ISSN 2348-1218 (print)
International Journal of Interdisciplinary Research and Innovations ISSN 2348-1226 (online)
Vol. 12, Issue 2, pp: (15-25), Month: April 2024 - June 2024, Available at: www.researchpublish.com

Exploring Drivers of Mobile Learning Adoption among Universities Students in Jordan

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DOI: https://doi.org/10.5281/zenodo.11082837

Published Date: 29-April-2024

Abstract: **This research endeavors to propose a model aimed at bolstering the adoption of m-learning services in developing nations, with a specific focus on Jordanian university students. The study aims to delve into their acceptance of m-learning services, specifically examining their intention to use and continued usage intention. By doing so, the proposed model seeks to illuminate the factors influencing the adoption of m-learning services in Jordan. The primary objective is to explore how Effort Expectancy (EE), Facilitating Condition (FC), Performance Expectancy (PE), Social Influence (SI), Cultural Factors (CF), Quality of Service (QoS), and Student Readiness (SR) impact the Usage Behavior (UB) of m-learning services. Identifying these influential factors is crucial for mitigating resistance among students towards adopting m-learning systems. Employing a quantitative research methodology, this study utilizes numerical measurement and analysis to investigate the factors influencing acceptance. The findings contribute practically to addressing the research problem of student acceptance of m-learning. Descriptive statistics reveal that respondents possess expertise and significant experience in utilizing m-learning in Jordan. Moreover, the study provides insights from the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, which encompasses hypothesis testing, measurement model evaluation, and structural model assessment. These findings offer valuable insights into the determinants of m-learning acceptance among Jordanian university students, thereby informing strategies to enhance the utilization of m-learning services in the region.**

Keywords: **m-learning services, developing nations, Social Influence (SI), Cultural Factors (CF), m-learning systems.**

1. INTRODUCTION

Mobile technologies have fundamentally transformed our daily lives, enhancing connectivity, facilitating communication, and fostering collaboration (Haleem, Javaid, Qadri, & Suman, 2022). Specifically, smartphones and tablet computers have emerged as pivotal tools in revolutionizing both learning and teaching approaches (Matzavela & Alepis, 2021). However, it is noted that while mobile learning cannot replace formal education entirely, it does provide supplementary methods to enrich learning experiences beyond traditional classroom settings, offering numerous advantages for diverse forms of interaction (Köse & Güner-Yildiz, 2021). Higher education is witnessing a rising trend of m-learning, also known as electronic learning via mobile technologies (Efiloğlu Kurt, 2023). Research on the implementation of m-learning in developing countries like Jordan remains limited. This study aims to assess both the benefits and challenges associated with m-learning technology and its impact on instructional practices within Jordan's higher education system. As noted by Engel and Green (2011), the swift uptake of mobile technology as an educational tool holds the potential to become a foundational element of the educational landscape. In today's digitally advanced era, mobile devices are considered essential for accessing educational materials, creating content, and enabling communication, as highlighted by Garcia et al. (2015).

Statistically, projections indicate a consistent upward trajectory in the number of smartphone users in Jordan from 2024 to 2028, with an estimated overall increase of 1.3 million users (equivalent to a 28.45 percent rise). This trend is anticipated to mark fifteen consecutive years of expansion, reaching an estimated peak of 5.83 million smartphone users in 2028. It's noteworthy that the number of smartphone users has demonstrated sustained growth in recent years, indicating a continual upward trajectory (Degenhard, 2023). In the realm of higher education institutions (HEIs), the implementation of m-learning faces two prominent challenges. These challenges encompass (a) disparities in technology perceptions between universities and students, and (b) inadequate consideration and integration of students' acceptance in technology investment decisions (Almatari et al., 2013; Alrasheedi, Capretz, & Raza, 2015). Hence, it becomes imperative to delve into the factors, constraints, and prerequisites influencing students' acceptance of m-learning within HEIs.

Expanding on the challenges previously mentioned, this study seeks to pinpoint the key factors or dimensions that impact students' willingness to embrace m-learning. Subsequently, the aim is to construct a model for understanding m-learning acceptance. Moreover, assessing students' readiness presents a considerable hurdle in determining their enthusiasm for m-learning. This entails evaluating to what degree individuals perceive the support of influential figures regarding the adoption of this new approach.

2. RESEARCH BACKGROUND

2.1 Mobile Learning

As technology increasingly integrates into education, various technological components are becoming integral to the learning process. Traditionally, educators have been the primary purveyors of knowledge to students. However, with the advent of modern technology, particularly mobile phones, these devices have assumed a crucial role within educational frameworks. Scholars have proposed multiple definitions to elucidate this phenomenon over time. Mobile learning, commonly known as m-learning, involves delivering educational content to learners via mobile devices, encompassing both specific information and comprehensive curricula. The acceptance of mobile learning by students is recognized as a pivotal factor in enhancing the utilization of this technology (Haleem et al., 2022). Despite the widespread availability of smart devices, m-learning is often perceived as a supplementary learning tool, with teachers' roles remaining foundational due to various social and technical considerations. Nonetheless, previous research has indicated that many students express a desire to leverage mobile devices, primarily for their ability to facilitate rapid communication with both teachers and peers compared to traditional methods.

Moreover, m-learning makes the educational process more engaging for students, particularly among the younger demographic that is inclined to embrace and leverage new technologies. It empowers students to engage in independent learning, fostering increased interaction with peers and facilitating the dissemination of information. Additionally, the flexibility of m-learning allows learning to take place anytime and anywhere, surpassing the limitations of physical classrooms. Furthermore, m-learning enables learners to optimize their time investment, removing the necessity for information dissemination solely within traditional classroom settings. Therefore, there is a pressing need to integrate mobile devices into the knowledge acquisition process across various demographics, ensuring affordability and accessibility. However, m-learners may face challenges when transitioning between countries with differing mobile and network standards. Users in developing countries may encounter obstacles such as technical issues during the implementation of m-learning. Moreover, educators may possess moderate proficiency levels in utilizing digital technologies, particularly when adopting alternative teaching methods like flipped learning. Additionally, educational materials originally designed for desktop or laptop platforms may not be compatible with the smart devices or phones used by students, necessitating adjustments to ensure compatibility across both platforms. Notably, many educational platforms have addressed this issue by offering support for both desktop and mobile views, thereby resolving compatibility concerns (Degenhard, 2023).

2.2 Related Studies on M-Learning

Over the past five years, mobile learning (m-learning) has garnered increasing scholarly attention in Jordan due to its scarcity and potential impact. This study aims to investigate the factors influencing m-learning and adapt technology acceptance theories to Jordan's business and cultural context. Local and international scholars have adapted Western theoretical models of technology acceptance to suit non-Western settings. Thus, recent research on m-learning in Jordan will be scrutinized to comprehend its contributions and identify any gaps in the literature. A study conducted at American

University observed college students frequently utilizing smartphones for learning purposes, including accessing information from search engines like Google and online dictionaries, libraries, and student portals (Al-Daihani, 2018). Additionally, students utilize social media apps and websites to interact with writers and verify data accuracy in their research (Safdar et al., 2020). The easy access to the internet benefits both students and medical staff, facilitating access to medical teaching and learning resources such as e-books and textbooks (Abbas & Sagsan, 2020). However, students encounter limitations such as time constraints, small screen sizes, lack of awareness, knowledge, training, and experience when learning online via smartphones (Abbas & Sagsan, 2020).

Several studies have explored the impact of smartphone usage on academic attributes, such as grade point average (GPA). Al-Daihani (2018) discovered a negative correlation between heavy use of mobile social media and GPA. Moreover, excessive smartphone use during lectures has been linked to decreased attention span and academic disengagement (Ahmed et al., 2020). Studies in the United States, India, and elsewhere have also demonstrated negative associations between smartphone usage and academic achievement (Campbell, 2006; Junco, 2012; Biswas et al., 2020). Despite the negative impacts, some studies suggest that smartphones have a positive effect on students' learning behavior (Biswas et al., 2020). However, excessive use of smartphones for socializing and non-academic activities has been associated with academic underachievement (Lepp, Barkley & Karpinski, 2015). Multitasking, such as using smartphones during lectures, has been found to adversely affect academic performance (Hossain, 2019). Nevertheless, smartphones offer opportunities for accessing educational resources and improving learning outcomes, provided they are used judiciously (Ng et al., 2017).

In conclusion, while smartphones offer numerous benefits for learning, their excessive use can have detrimental effects on academic performance. Understanding the impact of smartphone usage on learning activities and academic success is essential for developing effective strategies to harness their potential while mitigating negative consequences. Further research is needed to explore the nuanced relationship between smartphone usage patterns and academic achievement in higher education settings.

2.3 Theoretical background

The Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates four crucial factors: Facilitating Conditions (FC), Effort Expectancy (EE), Social Influence (SI), and Performance Expectancy (PE), along with four moderating variables: Gender (GEN), Age (A), Experience (EXP), and Voluntaryness of Use (VoU). These factors and variables are recognized as significant determinants influencing users' behavioral intentions and usage behavior towards technology, and they are effectively integrated with EE (Al-Shafi, Weerakkody & Janssen, 2009; Venkatesh et al., 2003). UTAUT theories are examined in a similar manner to gain insights into the roles their structures play in users' adoption of new technologies (Genuardi, 2004). This exploration is pivotal as it aims to evaluate students' readiness to adopt and utilize new technologies in the future, particularly m-learning services. Additionally, exploring theories in diverse contexts presents opportunities for generating new knowledge (Alvesson & Kärreman, 2007). Consequently, UTAUT can be applied in novel situations, such as conflicts and violent environments, contributing to the accumulation and creation of new information. Regarding usage performance, UTAUT emerges as a contemporary and robust tool for investigation, highlighting its utility in determining long-term usage intentions in Jordan even amidst civil unrest (Abdul Rahman, Jamaluddin, & Mahmud, 2011). Venkatesh et al. (2003) introduced a synthesis model to offer a comprehensive view of process acceptability compared to earlier standalone models in a similar context (AlAwadhi & Morris, 2009). Despite its relatively nascent stage, the UTAUT model is deemed acceptable and viable (AlAwadhi & Morris, 2009). Furthermore, UTAUT's reliability has been evaluated across diverse contexts of technology adoption (Yahya et al., 2011), with numerous researchers validating its robustness, including Genuardi (2004), Shafi, Weerakkody, and Janssen (2009), and Abdul Rahman et al. (2011). This underscores its suitability as a diagnostic tool for assessing whether specific information is tailored to users' needs. While Venkatesh and Davis (2000) initially examined UTAUT in private domains within the United States, the current study extends its assessment to the public sector within a conflict-affected setting. In this highly precarious scenario, essential variables such as PE, EE, SI, and FC are concurrently measured. Thus, UTAUT serves as a comprehensive framework for delving into the factors that influence the acceptance and adoption of m-learning services among Jordanian residents in this study. By incorporating essential elements such as Facilitating Conditions, Effort Expectancy, Social Influence, and Performance Expectancy, alongside moderating variables like Gender, Age, Experience, and Voluntaryness of Use, UTAUT provides a robust foundation for examining the complexities of technology acceptance in this context. This framework allows for a deeper understanding of how these factors interact and shape individuals' attitudes and intentions towards embracing m-learning, thereby offering valuable insights for designing effective strategies to promote its uptake and utilization within Jordanian communities.

3. PROPOSED MODEL AND HYPOTHESES

Factors influencing the integration of Information and Communication Technology (ICT) into education, particularly the utilization of mobile phones for learning, can be examined through diverse perspectives and methodologies. Demographic characteristics such as gender, age, and occupation influence individuals' utilization and perceptions of technology (Baker, Lusk, & Neuhauser, 2012; Shahriza Abdul Karim, Oyefolahan Oyebisi & Mahmud, 2010). Additionally, personal factors such as learning styles and personal innovativeness impact how students engage with technology in educational contexts (Bhuasiri et al., 2012; Liu, Li & Carlsson, 2010). Moreover, users' perceptions regarding the practicality, accessibility, benefits, and drawbacks of technology play a significant role in its adoption (Bhuasiri et al., 2012; Iqbal & Qureshi, 2012; Liu, Han & Li, 2010). Failures in e-learning projects are often attributed not to inherent technological shortcomings but rather to institutional and human errors in implementing innovations (Rajasingham, 2011). Hence, attributing the failure to utilize specific technological affordances, like mobile phones, solely to technology or inherent human attributes overlooks institutional strategies that may influence behavior or performance. Several factors influence the usage of mobile phones in learning, including faculty availability, financial rewards, career advancement opportunities, flexibility, and intellectual property ownership (Cook et al., 2009; Traxler, 2007). Cultural perspectives also play a vital role in predicting the success or failure of technological adoption, as different cultural and social contexts shape the reception of new technologies. Hofstede's cultural dimensions, encompassing uncertainty avoidance, power distance, masculinity, individualism versus collectivism, and long-term orientation, provide frameworks for understanding how culture influences technology acceptance. These dimensions impact attitudes towards technology, interpersonal relationships, and societal norms, thus affecting technology adoption in diverse regions (Hofstede, 1980; Hofstede, 1991; Hofstede & Bond, 1984).

Quality of service, including factors such as accessibility, reliability, interface design, content quality, and security and privacy, significantly influences the acceptance of mobile learning services (Al-Mushasha & Hassan, 2009; El Saghier & Nathan, 2013; Parsons & Ryu, 2006). Personalization and students' self-perceptions of their abilities (Student Readiness) also play crucial roles in technology adoption. Understanding these factors and their interactions is crucial for designing effective technology integration strategies in educational settings, particularly in Jordanian higher education institutions.

This study aims to develop a hypothetical model to predict and elucidate people's adoption and use of mobile learning (m-learning) services within the context of a website. The model will be grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), which postulates a belief-intention-behavior connection. According to this connection, the intention to use m-learning is directly influenced by users' behavioral beliefs (Venkatesh et al., 2003). Additionally, this study will investigate citizens' intentions to utilize m-learning services to analyze the aspect of citizens' acceptance. This concept was selected to gauge the level of acceptance, and to achieve this objective, both Usage Intention (UI) and Usage Behavior (UB) data will be assessed. The rationale for utilizing these data in the context of m-learning is that Usage Intention (UI) data offer a strong indicator of future usage, which is crucial for assessing acceptance (Parthasarathy & Bhattacherjee, 1998).

The model proposed in this study extends the UTAUT framework by incorporating the following constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Quality of Service (QoS), Culture Factors (CF), Student Readiness (SR), Continued Usage Intention (CUI), and Usage Behavior (UB). These constructs are deemed essential for comprehensively understanding the factors influencing m-learning acceptance and usage behavior.

The hypotheses of the present study are outlined as follows:

H1: Usage Behavior (UB) of m-learning services has a direct effect on Continued Usage Intention (CUI) of m-learning.

H2: Performance Expectancy (PE) of m-learning services has a direct effect on Usage Behavior (UB) to use m-learning services.

H3: Social Influence (SI) of m-learning services has a direct effect on Usage Behavior (UB) to use m-learning services.

H4: Facilitating Conditions (FC) of m-learning services has a direct effect on Usage Behavior (UB) to use m-learning services.

H5: Effort Expectancy (EE) of m-learning services has a direct effect on Usage Behavior (UB) to use m-learning services.

H6: Culture Factors (CF) have a direct effect on Usage Behavior (UB) to use m-learning services.

H7: Quality of Service (QoS) of m-learning services has a direct effect on Usage Behavior (UB) to use m-learning services.

H8: Student Readiness (SR) has a direct effect on Usage Behavior (UB) to use m-learning services.

4. METHOD

4.1. Research Approach

In this study, a quantitative methodology was employed to fulfill the research objectives. Questionnaires were distributed to gather data from a selected sample of respondents (Babbie, 2001). As defined by Stacks (2002), a questionnaire serves as a method to obtain detailed information on respondents' beliefs and attitudes. It is a significant research tool used for collecting data on various variables and testing multiple hypotheses (Neuman, 2007). The use of questionnaires in this study is appropriate as it allows the researcher to gain insights into the thoughts and attitudes of respondents towards the social phenomenon being investigated (Sekaran & Bougie, 2016). Additionally, questionnaires are a common research strategy in many social science investigations (Neuman, 2007), and respondents in Jordan are familiar with this approach. The unit of analysis in this study was the organizational unit, with each response treated as a data source. The researcher opted for a quantitative approach due to a preference for unbiased methods and the utilization of statistical procedures in quantitative inquiries (Creswell, 1999). Quantitative methods are employed to assess respondents' behaviors, opinions, and personal characteristics, focusing on quantifying and measuring concepts or variables. These methods involve explicit problem-solving procedures consistent with well-defined techniques for measuring ideas. The primary objective of quantitative research is to determine if a hypothesis holds true for the sample and subsequently for the entire population. Statistical tests are applied to evaluate whether a hypothesis is supported or rejected, and findings are often projected to a larger population. Therefore, quantitative research entails the development of a structured questionnaire that is distributed to a broader range of individuals. Quantitative approaches are associated with high levels of validity and reliability and have been widely used in past studies on research factors (Backhaus et al., 2002; Fulmer et al., 2003; Mcguire et al., 1988; Turban & Greening, 1997). The design of the instrument significantly influences data quality (Eccles, Weijer, & Mittman, 2011), and the data collection in this study was conducted using a prepared questionnaire based on principles outlined by Gay et al. (2006). It is crucial for a questionnaire to be appealing to participants and should be brief, containing elements that accurately represent the study's objectives. Additionally, the questionnaire should collect demographic information, focus on specific subjects or concepts, clarify difficult phrases, use simple language, avoid leading questions, and be pilot-tested. The questionnaire used in this study is adapted from previous studies, including:

- **Performance Expectancy**: Abdulwahab & Dahalin (2011), Venkatesh et al. (2003).
- **Social Influence**: Abdulwahab & Dahalin (2011), Venkatesh et al. (2003).
- **Facilitating Conditions**: Abdulwahab & Dahalin (2011), Venkatesh et al. (2003).
- **Effort Expectancy**: AlAwadhi & Morris (2009).
- **Culture Factors**: Du, Li, Din, & Tam (2015), Lee et al. (2009).
- **Quality Service**: Abu-Al-Aish & Love (2013).**Student Readiness**: Compeau & Higgins (1995), Lopez & Manson (1997), Malhotra & Galletta (2005), Smith, Murphy, & Mahoney (2003).
- **Usage Behavior to Use M-Learning Services**: Bettayeb, Alshurideh, & Al Kurdi (2020).
- **Continued Usage Intention of M-Learning Services**: Abdulwahab & Dahalin (2011), Bhattacherjee (2001), Chiu & Wang (2008).

4.2. Sampling and Data Collections

The researcher distributed questionnaires to 484 Jordanian university students who are utilizing m-learning services, opting to target the entire population. However, only 384 questionnaires were returned out of the total of 480 distributed. Following the recommendation by Hair et al. (2006), which suggests excluding cases with missing data exceeding 50%, a total of 10 questionnaires were discarded.

Table 1. Descriptive information.

Variables	Coding	Frequency
Gender	Male Female	204 180
Age	Less than 20 years 20-25 years 26-30 years Over 30 years	68 277 29 10
Education background	Arts Studies Sciences Studies Business Studies Sport Archaeology	69 78 227 6 4
Programme	BA Master's PhD	335 41 8
Experience	Less than 1 years 1-3 years 4-6 years More than 6 years	98 248 24 14

5. DATA ANALYSIS AND RESULTS

The hypotheses of this study were examined using Structural Equation Modeling (SEM), a technique widely embraced by researchers to overcome the limitations of traditional statistical analysis methods. SEM comprises two primary techniques: covariance-based SEM (CB-SEM) and partial least squares (PLS-SEM), both of which were employed in this study. SEM offers several advantages, including its ability to efficiently handle both reflective and formative measurement models, even with constructs consisting of only one item. Numerous researchers across various disciplines have utilized SEM in their investigations. For the analysis, Smart-PLS version 3.2.9 software was selected due to its integration of advanced statistical methods with a user-friendly interface. Several factors contributed to the choice of Smart-PLS:

1. It accommodates predictive factors within the proposed model, facilitating the confirmation of other factors that can be applied in different contexts, akin to AMOS.

2. It can be utilized when the data distribution is non-normal.

3. It can manage constructs with fewer than three indicators.

4. Smart-PLS is appropriate for both small and large sample sizes.

Following the approach delineated by Anderson et al. (1988), a two-step modeling approach was adopted in this study. Initially, the measurement model was evaluated through validity and reliability tests. Subsequently, the structural model was assessed to examine the underlying theory and relationships among variables.

5.1. Measurement Model Analysis

Internal consistency reliability assesses how consistently items in a construct's instrument measure the intended concept. Cronbach's alpha and composite reliability (CR) are the primary statistics used for this purpose, with CR being considered more robust, especially for users of Partial Least Squares Structural Equation Modeling (PLS-SEM). Therefore, this study employs CR with a threshold value of 0.70 or higher (Hair et al., 2013). Convergent validity refers to the extent of agreement among multiple items measuring the same construct. Traditionally, convergent validity is evaluated based on the correlation between responses obtained through different testing approaches for a given concept. The Average Variance Extracted (AVE), recommended by Hair et al. (2010), is utilized to assess convergent validity. To validate the use of a construct, the variance captured by its indicators, indicating measurement error, should exceed 0.50 (Fernandes, 2012; Hair et al., 2011). The findings presented in Table 2 demonstrate that the CR values for all constructs surpassed the recommended threshold of 0.70, affirming the internal consistency reliability of each construct. Moreover, the AVE values ranged from 0.550940 to 0.696908, all falling within the acceptable range. Hence, it can be concluded that all latent variables adhered to the standard guidelines for both internal consistency reliability (ICR) and convergent validity (CV) by meeting the threshold value.

Table 2. Convergent validity results.

Model Construct	Measurement Item	Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Performance Expectancy	PE1	.847	0.821356	0.696908
	PE5	.823		
Social Influence	SI2	.701	0.823748	0.612051
	SI4	.860		
	SI5	.816		
Facilitating Condition	FC1	.712	0.848285	0.584464
	FC2	.712		
	FC3	.859		
	FC5	.765		
Effort Expectancy	EE1	.750	0.900515	0.645877
	EE2	.793		
	EE3	.714		
	EE4	.833		
Culture Factors	CF1	.834	0.868131	0.686981
	CF3	.816		
	CF4	.836		
Quality of Service	QS1	.710	0.877945	0.644030
	QS2	.861		
	QS3	.773		
	QS4	.856		
Student Readiness	SR2	.844	0.851469	0.590002
	SR3	.772		
	SR4	.721		
	SR5	.728		
Usage Behaviour	UB2	.888	0.866320	0.684519
	UB3	.834		
	UB4	.754		
Continued Usage Intention	CUI1	.700	0.785952	0.550940
	CUI3	.733		
	CUI3	.735		

Distinguishing between constructs or measuring distinct concepts is known as discriminant validity (DV). According to Hair et al. (2011), the Average Variance Extracted (AVE) for a latent construct should exceed the construct's highest squared correlation with other latent constructs, as per Fornell and Larcker's (1981) criteria. Hence, in this study, the discriminant validity of measures was assessed using this criterion. The correlation matrix depicted in Table 3 shows that the diagonal elements represent the square root of the average variance extracted from latent components. Discriminant validity is established when the diagonal elements in rows and columns surpass the off-diagonal elements. It was observed that the square root of AVE for each of the eight latent constructs exceeded its correlation with any other construct in the research model, thus confirming discriminant validity.

Table 3. Fornell-Larcker criterion.

	Continued Usage	Culture Factors	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Quality of Service	Social Influence	Student Readiness	Usage Behaviour
Continued Usage	0.550940								
Culture Factors	0.486823	0.686981							
Effort Expectancy	0.544961	0.667882	0.645877						
Facilitating Conditions	0.488519	0.542405	0.528302	0.584464					

Performance Expectancy	0.465338	0.422221	0.439770	0.552607	0.696908				
Quality of Service	0.151212	0.278285	0.242095	0.125240	0.217441	0.644030			
Social Influence	0.527378	0.521192	0.594367	0.463145	0.433555	0.081758	0.612051		
Student Readiness	0.500306	0.609630	0.640673	0.562266	0.604847	0.200489	0.413848	0.590002	
Usage Behaviour	0.532478	0.649289	0.508340	0.526924	0.610443	0.299779	0.519922	0.517322	0.684519

5.2. Assessment of The Structural Model

When evaluating the structural model and examining the inner model, Partial Least Squares (PLS) analysis was utilized. The researcher applied criteria established by Fernandes (2012) and Hair et al. (2011, 2013) to test the hypotheses, considering R^2 values, GoF, effect size (f^2), predictive relevance of the model, and assessing the significance level of the path coefficients using bootstrapping. As per Hair et al. (2011), R^2 values, in conjunction with the level and significance of the path coefficients, serve as the initial criterion for assessing the PLS-SEM structural model. The primary objective of the prediction-oriented PLS-SEM approach is to elucidate the endogenous latent variable using external latent variables. Interpretations of R^2 values vary across different fields of study; for instance, R^2 scores of 0.20 are deemed excellent in consumer behavior studies, whereas in research on success drivers, R^2 values of 0.75 would be considered high. In marketing research studies, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model might be categorized as considerable, moderate, or weak, respectively. Thus, the quality of the structural model can be assessed by the R^2 value, which reveals the variance in the endogenous variable explained by the exogenous variables.

The R^2 of Usage Behavior was determined to be 0.833966, indicating that Performance Expectancy, Social Influence, Facilitating Condition, Effort Expectancy, Culture Factors, Quality of Service, and Student Readiness collectively account for 83.3% of the variance in Usage Behavior, signifying its substantial explanatory power. Additionally, the R^2 value of Continued Usage Intention to use was 0.425727, suggesting that Usage Behavior cumulatively explains 42.57% of the variance in Continued Usage Intention, which also indicates a substantial explanatory capability.

The final phase of the structural model in Partial Least Squares Structural Equation Modeling (PLS-SEM) involves evaluating the predicted correlations by employing bootstrapping and the PLS algorithm in SmartPLS 3.0. Insignificant coefficient routes in PLS analysis or indicators contradicting the hypothesized direction suggest that the prior hypotheses should be rejected (Hair et al., 2011). Conversely, significant pathways reflecting the anticipated direction experimentally support the claimed causal link. The bootstrapping process is employed to assess the relevance of each route coefficient based on weights and loadings indicators. Item loadings, route coefficients, and R^2 values are depicted in Figure 2.

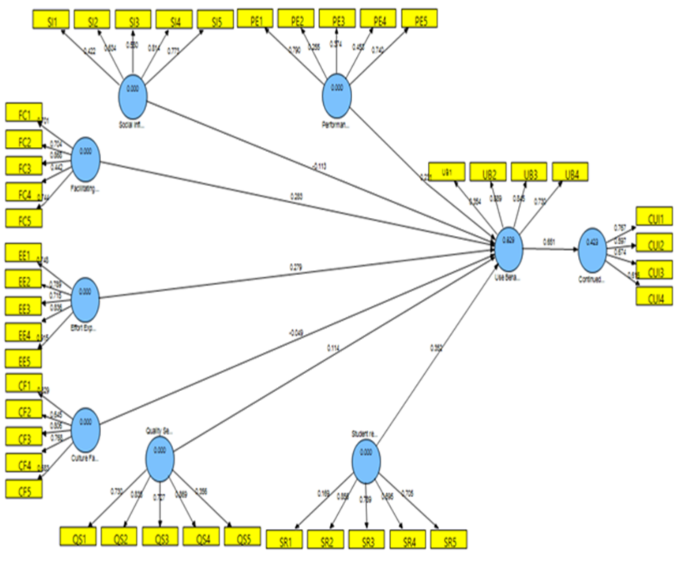

Figure 1. Results of Path coefficient analysis.

ISSN 2348-1218 (print)
International Journal of Interdisciplinary Research and Innovations ISSN 2348-1226 (online)
Vol. 12, Issue 2, pp: (15-25), Month: April 2024 - June 2024, Available at: www.researchpublish.com

Evaluating the path coefficients through the bootstrapping procedure necessitates a minimum of 500 bootstrap samples, with the number of observations matching the cases in the original sample (Ahmad Radzi et al., 2018; Henseler, 2012; Iivari, 2005; Lorenzo-Romero, Alarcón-del-Amo, & Constantinides, 2014; Monecke & Leisch, 2012; Rubel & Kee, 2014; Sumo et al., 2016; Wong, Lo, & Ramayah, 2014). Critical t-values for a two-tailed test stand at 2.58 (at a significance level of 1%), 1.96 (at a significance level of 5%), and 1.65 (at a significance level of 10%). The researcher employed 500 re-samplings with a replacement number of bootstrap instances equating the original sample size (384) to establish standard errors and obtain t-statistics. The coefficient routes and bootstrapping results are delineated in Figure 2 and Table 4, respectively.

Table 4*:* Result of Hypothesis Testing

Hypothesis	Relationship	Path Coefficient	*T* Value	Supported	
H1	Usage Behaviour → Continued Usage Intention	.652	15.960	***	Yes
H2	Performance → Usage Behaviour	.297	3.270	***	Yes
H3	Social Influence → Usage Behaviour	-0.074	1.306	n.s.	No
H4	Facilitating Condition → Usage Behaviour	.204	2.300	***	Yes
H5	Effort Expectancy → Usage Behaviour	.356	3.888	***	Yes
H6	Culture → Usage Behaviour	-0.057	1.049	n.s.	No
H7	Quality of Service → Usage Behaviour	0.087	2.315	***	Yes
H8	Student Readiness → Usage Behaviour	0.305	2.315	***	Yes

Note. *t* values

* indicates that ***t* value** is significant at $p < 0.05$

** indicates that ***t* value** is significant at $p < 0.01$.

*** indicates that ***t* value** is significant at $p < 0.001$

n.s. indicates that ***t* value** is not significant at $p > 0.1$.

6. DISCUSSION

In recent years, the educational sphere has undergone significant shifts, embracing diverse learning resources to facilitate knowledge acquisition. Technological advancements have notably transformed teaching methodologies, with mobile learning (m-learning) emerging as a prominent educational tool. This study concentrated on Jordanian Universities to delve into the impact of m-learning adoption among students. The outcomes of the model testing were predominantly positive and influential, with affirmation for 6 out of 8 hypotheses posited in the study. Comparisons with the original Unified Theory of Acceptance and Use of Technology (UTAUT) model uncovered several resemblances. Within the proposed model, Performance Expectancy (PE) wielded a notable influence on students' intention to employ mobile devices for educational purposes, echoing findings from the UTAUT model. Nevertheless, Effort Expectancy emerged as a more potent determinant in the proposed model, particularly among student users. In contrast to prior studies emphasizing the sway of Social Influence (SI) on specific demographic cohorts, such as the elderly and women, the present study revealed that students did not perceive SI as a significant factor shaping their acceptance of m-learning. The proposed model aptly captured the variability in factors influencing students' intention to embrace m-learning, achieving a 63% explanatory rate, underscoring its efficacy in elucidating the intricacies of m-learning adoption among University of Hail students.

7. CONCLUSION

This study introduces a pioneering model aimed at assessing the influence of technical factors on mobile learning usage, drawing from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Structural equation modeling (SEM) was utilized to scrutinize the formulated hypotheses within the proposed model. However, empirical data did not support two hypotheses, specifically concerning culture and social influence. In essence, this research enriches existing knowledge by presenting a fresh model that deepens our comprehension of students' intentions regarding mobile learning adoption. The conceptual framework illustrated in Figure 4 serves as a pragmatic guide for the effective implementation of mobile learning initiatives.

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