Muntean, 2023). The evolution of cutting-edge mobile devices has captured the attention of educators, positioning m-learning as a valuable tool for language acquisition (Chau, 2024). Through mobile tools and social networks, users can seamlessly create and share content, fostering a ubiquitous, autonomous, and personalized learning environment (Afzal & Anwar, 2023). Additionally, the versatility of mobile tools provides a wide range of functions and activities that enhance multisensory learning, offering significant cognitive benefits (Sidik & Syafar, 2020). Despite the advantages of mobile learning, educators harbor concerns regarding the effective integration of mobile tools for educational purposes (Kebah et al., 2019). The implementation of new media is influenced by educators' beliefs and attitudes, underscoring the necessity for training to showcase the efficacy of mobile learning (Afacan & Muhametjanova, 2021). Moreover, the utilization of mobile tools in educational settings raises apprehensions among educators, emphasizing the impact of their beliefs and attitudes on the adoption of new media (Al-Bashayreh et al., 2022). The challenge with mobile learning intention stems from the underutilization of mobile devices in educational settings, despite their increasing availability and prevalence (Do Huynh et al., 2023). Students tend to use mobile devices more frequently outside the classroom for personal use rather than for academic purposes, with educational mobile apps seldom utilized during class time (Tarhini et al., 2024). This underscores the imperative for strategies that effectively integrate mobile technologies into traditional classroom settings to mitigate the adverse effects of mobile device misuse on the learning experience (Al-Rahmi et al., 2022). There exists a research gap in comprehending the intention to use mobile learning among students and educators in online open flexible distance learning higher education institutions (Irwanto et al., 2023). While previous studies have explored the benefits of mobile learning in language acquisition, a comprehensive investigation is needed to delve into the factors influencing the intention to use mobile learning in these institutions (Gharaibeh & Ghraibeh, 2020). This study aims to evaluate the direct and indirect relationships between effort expectancy, performance expectancy, facilitating conditions, self-management learning, and the intention to use mobile learning, with self-efficacy serving as a mediator among students in online open flexible distance learning higher education institutions. The findings of this study hold significant promise in providing policymakers, institutions, and students with valuable insights to enhance the integration and utilization of mobile learning technologies in educational settings.

Literature Review

Underpinning Theory

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a prominent theoretical framework that explains individuals' acceptance and use of technology. UTAUT integrates various technology acceptance models and identifies key factors influencing technology adoption, including Performance Expectancy, Effort Expectancy, Social Influence, and

Facilitating Conditions, among others (Venkatesh et al., 2003). This comprehensive model has been widely used to understand users' intentions and behaviors towards technology adoption in different contexts. In the study by Alowayr (2022), the UTAUT model was extended to investigate mobile learning adoption in Saudi Arabia. The research framework included intrinsic motivation, mobile learning self-efficacy, and perceived satisfaction as additional factors to the UTAUT model. The study involved 200 higher education students and found that the extended UTAUT model adequately predicted mobile learning adoption in Saudi Arabia, emphasizing the importance of intrinsic motivation and self-efficacy in influencing learners' acceptance of mobile learning technology (Alowayr, 2022). Furthermore, the study by Donaldson (2011) focused on understanding the intent to use mobile devices for learning in university contexts based on the UTAUT model. The research aimed to identify factors affecting technological acceptance and intent to use mobile learning strategies among university students. By adapting and extending the UTAUT model to suit the specific context of mobile learning in higher education, the study highlighted the significance of factors such as Performance Expectancy, Effort Expectancy, and Social Influence in shaping students' perceptions and acceptance of mobile learning technologies (Donaldson, 2011).

Relationship between Effort Expectancy, Self-Efficacy, and Intention

The relationship between Effort Expectancy and Intention to use, with self-efficacy as a mediator in mobile learning, has been extensively studied in various contexts. Dahri et al. (2023) explored the acceptance of mobile learning technology by teachers, highlighting the influence of mobile self-efficacy and 21st-century skills-based training. Yu et al. (2021) delved into the behavioral intention to use a mobile health education website, extending the UTAUT 2 model. Sharma and Saini (2022) focused on teachers' acceptance, continuance intention, and self-efficacy in using digital technologies for teaching practices. Chao and Chen (2023) investigated factors influencing the behavioral intention of nursing students to use mobile learning, applying and extending the UTAUT model. Additionally, Sang et al. (2023) found that effort expectancy mediates the relationship between instructors' digital competence and work engagement, particularly in universities in China. These studies collectively contribute to understanding the complex interplay between effort expectancy, intention to use, and self-efficacy in the realm of mobile learning (Kebah et al., 2019). Thus, the following hypotheses were proposed for this study:

H1: There is a relationship between effort expectancy and intention to use mobile learning among students in online flexible distance learning higher education institutions.

H2: There is a relationship between effort expectancy and self-efficacy in the intention to use mobile learning among students in online flexible distance learning higher education institutions.

H3: There is a mediating effect of self-efficacy on the relationship between effort expectancy and intention to use mobile learning among students in online flexible distance learning higher education institutions.

Relationship between Facilitating Conditions, Self-Efficacy, and Intention

The relationship between Facilitating Conditions and Intention to use, with self-efficacy as a mediator in mobile learning, has been a subject of interest in recent research. Dahri et al. (2023) explored the acceptance of mobile learning technology by teachers, emphasizing the influence of mobile self-efficacy and 21st-century skills-based training. Mshali and Al-Azawei (2022) focused on predicting online learning adoption, highlighting the role of compatibility, self-efficacy, knowledge sharing, and knowledge acquisition. Afari et al. (2023) delved into computer self-efficacy and ICT integration in education, examining the structural relationship and mediating effects. Additionally, Deng et al. (2023) investigated students' continued intention to use E-learning platforms, emphasizing the mediating effect of E-satisfaction and habit. Rajam et al. (2024) explored the role of Perceived Reputation and Self-efficacy on Continuous Use Intention of MOOCs, examining the potential of MOOCs as a medium for lifelong learning. These studies collectively contribute to understanding how Facilitating Conditions, Intention to use, and self-efficacy interact in the context of mobile learning, shedding light on factors influencing technology adoption and educational outcomes (Osman et al., 2019). Therefore, the following hypotheses were proposed for this study:

H4: There is a relationship between facilitating conditions and intention to use mobile learning among students in online flexible distance learning higher education institutions.

H5: There is a relationship between facilitating conditions and self-efficacy in the intention to use mobile learning among students in online flexible distance learning higher education institutions.

H6: There is a mediating effect of self-efficacy on the relationship between facilitating conditions and intention to use mobile learning among students in online flexible distance learning higher education institutions.

Relationship between Performance Expectancy, Self-Efficacy, and Intention

Performance expectancy, the belief that using technology will enhance performance, significantly influences the intention to use mobile learning (m-learning). When learners perceive that m-learning tools will improve their academic or skill-based performance, they are more likely to intend to use these technologies (Chao, 2019). Self-efficacy, defined as one's belief in their capability to execute specific tasks, acts as a critical mediator in this relationship. High self-efficacy can enhance the effect of performance expectancy on the intention to use m-learning (Latip et al., 2020). When individuals are confident in their ability to use m-learning tools effectively, they are more likely to believe that these tools will improve their performance (N Wickneswary et al., 2024). This increased confidence can amplify their intention to adopt and utilize m-learning solutions (Ahadzadeh et al., 2021). Conversely, low self-efficacy may weaken the impact of performance expectancy. Even if learners recognize the potential benefits of m-learning, a lack of confidence in their ability to use the technology might deter them from intending to use it (Yu et al., 2021). Thus, self-efficacy not only mediates but also modulates the strength of the relationship between performance expectancy and the intention to use m-learning, highlighting its pivotal role in technology acceptance (Chen, 2022). Hence, the following hypotheses were proposed for this study:

H7: There is a relationship between performance expectancy and intention to use mobile learning among students in online flexible distance learning higher education institutions.

H8: There is a relationship between performance expectancy and self-efficacy in the intention to use mobile learning among students in online flexible distance learning higher education institutions.

H9: There is a mediating effect of self-efficacy on the relationship between performance expectancy and intention to use mobile learning among students in online flexible distance learning higher education institutions.

Relationship between Self-Management Learning, Self-Efficacy, and Intention

The relationship between Self-Management Learning and Intention to use, with self-efficacy as a mediator in mobile learning, is a crucial aspect of understanding the dynamics of mobile learning adoption and continuance (Li et al., 2020). Research has consistently shown that self-management of learning plays a significant role in influencing learners' intentions to use mobile learning platforms (Ghaleb & Alshiha, 2023; Chen et al., 2023). Self-management of learning encompasses learners' ability to regulate their learning processes, including setting goals, monitoring progress, and adapting to new information (Chen et al., 2023). This ability is closely linked to self-efficacy, which refers to learners' confidence in their ability to successfully use mobile learning tools and navigate through the learning process effectively (Ghaleb & Alshiha, 2023; Chen et al., 2023). Studies have demonstrated that self-management of learning has a positive influence on mobile English learning continuance intention and performance (Magsayo, 2023). Furthermore, personal learning initiative, which involves proactive and self-starting behaviors, moderates the relationship between perceived flexibility advantage and mobile English learning continuance intention (Magsayo, 2023). The findings suggest that learners who are more self-efficacious and have a higher level of self-management of learning are more likely to continue using mobile learning platforms, as they perceive the flexibility advantage of mobile learning as a key factor in their learning outcomes (Magsayo, 2023). Thus, the following hypotheses were proposed for this study:

H10: There is a relationship between self-management learning and the intention to use mobile learning among students in online flexible distance learning higher education institutions.

H11: There is a relationship between self-management learning and self-efficacy in the intention to use mobile learning among students in online flexible distance learning higher education institutions.

H12: There is a relationship between self-efficacy and intention to use mobile learning among students in online flexible distance learning higher education institutions.

H13: There is a mediating effect of self-efficacy on the relationship between self-management learning and intention to use mobile learning among students in online flexible distance learning higher education institutions.

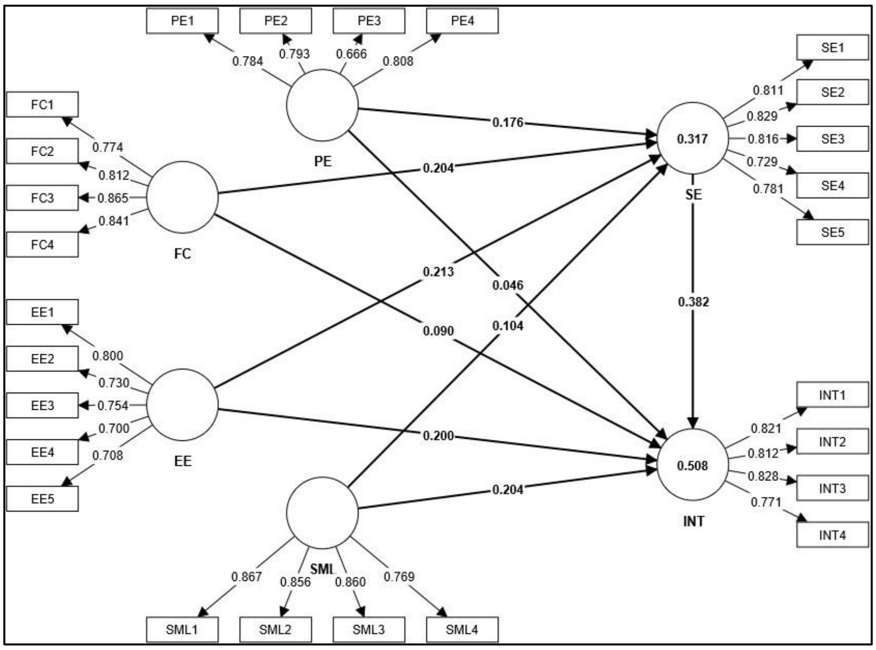

Figure 1: Research Framework
Note: PE=Performance Expectancy EE=Effort Expectancy FC=Facilitating Condition SML=Self-Management Learning SE=Self Efficacy INT=Intention to Use

Methodology
This study aimed to evaluate the direct and indirect impact of performance expectancy, facilitating conditions, effort expectancy, and self-management learning on the intention to use mobile learning among students in higher education institutions, with self-efficacy serving as a mediator. To achieve this objective, researchers surveyed to gather primary data, carefully selecting reliable and valid measurements based on an extensive review of prior research. Survey questionnaires were then distributed to selected participants via email, utilizing purposive sampling due to the absence of a comprehensive population list. A total of 26 observed variables were scrutinized, encompassing exogenous variables such as performance expectancy, adapted from Al-Adwan et al (2018) (4 items); facilitating conditions, adapted from Venkatesh et al (2003) (4 items); effort expectancy, adapted from Al-Adwan et al (2018) (5 items); and self-management learning, adapted from Al-Adwan et al (2018) (4 items). The mediating variable of self-efficacy was adopted from Ozturk et al (2016), and the dependent variable of intention to use was adopted from Davis (1989) (4 items). Utilizing a Likert scale with five response options, ranging from strongly disagree to strongly agree, the study assessed elements within each construct. Out of 544 surveys distributed, 431 were retrieved, resulting in a response rate of 79.2%, deemed satisfactory for employing structural equation modeling (SEM) in data analysis. Among the collected surveys, 403 were deemed clean and suitable for analysis. Researchers selected Smartpls4 software, known for its proficiency in employing SEM techniques, to conduct data analysis and hypothesis testing. This choice was influenced by the software's robust evaluation capabilities and expertise in managing multivariate data analysis, aligning with the study's objectives and following the recommendations of (Ringle et al., 2022). Smartpls4 played a pivotal role in meticulously assessing the proposed hypotheses and conducting comprehensive multivariate data analysis, facilitating a thorough evaluation of both measurement and structural models.

Data Analysis

Respondents' Profiles

Based on the data collection, an analysis of each respondent profile item in terms of frequency and percentage reveals notable trends. In terms of gender distribution, females constitute a significant majority, comprising 64.0% of respondents compared to males, who represent 36.0%. Regarding age demographics, the largest proportion of respondents falls below the age of 30, making up 44.4%, followed closely by those aged between 31 and 40, accounting for 40.4%. Older age groups are less represented, with 13.2% between 41 and 50 years old and a mere 2.0% aged 51 to 60. When examining the year of study, the majority of respondents are in their earlier academic years, with 29.3% in the first year, 18.1% in the second, and 25.1% in the third. The percentages decrease for higher academic years, with 16.1% in the fourth year, 5.2% in the fifth, and 6.2% beyond the fifth year. Looking at the level of study, bachelor's degree students form the largest group, representing 63.5% of respondents, followed by diploma holders at 14.1%, masters students at 9.0%, and doctorate students at 12.9%. Lastly, in terms of recommendations for peers to use mobile learning, an overwhelming majority of 99.3% of respondents endorse it, while only a marginal 0.7% do not. These statistics offer valuable insights into the demographics and preferences of the surveyed population, which can inform educational strategies and initiatives tailored to their needs and interests, particularly highlighting the widespread acceptance and endorsement of mobile learning among the respondents.

Common Method Bias

Kock (2015); Kock & Lynn (2012) introduced a comprehensive methodology termed the collinearity test, which addresses both vertical and horizontal collinearity dimensions. This method employs variance inflation factors (VIFs) to identify pathological collinearity, with a threshold of 3.3 indicating significant concern for common method bias within the model (Kock & Lynn, 2012). Thus, if the VIFs obtained from the thorough collinearity assessment remain below 3.3, it implies that the model remains unaffected by common method bias (Kock, 2015). The analysis presented in Table 1 reveals that the VIFs resulting from the overall collinearity assessment were consistently below 3.3, thereby confirming the absence of any common method bias issue within the model.

Table 1
Full Collinearity Test

	INT	MPE	MFC	MEE	MSL	MSE
INT		1.985	1.983	1.914	1.867	1.651
MPE	1.720		1.497	1.713	1.700	1.700
MFC	2.273	1.980		1.861	2.276	2.249
MEE	1.975	2.041	1.676		2.029	2.043
MSL	1.290	1.355	1.372	1.358		1.376
MSE	1.448	1.721	1.721	1.737	1.746	

Measurement Model

In this study, we adhered to the methodology advocated by Hair et al (2017) to evaluate each measurement in both the first and second order, facilitating the identification of items with loadings below the 0.7 threshold. Our analysis of construct reliability and validity revealed that the Average Variance Extracted (AVE) for all constructs ranged from 0.547 to 0.704, surpassing the 0.5 benchmark, thereby indicating well-established convergent validity Hair et al (2017) (Table 2). Furthermore, the composite reliability for all constructs exceeded 0.7, falling within the range of 0.763 to 0.862. Additionally, Cronbach's alpha values for all constructs were greater than 0.7, varying from 0.760 to 0.859 (Table 2). To ensure discriminant validity, we initially evaluated cross-loadings, ensuring appropriate representation and measurement of respective constructs (Table 3). Subsequently, we employed the Heterotrait-Monotrait (HTMT) ratio for further assessment, adhering to the recommended criterion for examining discriminant validity in Variance-Based Structural Equation Modeling (VB-SEM) (Henseler, Ringle & Sarstedt, 2015). Table 4 presented the HTMT ratios, original sample, and 95% confidence intervals, affirming compliance with the HTMT threshold of 0.85.

Table 2
Construct Reliability and Validity & Item Loadings

Constructs	Items	Loadings	CA	CR	AVE
Effort Expectancy	EE1	0.800	0.792	0.793	0.547
	EE2	0.730			
	EE3	0.754			
	EE4	0.700			
	EE5	0.708			
Facilitating Condition	FC1	0.774	0.843	0.862	0.678
	FC2	0.812			
	FC3	0.865			
	FC4	0.841			
Intention	INT1	0.821	0.824	0.830	0.653
	INT2	0.812			
	INT3	0.828			
	INT4	0.771			
Performance Expectancy	PE1	0.784	0.760	0.763	0.585
	PE2	0.793			
	PE3	0.666			
Self-Efficacy	PE4	0.808	0.853	0.857	0.630
	SE1	0.811			
	SE2	0.829			
	SE3	0.816			
	SE4	0.729			
	SE5	0.781			
Self-Management Learning	SML1	0.867	0.859	0.860	0.704
	SML2	0.856			
	SML3	0.860			
	SML4	0.769			

Notes: CA=Cronbach Alpha CR=Composite Reliability AVE=Average Variance Extracted

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	EE	FC	INT	PE	SE
FC	0.807				
INT	0.666	0.606			
PE	0.647	0.745	0.56		
SE	0.575	0.571	0.725	0.549	
SML	0.495	0.464	0.555	0.465	0.396

Structural Model
In this study, the evaluation of the structural model followed the methodology outlined by Hair et al (2017), which involved scrutinizing pathway coefficients (β) and coefficients of determination (R^2). The Partial Least Squares (PLS) method was utilized, employing 5000 sub-samples to ascertain the significance level of path coefficients. The findings from hypothesis testing for confidence intervals, covering path coefficients (beta), corresponding t-statistics, and p-values, are presented in Table 4. This rigorous examination offers valuable insights into the significance and robustness of the relationships among the variables within the structural model. The detailed hypotheses testing results in Table 4 provide a nuanced analysis of each hypothesis, with a focus on Beta coefficients, T-statistics, P-values, and the final decisions regarding hypothesis support.

The hypotheses testing results provide a nuanced understanding of the relationships between various factors and the intention to use mobile learning, visualized through path figures. Hypothesis 1 (H1) proposes a path (0.200) from effort expectancy to intention to use, illustrated by a significant positive relationship (t = 3.311, p = 0.001), depicted in the path figure. Similarly, H2 suggests a path (0.213) from effort expectancy to self-efficacy, supported by a significant positive relationship (t = 3.651, p = 0.000), as shown in its corresponding path figure. Extending the previous relationship, H3 includes self-efficacy in the pathway (0.081) from effort expectancy to intention to use, which is also found to be significant (t = 3.343, p = 0.001), depicted in its path figure, emphasizing the mediating role of self-efficacy. Conversely, H4 posits a path (0.090) from facilitating conditions to intention to use, but lacks significant support (t = 1.476, p = 0.140), leading to its rejection, illustrated in the corresponding path figure. However, H5 presents a significant positive path (0.204) from facilitating conditions to self-efficacy (t = 3.024, p = 0.003), as shown in its path figure, highlighting the influence of favorable conditions on individuals' self-beliefs. Extending this pathway, H6 introduces self-efficacy in the relationship (0.078) between facilitating conditions and intention to use, which is significant (t = 2.811, p = 0.005), as depicted in its path figure, further emphasizing the mediating role of self-efficacy. Moving to H7, which suggests a path (0.046) from perceived enjoyment to intention to use, the analysis fails to find significant support for this relationship (t = 0.900, p = 0.368), resulting in its rejection, illustrated in its path figure. Conversely, H8 reveals a significant positive association (0.176) between perceived enjoyment and self-efficacy (t = 3.164, p = 0.002), depicted in its path figure, emphasizing its role in bolstering individuals' self-beliefs. Extending this path, H9 demonstrates a significant positive relationship (0.067) between perceived enjoyment, self-efficacy, and intention to use (t = 2.727, p = 0.006), as shown in its path figure, indicating the sequential influence of these factors. Furthermore, H10 asserts a significant positive path (0.204) from self-management learning to intention to use (t = 4.247, p = 0.000), depicted in its path figure, underlining the importance of learning strategies in shaping individuals' intentions. Similarly, H11 posits a significant positive relationship (0.104) between self-management learning and self-efficacy (t = 2.210, p = 0.027), as shown in its path figure, suggesting that learning experiences can contribute to enhancing individuals' self-beliefs. H12, focusing on the direct relationship (0.382) between self-efficacy and intention to use, reveals a highly significant positive path (t = 7.773, p = 0.000), illustrated in its path figure, highlighting the central role of self-efficacy in driving intentions. Finally, H13 extends the previous relationship by including self-efficacy in the pathway (0.04) from self-management learning to intention to use, which is significant (t = 2.115, p = 0.034), as depicted in its path figure, emphasizing the mediating role of self-efficacy in this process.

Table 4 provides a comprehensive summary of effect sizes, evaluated according to Cohen's criteria (1992), categorizing them as small (0.020 to 0.150), medium (0.150 to 0.350), or large (0.350 or greater). The observed effect sizes spanned from small (0.007) to large (0.203). Intrinsic Variance Inflation Factor (VIF) values, detailed in Table 4, remained below the more lenient threshold of 5, with the highest value recorded at 2.280. This level of collinearity enables meaningful comparisons of sizes and interpretation of coefficients within the structural model. A noteworthy degree of explained variance for the endogenous construct is evident, with an R^2 value of 0.508 (Figure 1). Regarding the mediator, the model elucidated approximately 31.7% of the variance in the structure, as indicated by an R^2 value of 0.317.

The assessment of the model's inference and managerial recommendations was conducted through out-of-sample predictive analysis utilizing the PLSpredict method (Shmueli et al., 2016, 2019). Table 5 demonstrates that PLS-SEM yielded superior Q^2 predictions (>0) compared to naive mean predictions, while consistently displaying lower RMSE values than linear model (LM) benchmarks, indicating its predictive strength. Furthermore, the RMSE values for PLS-SEM predictions were consistently lower than those of the linear model (LM) prediction benchmark in all nine instances, highlighting the predictive capability of the proposed model as depicted in Table 6. The introduction of the Cross-Validated Predictive Ability Test (CVPAT) by Hair et al (2022), and its utilization in combination with PLSpredict analysis by Liengaard et al (2021), are noteworthy. Table 6 reaffirms the superior predictive capabilities of PLS-SEM, with lower average loss values compared to indicator averages and LM benchmarks, providing further evidence of its enhanced predictive performance.

Ringle and Sarstedt (2016); Hair et al (2018) introduced the Importance of Performance Map Analysis (IPMA) as a method for evaluating the significance and effectiveness of latent variables in explaining acceptance, as outlined in Table 7. The relative impact on intention was most notable for self-efficacy (0.382), followed by effort expectancy (0.281), self-management learning (0.244), facilitating conditions (0.167), and performance expectancy (0.114), underscoring their importance in intention. Effort expectancy received the highest score (67.282) on a 0-100 scale, whereas self-efficacy obtained the lowest score (60.610), indicating superior performance by effort expectancy and comparatively lower performance by self-efficacy. Despite being ranked first in terms of intention importance, self-efficacy demonstrated the lowest performance. These findings imply a need to prioritize initiatives aimed at enhancing self-efficacy among students, potentially bolstering overall intention to use mobile learning.

Table 4
Hypotheses Testing Results, Effect Sizes (f2) & Variance Inflation Factors (VIF)

Hypotheses	Path(β)	T statistics	P values	f^2	VIF	2.50%	97.50%	Decision
H1: EE -> INT	0.200	3.311	0.001	0.041	1.999	0.085	0.323	*Accepted*
H2: EE -> SE	0.213	3.651	0.000	0.034	1.932	0.095	0.325	*Accepted*
H3: EE -> SE -> INT	0.081	3.343	0.001			0.037	0.132	*Accepted*
H4: FC -> INT	0.090	1.476	0.140	0.007	2.280	-0.03	0.207	*Rejected*
H5: FC -> SE	0.204	3.024	0.003	0.027	2.220	0.071	0.332	*Accepted*
H6: FC -> SE -> INT	0.078	2.811	0.005			0.029	0.137	*Accepted*
H7: PE -> INT	0.046	0.900	0.368	0.003	1.713	-0.05	0.148	*Rejected*
H8: PE -> SE	0.176	3.164	0.002	0.027	1.668	0.062	0.28	*Accepted*
H9: PE -> SE -> INT	0.067	2.727	0.006			0.023	0.119	*Accepted*
H10: SML -> INT	0.204	4.247	0.000	0.066	1.294	0.104	0.294	*Accepted*
H11: SML -> SE	0.104	2.210	0.027	0.012	1.278	0.014	0.198	*Accepted*
H12: SE -> INT	0.382	7.773	0.000	0.203	1.465	0.286	0.476	*Accepted*
H13: SML -> SE -> INT	0.040	2.115	0.034			0.006	0.08	*Accepted*

Table 5
PLSpredicts

Indicators	Q^2predict	PLS-RMSE	LM_RMSE	PLS-LM
INT1	0.346	0.617	0.618	-0.001
INT2	0.233	0.618	0.625	-0.007
INT3	0.260	0.667	0.685	-0.018
INT4	0.164	0.716	0.717	-0.001
SE1	0.242	0.607	0.609	-0.002
SE2	0.202	0.619	0.633	-0.014
SE3	0.163	0.669	0.671	-0.002
SE4	0.142	0.692	0.708	-0.016
SE5	0.179	0.622	0.640	-0.018

Table 6
Cross-Validated Predictive Ability Test

	Average loss difference	t-value	p-value
INT	-0.144	6.681	0.000
SE	-0.093	4.967	0.000
Overall	-0.116	6.924	0.000

Table 7
Importance-Performance Map Analysis (IPMA)

Constructs	Total Effect	Performance
EE	0.281	67.282
FC	0.167	66.950
PE	0.114	66.677
SE	0.382	60.610
SML	0.244	66.844

Discussion & Conclusion

The findings from the study shed light on effective strategies to influence intention to use mobile learning among Online Flexible Distance Learning Higher Education Students, with self-efficacy playing a crucial mediating role. Performance expectancy, effort expectancy, facilitating conditions, and self-management learning emerge as significant factors in shaping students' intentions. Performance expectancy, defined as the perceived utility derived from using mobile learning, can be enhanced through various strategies. For instance, incorporating interactive and engaging features into mobile learning platforms can increase students' perception of the usefulness of these tools in enhancing their learning outcomes. Additionally, highlighting success stories and testimonials from peers who have benefited from mobile learning can bolster students' confidence in the efficacy of these platforms. Effort expectancy, referring to the perceived ease of use of mobile learning systems, can be influenced by simplifying user interfaces, providing clear instructions, and offering technical support. Designing intuitive navigation and user-friendly interfaces can reduce cognitive load and frustration, thereby increasing students' willingness to engage with mobile learning platforms. Moreover, offering tutorials, help guides, and troubleshooting resources can alleviate concerns about technical difficulties, making mobile learning more accessible and appealing. Facilitating conditions, encompassing the external factors that support or hinder mobile learning adoption, can be addressed through institutional support and infrastructure development. Institutions can provide access to reliable internet connectivity, adequate devices, and technical support services to ensure that students have the necessary resources to engage with mobile learning effectively. Moreover, fostering a supportive learning environment and promoting a culture of innovation can encourage students to embrace mobile learning as a valuable tool for their educational journey. Self-management learning, involving students' ability to regulate their learning processes and strategies, can be cultivated through educational interventions aimed at enhancing self-regulation skills. Encouraging self-reflection, goal-setting, time management, and study planning can empower students to take ownership of their learning and make effective use of mobile learning resources. Additionally, providing personalized feedback and adaptive learning pathways can cater to individual learning needs and preferences, further enhancing students' self-efficacy and motivation to engage with mobile learning.

Theoretical Implications

The findings of the study hold significant theoretical implications for understanding the factors influencing intention to use mobile learning in Online Flexible Distance Learning Higher Education settings, particularly with self-efficacy as a mediator. Firstly, the study contributes to the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by highlighting the importance of various factors beyond perceived usefulness and ease of use. While performance expectancy and effort expectancy align with the UTAUT constructs, the inclusion of facilitating conditions and self-management learning expands the model's scope, emphasizing the role of external support and learners' self-regulation abilities in technology adoption. Moreover, the study underscores the significance of self-efficacy as a key mediator in the relationship between students' perceptions of mobile learning and their intentions to use it. This aligns with Bandura's Social Cognitive Theory, which posits that individuals' beliefs in their capabilities influence their behaviors and outcomes. By demonstrating the mediating role of self-efficacy, the study emphasizes the importance of fostering learners' confidence in their ability to utilize mobile learning effectively.

Additionally, the study contributes to educational psychology literature by highlighting the interplay between cognitive, motivational, and contextual factors in technology adoption within educational contexts. Understanding how factors such as performance expectancy, effort expectancy, facilitating conditions, and self-management learning interact to influence intention to use mobile learning provides valuable insights into designing effective educational interventions and support mechanisms for online learners. Overall, the theoretical implications of the study extend beyond traditional technology acceptance models, offering a holistic understanding of the multifaceted factors that shape students' intentions to engage with mobile learning in flexible distance learning environments.

Contextual Implications

The study's findings have several contextual implications for educators, policymakers, and institutions involved in Online Flexible Distance Learning Higher Education. Firstly, recognizing the importance of factors such as performance expectancy, effort expectancy, facilitating conditions, and self-management learning can guide the development and implementation of mobile learning initiatives. Institutions can prioritize resources towards enhancing the usability and accessibility of mobile learning platforms, providing technical support, and fostering a supportive learning environment to facilitate student engagement. Furthermore, understanding the mediating role of self-efficacy underscores the importance of promoting learners' confidence and self-belief in their ability to utilize mobile learning effectively. Educators can incorporate strategies to enhance students' self-efficacy, such as providing scaffolding support, fostering a growth mindset, and offering opportunities for self-directed learning. Additionally, the study highlights the need for ongoing evaluation and refinement of mobile learning interventions to align with the evolving needs and preferences of online learners. By continuously monitoring and assessing the effectiveness of mobile learning initiatives, institutions can ensure that they remain relevant and impactful in enhancing students' learning experiences and outcomes in online flexible distance learning higher education contexts.

Practical Implications

The study's findings offer several practical implications for educators, instructional designers, and administrators in Online Flexible Distance Learning Higher Education. Firstly, recognizing the importance of factors such as performance expectancy, effort expectancy, facilitating conditions, and self-management learning can inform the design and implementation of mobile learning platforms. Instructional designers can prioritize user-friendly interfaces, clear instructions, and seamless integration with existing learning systems to enhance students' perceptions of usefulness and ease of use. Moreover, understanding the mediating role of self-efficacy highlights the importance of fostering students' confidence in their ability to engage with mobile learning effectively. Educators can incorporate activities that promote self-efficacy, such as goal-setting exercises, self-assessment opportunities, and peer collaboration, to empower students and enhance their motivation to use mobile learning tools. Additionally, institutions can provide comprehensive support structures, including technical assistance, access to resources, and professional development opportunities, to ensure that both students and faculty are equipped to utilize mobile learning effectively. By investing in faculty training and infrastructure development, institutions can create a supportive environment that encourages the successful integration of mobile learning into

Online Flexible Distance Learning Higher Education programs, ultimately enhancing students' learning experiences and outcomes.

Suggestions for Future Study

Building on the findings of this study, future research could explore several avenues to deepen our understanding of the factors influencing intention to use mobile learning in Online Flexible Distance Learning Higher Education. Firstly, longitudinal studies could investigate the long-term effects of mobile learning interventions on students' learning outcomes and academic performance. By tracking students' usage patterns and performance over an extended period, researchers can assess the sustainability and effectiveness of mobile learning initiatives. Additionally, comparative studies could examine the effectiveness of different instructional strategies and pedagogical approaches within mobile learning environments. Investigating the impact of factors such as gamification, personalized learning pathways, and collaborative activities on students' engagement and motivation could provide valuable insights into optimizing mobile learning experiences. Furthermore, qualitative research methods, such as interviews and focus groups, could be employed to explore students' perceptions, experiences, and challenges with mobile learning in greater depth. Understanding the lived experiences of online learners and their interactions with mobile learning technologies can inform the design of more tailored and user-centered interventions. Lastly, cross-cultural studies could examine the influence of cultural factors on students' acceptance and use of mobile learning in diverse educational contexts. By comparing attitudes, preferences, and behaviors across different cultural settings, researchers can identify universal principles as well as culturally specific considerations for implementing mobile learning initiatives effectively.

Conclusion

This study underscores the multifaceted nature of factors influencing the intention to use mobile learning among Online Flexible Distance Learning Higher Education students, with self-efficacy playing a pivotal mediating role. The findings highlight the significance of performance expectancy, effort expectancy, facilitating conditions, and self-management learning in shaping students' intentions to engage with mobile learning platforms. Moreover, the study emphasizes the importance of fostering students' self-efficacy beliefs to enhance their confidence and motivation in utilizing mobile learning effectively. These insights have theoretical implications for extending technology acceptance models and practical implications for designing tailored interventions and support mechanisms to promote mobile learning adoption. Moving forward, future research should explore longitudinal, comparative, qualitative, and cross-cultural approaches to further enrich our understanding of mobile learning adoption and optimize its implementation in online flexible distance learning higher education settings.

References

Adanır, A. G., & Muhametjanova, G. (2021). University students' acceptance of mobile learning: A comparative study in Turkey and Kyrgyzstan. *Education and Information Technologies*, *26*(5), 6163-6181.

Afari, E., Eksail, F. A. A., Khine, M. S., & Alaam, S. A. (2023). Computer self-efficacy and ICT integration in education: Structural relationship and mediating effects. *Education and Information Technologies*, *28*(9), 12021-12037.

Afzal, J., & Anwar, G. (2023). An empirical study on academic sustainability of mobile learning at university level. *Pakistan Journal of Educational Research*, *6*(2).

Ahadzadeh, A. S., Wu, S. L., Ong, F. S., & Deng, R. (2021). The mediating influence of the unified theory of acceptance and use of technology on the relationship between internal health locus of control and mobile health adoption: cross-sectional study. *Journal of medical Internet research*, *23*(12), e28086.

Al-Adwan, A. S., Al-Adwan, A., & Berger, H. (2018). Solving the mystery of mobile learning adoption in higher education. *Int. J. Mobile Communications*, 16(1), 24-49

Al-Bashayreh, M., Almajali, D., Altamimi, A., Masa'deh, R. E., & Al-Okaily, M. (2022). An empirical investigation of reasons influencing student acceptance and rejection of mobile learning apps usage. *Sustainability*, *14*(7), 4325.

Alowayr, A. (2022). Determinants of mobile learning adoption: extending the unified theory of acceptance and use of technology (UTAUT). *The International Journal of Information and Learning Technology*, *39*(1), 1-12.

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Education and Information Technologies*, *27*(6), 7805-7826.

Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 446627.

Chao, C. M., & Chen, W. R. (2023). Factors determining behavioural intention of nursing students to use mobile learning: an application and extension of the UTAUT model. *International Journal of Mobile Communications*, *21*(4), 472-493.

Chau, K. F. (2024). Understanding mature students' intention to use mobile learning in higher education: integrating personality traits and UTAUT. *International Journal of Educational Management*.

Chen, J. (2022). Adoption of M-learning apps: A sequential mediation analysis and the moderating role of personal innovativeness in information technology. *Computers in Human Behavior Reports*, *8*, 100237.

Chen, Y., Yang, S., Zhang, S., & Yao, J. (2023). Does self-management of learning matter? Exploring mobile learning continuance from a valence framework perspective. *International Journal of Mobile Communications*, *22*(4), 429-448.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112, 155–159. doi:10.1037/0033-2909.112.1.155

Dahri, N. A., Al-Rahmi, W. M., Almogren, A. S., Yahaya, N., Vighio, M. S., Al-maatuok, Q., & Al-Adwan, A. S. (2023). Acceptance of mobile learning technology by teachers: influencing mobile self-efficacy and 21st-century skills-based training. *Sustainability*, *15*(11), 8514.

Davis, F.D. (1989), Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, 13(3), 319-340.

Deng, P., Chen, B., & Wang, L. (2023). Predicting students' continued intention to use E-learning platform for college English study: the mediating effect of E-satisfaction and habit. *Frontiers in Psychology*, *14*, 1182980.

Do Huynh, C. B., Nguyen, A. H., Nguyen, T. H. T., & Le, A. H. (2023). Factors affecting students' intention to use mobile learning at universities: an empirical study. *Journal of System and Management Sciences*, *13*(1), 281-304.

Donaldson, J. L. (2011). Mobile learning in university contexts based on the unified theory of acceptance and use of technology (UTAUT). *NAER Journal*, 8(1), 1-15.

Ghaleb, M. M. S., & Alshiha, A. A. (2023). Empowering Self-Management: Unveiling the Impact Of Artificial Intelligence in Learning on Student Self-Efficacy and Self-Monitoring. *Eurasian Journal of Educational Research*, *107*(107), 68-94.

Gharaibeh, M. K., & Gharaibeh, N. K. (2020). An empirical study on factors influencing the intention to use mobile learning. *Adv. Sci. Technol. Eng. Syst. J*, *5*(5), 1261-1265.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: SAGE.

Hair, J. F., Sarstedt, M., Ringle, C. M., and Gudergan, S. P. (2018). *Advanced issues in partial least squares structural equation modeling.* Thousand Oakes, CA: Sage Publications

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3 ed.).* Thousand Oaks, CA: Sage.

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling, *Journal of the Academy of Marketing Science*, 43(1): 115-135.

Irwanto, I., Saputro, A. D., Widiyanti, W., & Laksana, S. D. (2023). Global trends on mobile learning in higher education: A bibliometric analysis (2002–2022). *IJIET: International Journal of Information and Education Technology*, *13*(2), 223-231.

Kebah, M., Raju, V., & Osman, Z. (2019). Growth of online purchase in Saudi Arabia retail industry. *International Journal of Recent Technology and Engineering*, 8(3), 869-872.. ISSN: 2277-3878

Kebah, M., Raju, V., & Osman, Z. (2019). Online purchasing trend in the retail industry in Saudi. *International Journal of Recent Technology and Engineering (IJRTE)*, 8(3), 865-868. ISSN: 2277-3878

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.

Latip, M. S. A., Noh, I., Tamrin, M., & Latip, S. N. N. A. (2020). Students' acceptance for e-learning and the effects of self-efficacy in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, *10*(5), 658-674.

Li, X. T., Rahman, A., Connie, G., & Osman, Z. (2020). Examining customers' perception of electronic shopping mall's e-service quality. *International Journal of Services, Economics and Management*, 11(4), 329-346.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, Yet Forsaken? Introducing a Cross-validated Predictive Ability Test in Partial Least Squares Path Modeling. *Decision Sciences*, 52(2), 362-392.

Magsayo, R. T. (2023). Mobile learning adoption continuance: Role of locus of control on its determinants. *Interactive Technology and Smart Education*, *20*(2), 177-208.

Mshali, H., & Al-Azawei, A. (2022). Predicting online learning adoption: The role of compatibility, self-efficacy, knowledge sharing, and knowledge acquisition. *Journal of Information Science Theory and Practice*, *10*(3), 24-39.

Osman, Z., Mohamad, W., Mohamad, R. K., Mohamad, L., & Sulaiman, T. F. T. (2018). Enhancing students' academic performance in Malaysian online distance learning institutions. *Asia Pacific Journal of Educators and Education*, 33, 19-28.

Ozturk, A. B., Bilgihan, A., Nusair, K., and Okumus, F. (2016). What keeps the mobile hotel booking users loyal? Investigating the roles of self-efficacy, compatibility, perceived ease of use, and perceived convenience. *Int. J. Inf. Manag*. 36, 1350–1359. doi: 10.1016/j.ijinfomgt.2016.04.005

Rahman, M. K., Bhuiyan, M. A., Mainul Hossain, M., & Sifa, R. (2023). Impact of technology self-efficacy on online learning effectiveness during the COVID-19 pandemic. *Kybernetes*, *52*(7), 2395-2415.

Rajam, V., Banerjee, S., & Alok, S. (2024). Can MOOC be a medium of lifelong learning? Examining the role of Perceived Reputation and Self-efficacy on Continuous Use Intention of MOOC. *Journal of e-Learning and Knowledge Society*, *20*(1), 1-14.

Ringle, C. M., and Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems.* 116: 1865–1886.

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2022). SmartPLS 4. *Oststeinbek*: SmartPLS. Retrieved from https://www.smartpls.com

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

Sharma, S., & Saini, J. R. (2022). On the role of teachers' acceptance, continuance intention and self-efficacy in the use of digital technologies in teaching practices. *Journal of Further and Higher Education*, *46*(6), 721-736.

Shaya, N., Baroudi, S., & Mohebi, L. (2023). Examining Factors Determining the Behavioral Intention To Use Mobile Learning Systems in Higher Education: an Integrative Framework During the Covid-19 Pandemic. *Journal of Educators Online*, *20*(1).

Shmueli, G., Ray, S., Estrada, J. M., and Chatla, S. B. (2016). The elephant in the room: predictive performance of PLS models. *Journal of Business Research*, 69: 4552–4564.

Sidik, D., & Syafar, F. (2020). Exploring the factors influencing student's intention to use mobile learning in Indonesia higher education. *Education and Information Technologies*, *25*(6), 4781-4796.

Ghaleb, S. M. M., & Alshiha, A. A. (2023). Empowering Self-Management: Unveiling the Impact of Artificial Intelligence in Learning on Student Self-Efficacy and Self-Monitoring. Eurasian Journal of Educational Research (EJER), (107).

Tarhini, A., AlHinai, M., Al-Busaidi, A. S., Govindaluri, S. M., & Al Shaqsi, J. (2024). What drives the adoption of mobile learning services among college students: An application of SEM-neural network modeling. *International Journal of Information Management Data Insights*, *4*(1), 100235.

Thomas, T. D., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development using Information and Communication Technology*, 9(3), 71-85.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.

Venkatesh, V., Morris, M. G., Davis, G. B., Davis, F. D. (2003) User acceptance of information technology: Toward a unified view. *MIS Q.*, 27, 425–478.

Voicu, M. C., & Muntean, M. (2023). Factors that influence mobile learning among university students in Romania. *Electronics*, *12*(4), 938.

Wu, Y., Wen, J., Wang, X., Wang, Q., Wang, W., Wang, X., & Cong, L. (2022). Associations between e-health literacy and chronic disease self-management in older Chinese patients with chronic non-communicable diseases: a mediation analysis. *BMC Public Health*, *22*(1), 2226.

Yu, C. W., Chao, C. M., Chang, C. F., Chen, R. J., Chen, P. C., & Liu, Y. X. (2021). Exploring behavioral intention to use a mobile health education website: an extension of the UTAUT 2 model. *Sage Open*, *11*(4), 21582440211055721.