Shish Pal Sinhmar, Prof. (Dr.) Reshma Nasreen **(Oct 2025) Factors Influencing Student's Acceptance of M-Learning for Higher Education in NCR**
International Journal of Economic Perspectives*,*19 **(10) 22-39**
ISSN: 1307-1637 UGC CARE GROUP II
Retrieved from https://ijeponline.com/index.php/journal

Factors Influencing Student's Acceptance of M-Learning for Higher Education in NCR

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Abstract: Mobile learning (m-learning) is the new way to learn in the 21st century because more and more people, especially college students, are using mobile devices. So, it's necessary to find and look into the things that can affect students' plans to use m-learning. Mobile learning (m-learning) is an innovative approach to education that utilizes mobile devices to deliver courses anytime and anywhere. This pedagogical approach has evolved from conventional e-learning and distance education, significantly transforming student engagement with educational materials in higher education institutions. The acceptability of technology by users will determine the successful implementation of m-learning in higher education. The objective of this work is to examine the factors influencing university students' willingness to use mobile learning as opposed to traditional learning methods. This study adopts a modified model suggested by Abu-Al-Aish and Love to discern the factors affecting the acceptability of m-learning in higher education, based on the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). The data was gathered from 206 students using an online questionnaire, and a structural equation model was employed for data analysis. The analysis of the results concluded that effort expectancy, social influence (lecturer's), facilitating Conditions, personal innovativeness significantly impacted the behavioral intention to utilize m-learning. Surprisingly, performance expectancy exhibited a negative but statistically insignificant relationship with BI. The outcome will furnish educators and institutions with enhanced insights to formulate construction of an effective mobile learning system.

Keywords: - *M-Learning, Students Intention, UTAUT*

Introduction

M-learning represents an advanced phase in the evolution of e-learning and distance education. This pertains to learning conducted using wireless mobile devices, including smartphones, PDAs, and tablet PCs, which enable learners to engage in education at any time and in any location (Naismith et al., 2006; Wang, Wu, & Wang, 2009). M-Learning turned out to be the saviour during corona virus pandemic, when all the students were confined to their homes to prevent the transmission of SARS-COV-2-coronavirus. It resulted in the closure of educational institutions worldwide. The unforeseen circumstance emphasized the necessity for

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Submitted: 27 Aug 2025, Revised: 09 Sep 2025, Accepted: 18 Sep 2025, Published: Oct 2025

learners of all ages to participate in a flexible learning mode accessible at any time and place (Dubovi & Adler, 2022; Sramová, 2023; Jatain et al., 2023; Hanaysha et al., 2023). Mobile learning rescued educational institutions in both developed and developing nations, facilitating the continuation of learning activities during the pandemic (Tang et al., 2023; Alarabiat et al., 2023; Revilla-Cuesta et al., 2023).

The rapid proliferation of mobile devices and wireless networks on university campuses renders higher education an appropriate environment for the integration of student-centered m-learning (Cheon et al., 2012). Mobile learning employing ubiquitous devices will prove to be an effective strategy both presently and, in the future, as these devices (PDA, tablet PC, smartphone) are more appealing to higher education students for various reasons; one being that mobile devices are more cost-effective than traditional PCs; additionally, they serve as satisfactory and economical tools (Mohamad et al., 2010).

M-learning facilitates wireless communication among lecturers and students, as well as among the students themselves. This can serve as supplementary assistance to enhance and enrich current educational frameworks (Motiwalla, 2007). Furthermore, it is anticipated to emerge as one of the most efficient methods for disseminating higher education materials in the future (El-Hussein & Cronje, 2010). The NEP *(National Education Policy)* also mandates the introduction of online courses by the universities.

Several challenges exist concerning the adoption of m-learning, particularly regarding pedagogical concerns related to the use of mobile devices in classrooms. Will this integration disrupt the learning process? (Corbeil & Valdes-Corbeil, 2007; Park, 2011). Additionally, will both students and lecturers embrace this technology? Individuals might exhibit reluctance towards embracing m-learning (Wang, Wu, & Wang, 2009). Furthermore, certain university lecturers may be reluctant to adopt this technology or may encounter challenges in utilizing it effectively, as the implementation of this new technology could demand significant effort (Abu-Al-Aish, Love, & Hunaiti, 2012).

Even while mobile devices and the internet are widely used and there has been a lot of money spent on mobile learning systems, students are not using them as much as predicted, and there is still a lot of room for development (Tlili et al., 2022; Sramova, 2023). In order for the mobile learning platform to be used for educational purposes, students need to know about its benefits and make it a part of their academic lives (Alshurideh et al., 2023). Therefore, it is essential to explore students' perceptions of m-learning as a foundational step in the implementation of m-learning within higher education (Cheon et al., 2012). Consequently, it is essential to carry out an investigation that determines the factors deemed significant by university students regarding the acceptance of m-learning.

Nonetheless, there has been no examination into how university lecturers and the quality of m-learning services affect students' intentions to adopt m-learning. Moreover, the level of confidence that students possess regarding mobile device technologies influences their willingness to embrace m-learning. Consequently, it is essential to elucidate the impact of mobile device experience on the acceptance of m-learning. It is essential for students to receive training in the fundamental functions and applications of m-learning technologies (Cheon et al., 2012). This study sought to investigate

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the determinants influencing university students' acceptance of mobile learning.

This study will focus on addressing the following two objectives: -

1.) To investigate the elements that affect university students' acceptance of mobile learning.
2.) To utilize Structural Equation Modeling (SEM) for evaluating the correlation and significance of intricate relationships among diverse constructs and to clarify the key constructs that impact students' choices regarding the adoption of mobile learning.

This document is structured as follows: the next section will focus on the literature review. Following this, Section 3 outlines the conceptual framework. Section 4 presents the methodology utilized in the study, whereas Section 5 elaborates on the findings acquired. Section 6 delves into the discussion, implications, limitations, and potential avenues for future research.

Literature Review

Mobile learning, or m-learning, has been variously characterized across studies, suggesting that it remains at an emerging stage (Peng et al., 2009). M-learning is defined as "e-learning utilizing mobile devices and wireless transmission" (Hoppe et al., 2003; Chang et al., 2003).

Mobile learning (m-learning), a subset of e-learning (Basak et al. 2018), involves the utilization of wireless mobile devices (such as smartphones and tablet personal computers) to provide teaching to learners at any time and in any location (Wang et al. 2009). Conversely, m-learning refers to e-learning that utilizes mobile devices and wireless connectivity (Hoppe et al. 2003).

Crompton (2013) says that M-learning is a type of e-learning that makes use of the learner's ability to move around, allowing them to learn "anytime, anywhere." Traxler (2007) builds on this description by saying that M-learning isn't just about the devices; it's also about the change in the way people learn that makespersonalized,positioned,andcontextual learning possible. Ally (2009) says that mobile learning is a great tool for improving educational results since it has unique features including real-time engagement and the capacity to access content in multiple settings. M-learning's flexibility is especially useful in higher education, as students typically need to be able to access educational materials on the move because of their busy schedules and other responsibilities (Kukulska-Hulme & Traxler, 2005).

One of the main reasons people are paying more attention to m-learning is that there are more mobile devices (such phones, PDAs, laptops, and iPads) and these devices are getting better at what they can do. As prices go down, more and more individuals can afford these mobile devices. These mobile gadgets can do a lot of things, such make phone calls, record audio and video, take pictures, store data, and connect to the Internet. You can use all of these features in a school setting (Maccallam & Jeffery, 2009). There are a number of m-learning projects that have been written about, such as the creation of m-portals (Mitchell, 2003), classrooms of the future (Dawabi et al., 2003), and hands-on scientific investigation and instruction (Milrad et al., 2004).

Mobile learning has only lately been added to university courses. Wireless technology has changed mobile telecommunications in a big way (Althunibat 2015). College and university education in institutions employ m-learning to improve their current learning systems since it makes students

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more interested in studying (Qashou, 2021). As a result, it makes their senses sharper so they may finish their learning tasks fast and easily (Normalini et al., 2024). There is a lot of research on how acceptable and useful mobile learning is (Mishra et al., 2023). This fascination came from how quickly information systems are changing, which is having a big impact on the world's technology.

Although we inhabit a digital era where information and communication technologies (ICTs) and digital media significantly influence daily life, especially among young, research indicates that the adoption and acceptance of m-learning by higher education students is obstructed by various factors across individual, institutional, social, and cultural dimensions (Alfalah, 2023). Herath and Mittal (2022) noted that numerous scholars have endeavoured to investigate and understand the possible influence of contemporary technologies on enhancing educational quality.

A study by Shaya et al. (2023) investigated the factors influencing university students' acceptance and behavioral intentions for mobile learning services in the United Arab Emirates. Behavioral intention was highly affected by performance expectancy, effort expectancy, perceived satisfaction, service quality, and mobile self- efficacy. Similarly, Camilleri and Camilleri (2023) discovered that conducive factors, social influence, and attitudes influenced the respondents' uptake of m-learning services. Zhu and Huang (2023) performed a meta- analysis and identified performance expectancy, attitude, perceived enjoyment, learning autonomy, facilitating conditions, effort expectancy, self-management, social influence, and personal innovativeness as the most significant factors, ranked by their influence. Moreover, Al-Mamary (2022a) identified perceived usefulness and attitudes as significant predictors of the utilization of learning management systems, aligning with prior research outcomes. Qazi et al. (2024) identified several barriers to the use of e-learning services in Pakistan, including inadequate resources and training, security concerns, insufficient infrastructure, lack of effective policies, and a prevailing skepticism about the benefits among both instructors and students.

A separate investigation into mobile learning sought to identify the primary factors influencing university students' behavioral intentions regarding mobile learning and their actual engagement with it in educational settings. This study, grounded in the Technology Acceptance Model, revealed insights regarding perceived mobile value, academic relevance, and m-learning. Self-management served as a predictor for students' acceptance of m-learning (Al-Rahmi et al., 2022). Consequently, embracing m-learning is essential for users to engage with it effectively.

Evaluation of the UTAUT Model and Its Implementation in the Context of M-Learning Acceptance

In the field of information systems, many models have been created to study how individuals feel about and plan to use new technology. Davis (1989) tried to find out what makes people accept or reject information technology. The technology acceptance model (TAM) is the most popular paradigm for studying how people adopt new technologies (Davis, 1989). The goal of TAM is to provide a theoretical framework for understanding how external factors (such objective system design features, training, and computer self- efficacy) affect people's beliefs, attitudes toward use, behavioral intentions, and actual system use (Ibrahim & Jaafar,2011).

The unified theory of acceptance and use of technology (UTAUT) is another well-known concept

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in the field of information technology adoption. Venkatesh et al. (2003) came up with this theory, which tries to combine and compare parts of multiple technology adoption models in real life. The UTAUT has four factors that affect how IT users behave. According to UTAUT, direct factors that affect behavior intention or user behavior are *performance expectancy*, *effort expectancy*, *social influence, and facilitating conditions*. This makes the model much better at explaining things. According to Venkatesh et al. (2003), UTAUT can explain around 70% of the differences in intention. Researchers have shown that UTAUT works better than the models that came before it (Venkatesh et al., 2003). It can also help managers figure out how well the new technology is working (Ibrahim & Jaafar, 2011).

Conceptual Framework

The proposed conceptual framework/model to be tested is illustrated in Fig. 1, and the subsequent subsections provide justification for the inclusion of each construct in the model according to the literature.

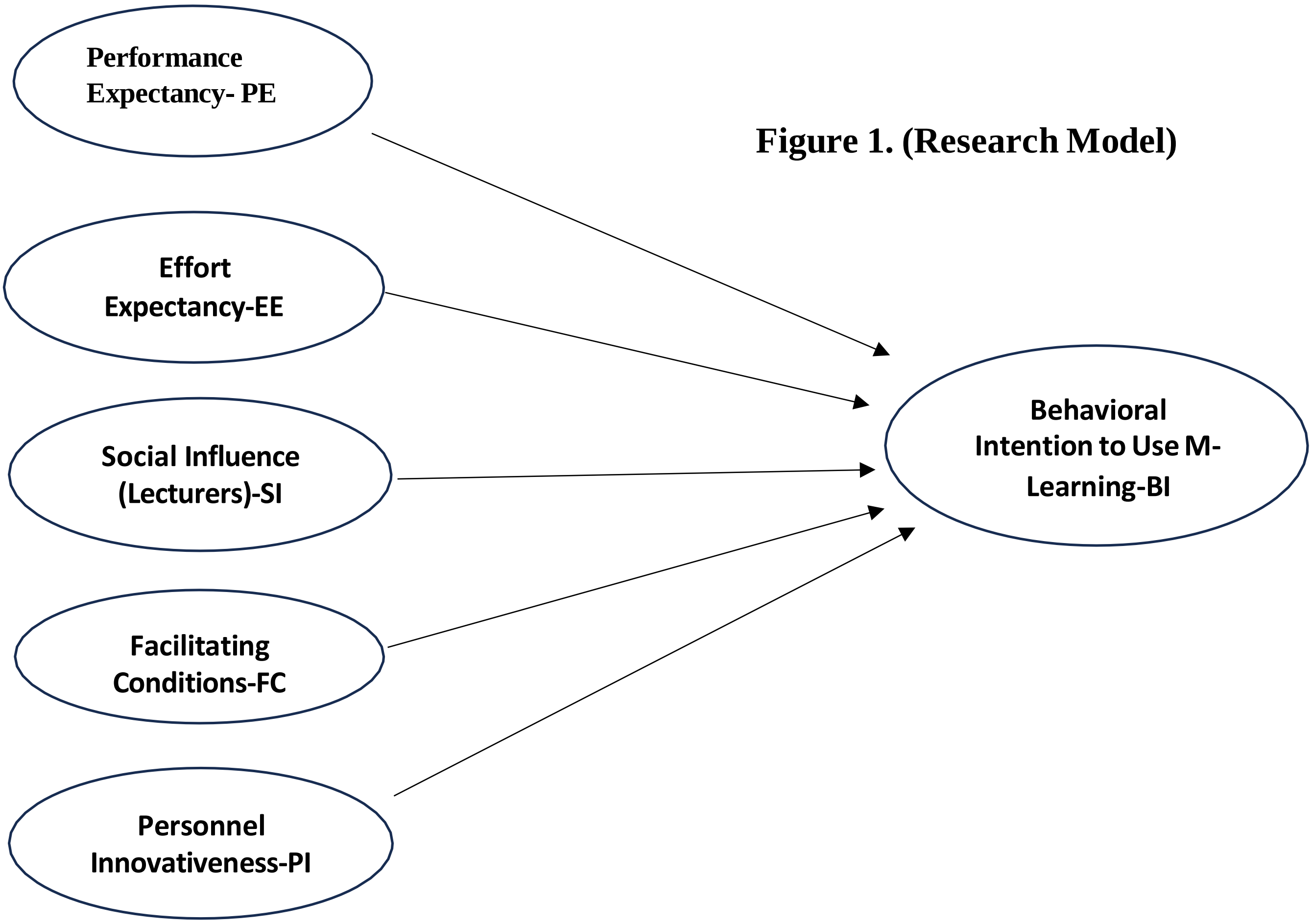

Figure 1. (Research Model)

Performance Expectancy (PE)

Venkatesh et al. (2003) characterized performance expectancy (PE) as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p.

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447). Five constructs from earlier models corresponding to PE were identified: "perceived usefulness (TAM/TAM2 and C-TAM- TPB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and result expectancies (SCT)". Across several models, performance anticipation has repeatedly proven to be the most significant predictor of behavioral intention to adopt information technology. Davis (1989) highlighted that perceived usefulness is a key factor affecting the rate of technology adoption. In the realm of mobile learning (m-learning), the application of the concept of perceived ease suggests that students are likely to view m-learning as advantageous due to its convenience, speed, and capacity to improve their learning productivity (Wang, Wu, & Wang, 2009). The Unified Theory of Acceptance and Use of Technology (UTAUT) model contends that performance expectancy (PE) significantly influences individuals' behavioral intentions to adopt and utilize information systems (Anthony et al., 2023; Edo et al., 2023; Chaudhry et al., 2023). The distinctive features of mobile phones, including accessibility, flexibility, ubiquity, and connectivity, can enhance students'

productivity and creativity (Mutambara & Bayaga, 2021; Al-Bashayreh et al., 2022; Almaiah et al., 2022; Šramová, 2023). This study states that students' perceptions of mobile phone use in education as beneficial and enhancing to their learning process will positively influence their learning performance and productivity. As a result, there will be a greater propensity to adopt and utilize m-learning services. This results in the formulation of the subsequent hypothesis:
H_1: Performance expectancy has a positive effect on students' intention to utilize mobile learning (m-learning) services.

Effort Expectancy (EE)

Effort Expectancy (EE), defined by Venkatesh et al. (2003) as "the degree of ease associated with the use of the system," is a key determinant in the adoption of information systems. It draws from earlier constructs such as perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT). The perceived ease of using a system is a critical factor influencing technology acceptance (Wu, Tao, & Yang, 2008).

In the context of mobile learning (m-learning), EE is particularly relevant, as users are more likely to adopt technologies that are perceived as convenient and easy to use (Ameri et al., 2020). Earlier studies advocate the positive relationship between EE and behavioral intention (BI) toward technology adoption in educational institutions. (Meet et al., 2022; Chahal & Rani, 2022; Al-Mamary, 2022b; Chaudhry et al., 2023). This study aims to examine whether the ease of adapting m-learning with minimal effort influences students' intentions to adopt them. If students perceive m-learning as user-friendly and easy to navigate, it can significantly enhance their likelihood of adoption.
H_2: Effort expectancy will positively influence students' behavioral intention to use mobile learning (m- learning) services.

Social Influence (SI)

Social Influence (SI) is characterized as "the extent to which an individual perceives that significant others expect him or her to utilize the new system" (Venkatesh et al., 2003, p. 451). It illustrates the influence of a user's social milieu—such as classmates, friends, or educators—on their technology

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ISSN: 1307-1637 UGC CARE GROUP II
Retrieved from https://ijeponline.com/index.php/journal

adoption behavior. Previous studies have repeatedly demonstrated that social influence is a direct factor influencing the intention to adopt new technology (Mathieson, 1991; Moore & Benbasat, 1991; Venkatesh & Davis, 2000). It is generally classified into two dimensions: peer influence and superior influence (Igbaria, Schiffman, & Wieckowski, 1994). In educational contexts, the influence of lecturers is categorized as superior influence, denoting the degree to which instructors actively promote or motivate students to engage with m-learning.

Instructors are crucial in influencing students' acceptance of new learning tools by offering direction, motivation, and emphasizing the significance of mobile learning. Research indicates that both the utilization and communication from authoritative persons can profoundly influence technological acceptability (Leonard- Barton & Deschamps, 1988; Karahanna & Straub, 1999). The wider social context, encompassing educators and classmates, enhances students' recognition of m-learning advantages and positively influences their behavioral intentions, resulting in better academic performance (Alshurideh et al., 2023; Chahal & Rani, 2022).

H_3: - The influence of lecturers positively affects the inclination to use m-learning.

Facilitating Conditions

The adoption of new technology is greatly affected by the surrounding environment or conditions accessible to the user. Venkatesh et al. (2003) characterized facilitating conditions (FC) as "the extent to which an individual perceives the presence of organizational and technical infrastructure that supports system utilization." In mobile learning (m-learning), enabling conditions encompass elements such as resource availability, user expertise, internet speed, technical assistance, and infrastructure that contribute to the effective implementation of m-learning systems.

Various technical constraints hamper the seamless shift from conventional e-learning to m-learning systems. These encompass restricted bandwidth, inadequate processing power, miniscule screen size, limited storage capacity, brief battery life, constrained input capabilities, and software compatibility challenges (Maniar & Bennett, 2002; Wang et al., 2009). Shiau, Lim, and Shen (2001) noted problems including suboptimal user interfaces, inadequate display resolution, restricted memory and computing capacity, and insufficient navigability. Such limitations may diminish users' propensity to embrace m-learning tools. Furthermore, users' view of external help, including the accessibility and caliber of technical assistance and training, significantly influences their intention to utilize m-learning systems. Students are more inclined to accept and interact with mobile learning tools when they see the presence of sufficient support and infrastructure.

H_4: Facilitating conditions positively influence the inclination to use m-learning.

Personal Innovativeness (PI)

Agarwal and Prasad (1998) described it as the individual's readiness to experiment with novel information technology. IDT contends that persons exhibiting a high degree of innovativeness are more inclined to embrace beneficial concepts and transformations in emerging information technology and possess greater aptitude for managing uncertainty than their less innovative counterparts (Lu, Yao, & Yu, 2005). If individuals are predisposed to adopt new information technology, they can serve as change agents and opinion leaders in the adoption of such technology inside organizational contexts (Agarwal & Prasad, 1998). Numerous studies examined the influence

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of personal innovativeness on intentions to adopt new information technology (Hung & Chang, 2005; Lu, Yao, & Yu, 2005; Lian & Lin, 2008; Fang, Shao, & Lan, 2009). The majority of students lack the experience or knowledge to build a clear understanding or belief on the adoption of mobile technologies for learning. Students displaying significant personal innovativeness were expected to show more risk-taking behavior and a more positive intention to employ m-learning in their academic pursuits. Therefore, the following hypothesis was assessed.

H_5: Personal innovativeness positively influences the behavioral intention to use mobile learning.

Research Methodology

This study utilized an online survey approach, employing a structured online questionnaire that included 6 constructs and 22 items, adopted from earlier empirical research related to UTAUT model. They were modified to align with a mobile learning context. Each item was assessed utilizing a 5-point Likert Scale, with responses

ranging from 1-Strongly agree to 5-Strongly disagree. The focus of the study was on university students located in Delhi and the National Capital Region. Both public and private universities were the focus of the investigation. This study is conducted among students because they embody the user perspective of m-learning, which is frequently utilized in distance learning contexts (see Biner, 1993; Roberts et al., 2005; Abbad etal.,2009). Participation in the study was completely optional. Despite the questionnaire items being derived from a well-established paradigm, we piloted the study with 40 participants prior to the actual research to ensure reliability and validity.

A total of 305 responses were collected, with 206 deemed complete and valuable for subsequent analyses. The questionnaire consisted of two sections: one focused on the demographic details of the participants and the other on their responses to the five predictors: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and personnel innovativeness (PI), along with one dependent variable, behavioral intention to adopt m-learning (BI).

The domains of analysis include: PE with 4 items, EE with 4 items, SI with 3 items, FCs with 4 items, Personnel Innovativeness with 3 items, and Behavioral intention (BI) with 4 items. In conclusion, we are studying 6 constructs and 22 items. The questions are presented in Table 1. (Appendix).

Demographic Characteristics

A total of 305 questionnaires were gathered. Following the review for absent or erroneous data, 99 questionnaires were discarded, resulting in 206 valid questionnaires. Among these participants, 49% were female and 51% were male, with the modal age spanning from 19 to 24 years. Regarding mobile utilization for educational reasons, approximately 79% of students reported utilizing mobile devices for this purpose, while only 21% indicated restricted usage (never and occasionally). Around 60% responses were from public universities and rest from private universities.

Results and Discussions

This study utilized a two-step technique inside the SEM framework, as recommended by Hair et al. (2018). Initially, CFA was conducted to evaluate the validity and reliability of the measurement model and its fit. This was subsequently succeeded by utilizing the structural model to assess the

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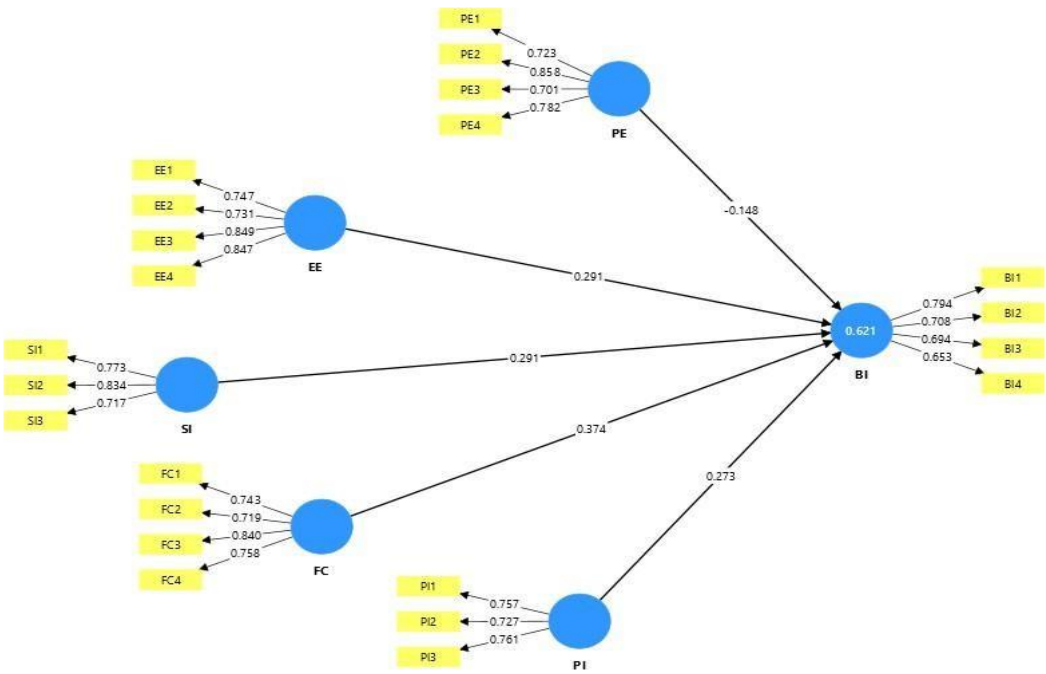
proposed links.

Measurement Model Assessment

The measuring model was assessed for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity in accordance with the recommendations established by Hair et al. (2021). Figure 2. Shows the results got through PLS-SEM.

Figure 2.



Indicator Reliability

All item outer loadings surpassed the minimum threshold of 0.70, signifying sufficient indication reliability. The lowest loading recorded was for BI (0.653), which is slightly acceptable (Hair et al., 2019).

Internal Consistency Reliability

Cronbach's alpha values varied from 0.792 to 0.873, while composite reliability (CR) values ranged from 0.793 to 0.877, beyond the recommended threshold of 0.70 (Nunnally & Bernstein, 1994), so demonstrating robust dependability.

Convergent validity and Discriminant validity

Convergent validity refers to the extent to which items within a measure exhibit shared variance, whereas discriminant validity pertains to the degree to which a construct is differentiated from other constructs (Hair et al., 2018). Hair et al. (2018) propose that validity and reliability are assessed through Composite Reliability (CR) and Average Variance Extracted (AVE). The AVE test assesses the total variance derived from all constructs within the model. It evaluates its relationship based

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on the measurement error. A composite reliability (CR) value exceeding 0.6 is preferred for assessing reliability. To assess convergent validity, the average variances extracted (AVEs) must exceed 0.5, concurrently supported by composite reliability (CR) values that are greater than the AVEs. All constructs attained Average Variance Extracted (AVE) values ranging from 0.510 to 0.633, above the 0.50 benchmark (Fornell & Larcker, 1981). thus, affirming convergent validity.

The Fornell-Larcker criterion demonstrated that the square roots of the Average Variance Extracted (AVE) exceeded the correlations with other variables, while the Heterotrait-Monotrait (HTMT) ratios remained below the conservative threshold of 0.85 (Henseler et al., 2015), hence confirming discriminant validity. Table 2 & 3 indicates that all aforementioned conditions were satisfied. Following the establishment of internal consistency and validity estimates for the constructs, the structural model was executed to evaluate the hypothesized model.

Table 1

Discriminant Validity- HTMT

	BI	**EE**	**FC**	**PE**	**PI**	**SI**
BI						
EE	0.469					
FC	0.632	0.345				
PE	0.459	0.791	0.390			
PI	0.562	0.303	0.385	0.380		
SI	0.553	0.296	0.379	0.463	0.381	

Notes: - "PE- *Performance Expectancy*, EE- *Effort Expectancy*, SI- *Social Influence*, FC- *Facilitating Conditions*, PI- *Personnel Innovativeness*, BI- *Behavioural Intention."*

Table 2
Fornell and Larcker Criterion

	BI	***EE***	***FC***	***PE***	***PI***	***SI***
BI	*0.714*					
EE	*0.472*	*0.795*				
FC	*0.634*	*0.345*	*0.766*			
PE	*0.465*	*0.787*	*0.394*	*0.768*		
PI	*0.561*	*0.303*	*0.389*	*0.379*	*0.748*	
SI	*0.557*	*0.296*	*0.382*	*0.456*	*0.382*	*0.776*

Notes: - "PE- *Performance Expectancy*, EE- *Effort Expectancy*, SI- *Social Influence*, FC- *Facilitating Conditions*, PI- *Personnel Innovativeness*, BI- *Behavioural Intention."*

Structural Model Assessment

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The outcomes of the structural equation model developed to evaluate the study's hypotheses are shown below. Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized to analyze the research model. The analysis was conducted with the SmartPLS 4.0.9.6 statistical program (Ringle et al., 2015). The structural model was assessed by route coefficients, coefficients of determination (R2), predictive relevance, and model fit indices. To assess the significance of PLS route coefficients was determined by calculating t-values using bootstrapping with 10,000 subsamples (two-tailed test, significance level=0.5) from the dataset.

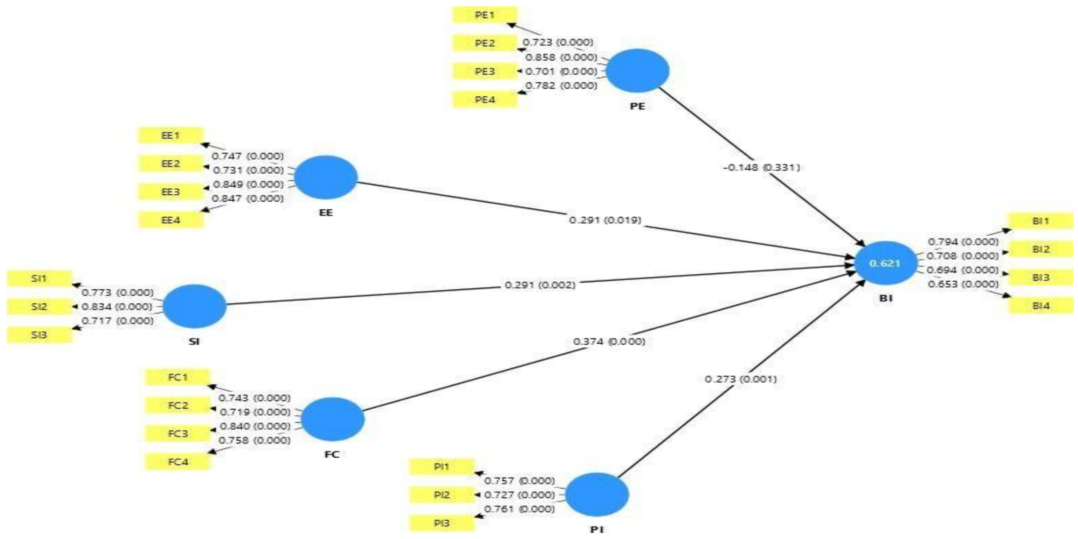
The endogenous construct, Behavioral Intention (BI), attained an R-squared value of 0.621, signifying that 62.1% of the variance in BI is elucidated by the external factors. This indicates significant explanatory capability (Chin, 1998). Results are summarized in Table 3. and also visible in Figure 3.

Table 3

Structural Model Results

Hypothesis	Relationship	Beta	t-value	P-value	Decision
H1	EE-BI	0.291	2.346	0.019	Supported
H2	FC-BI	0.374	4.432	0.000	Supported
H3	PE-BI	-0.148	0.972	0.331	Not-supported
H4	PI-BI	0.273	3.251	0.001	Supported
H5	SI-BI	0.291	3.092	0.002	Supported

***Figure 3*.**



Model Fit

The standardized Root Mean Square Residual (SRMR) was 0.050, beneath the 0.08 threshold,

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signifying a favourable model fit. The Normed Fit Index (NFI) was 0.840, which, while marginally below 0.90, is deemed acceptable in PLS-SEM because to its emphasis on prediction rather than precise model fit. Results are shown below in Table 4.

Table 4

	Saturated Model	Estimated Model
SRMR	0.050	0.050
d_ULS	0.641	0.641
d_G	0.373	0.373
Chi-square	388.318	388.318
NFI	0.840	0.840

Discussion

The findings demonstrate that the suggested model sufficiently elucidates and possesses the capability to forecast student behavioral intentions about the adoption of m-learning. Surprisingly, other than performance expectancy, effort expectancy, personnel innovativeness Social Influence (lecturers), and facilitating conditions were all important factors that affected the inclination to use m-learning.

The results demonstrate that facilitating conditions (beta = 0.374) exert the most significant positive influence on behavioral intention. This highlights the essential importance of infrastructure, resources, and organizational support in the adoption of technology. Effort expectancy and social influence significantly predict behavioral intention, underscoring the relevance of perceived ease of use and endorsement in moulding intentions. Notably, performance expectancy had a negative albeit statistically negligible correlation with behavioral intention. This implies that, in this situation, perceived performance advantages may not be the primary catalyst for adoption, potentially due to familiarity with similar technology.

Limitations and Future Research

This study has specific limitations that open up opportunities for further exploration. The practical application of m-learning was not included in the proposed paradigm of this study. As a result, students' responses have shown a tendency towards bias in their views on m-learning, which could change over time as they gain experience with using an m-learning system or application. Therefore, subsequent investigations should focus on understanding the views of students who have engaged with m-learning in their educational endeavours.

Secondly, the sampling method (i.e., convenience sampling) may introduce bias, as all participants were of the same age group. Additional research may be undertaken to examine the acceptance of m-learning among users of varying ages, cultural backgrounds, and academic disciplines. Ultimately, university educators profoundly

Submitted: 27 Aug 2025, Revised: 09 Sep 2025, Accepted: 18 Sep 2025, Published: Oct 2025

impact the execution of m-learning. They can improve their students' attitude towards m-learning and accelerate the incorporation of the technology within their departments. Additional research is necessary to examine lecturers' perspectives on m-learning and to identify the challenges they foresee in its implementation in the educational process.

Conclusion

This research examined the various elements that affect university students' willingness to engage with mobile learning in the context of higher education within the National Capital Region. The findings elucidate that 62.1% of the variance in Behavioural Intention is accounted for, specifically regarding the inclination to embrace m-learning within a higher education framework. The research has demonstrated the relevance of UTAUT in elucidating students' acceptance of mobile learning. This can be utilized to investigate the implementation of whiteboards with interactive features, mobile knowledge-driven learning systems, and workplace learning. It is crucial for educators and university administrators to motivate students about the benefits of mobile learning in their academic journeys. Some students displaying reduced personal innovativeness might need support in the early stages of embracing m-learning. Furthermore, it is essential for those involved in mobile learning design to develop applications that prioritize user-friendliness and contribute positively to students' performance.

The simplicity and practicality of a mobile learning system can significantly enhance the current learning management system by fostering improved educational outcomes and increasing students' receptiveness to mobile learning. Educators have the capacity to enhance students' embrace of mobile learning by integrating it into their conventional pedagogical approaches, thereby enriching the educational experience. Nonetheless, it is imperative for lecturers to acquire a thorough understanding of this emerging technology and to be prepared to engage actively in the implementation strategies. It is essential to incentivize university educators, enhance their understanding of m-learning, and furnish them with adequate training. Moreover, the quality of service provided by m-learning systems must encompass user-friendliness, the adaptation to diverse student requirements, and contemporary offerings, as these factors will draw a bigger student demographic to engage in m-learning. In summary, the findings suggest that institutions of higher learning must formulate strategic plans and establish guidelines that take into account student acceptance, thereby encompassing all essential success factors for the sustainable implementation of mobile learning. This study's findings offer valuable perspectives on the essential factors to consider when developing an m-learning system within the realm of higher education.

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ISSN: 1307-1637 UGC CARE GROUP II
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APPENDIX

Table 1.

Construct	Item	Scale	Scale Reference
Performance Expectancy	PE1	I find m-learning useful for my studies.	Abu-Al-Aish, A. & Love, S. (2013).
	PE2	Using m-learning would enable me to achieve learning tasks more quickly.	
	PE3	Using m-learning in my studying would not increase my learning productivity.	
	PE4	Using m-learning would not improve my performance in my studies.	
Effort Expectancy	EE1	I would find an m-learning system flexible and easy to use.	Abu-Al-Aish, A. & Love, S. (2013).
	EE2	Learning to operate an m-learning system does not require much effort.	
	EE3	My interaction with an m-learning system would be clear and understandable	
	EE4	It would be easy for me to become skillful at using an m-learning system.	
Social Influence (Lecturer's)	SI1	I would use m-learning if it was recommended to me by my lecturers.	Abu-Al-Aish, A. & Love, S. (2013).

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	SI2	I would like to use m-learning if my lecturers supported the use of it.	
	SI3	Lecturers in my Department have not been helpful in the use of m-learning systems.	
Facilitating Conditions	FC1	I have the resources necessary to use m-learning	Shakeel Iqbal and Ijaz A. Qureshi Iqra University, Pakistan (2012)
	FC2	I had the knowledge necessary to use m-learning	
	FC3	Internet speed is appropriate for m-learning	
	FC4	A specific person (or group) was available for assistance with m-learning difficulties or queries	
Personal Innovativeness	PI1	I like to experiment with new information technologies.	Abu-Al-Aish, A. & Love, S. (2013).
	PI2	When I hear about a new information technology I look forward to examining it.	
	PI3	Among my colleagues, I am usually the first to try out a new innovation in technology.	
Behavioural Intention	BI1	I plan to use m-learning in my studies.	Abu-Al-Aish, A. & Love, S. (2013).
	BI2	I predict that I will use m-learning frequently.	
	BI3	I will enjoy using m-learning systems.	
	BI4	I would recommend others to use m-learning systems.	

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