

FACTORS AFFECTING THE ADOPTION AND USE OF MOBILE LEARNING AMONG HIGHER EDUCATION STUDENTS IN NORTHEAST INDIA: A STRUCTURAL EQUATION MODELING APPROACH

Ujjal Tripura^{1*}, Dr. Sashapra Chakrawarty²

¹Research Scholar, Department of Education, Tezpur University, Assam

Email: tripuraujjal2015@gmail.com

²Associate Professor, Department of Education, Tezpur University, Assam

Email: sashapra@gmail.com

***Corresponding Author:** Ujjal Tripura, Research Scholar, Department of Education, Tezpur University, Assam

Email: tripuraujjal2015@gmail.com

Abstract- Mobile learning is a modern educational approach that enables students to access academic resources and participate in learning activities flexibly. This study examined factors influencing mobile learning adoption among higher education students in Northeast India by integrating UTAUT with the Information System Success Model. Data were collected from 460 students at Tezpur University, Assam, representing students across Northeast India, and analysed using structural equation modeling in SmartPLS 4. Findings revealed that behavioral intention was significantly influenced by effort expectancy, lecturers' attitudes, performance expectancy, social influence, and user satisfaction. Information quality influenced information and system satisfaction, while information satisfaction affected performance expectancy. System quality significantly influenced system and user satisfaction, and system satisfaction affected effort expectancy. The findings provide insights into students' readiness for m-learning in a geographically diverse and resource-constrained region and offer practical implications for educational institutions and developers in designing effective, context-responsive mobile learning systems.

Keywords- *Mobile learning, higher education students, UTAUT, Northeast*

Introduction

The rapid change of technology and its development have greatly influence on educational aspect to process and acquisition of knowledge, dissemination of knowledge, and access to it (Kinshuk et al., 2016; Ahmed & Opoku, 2022; Suryanto et al., 2023). In this modern era of digitalization, mobile devices with wireless internet technologies are powerfully used to make learning beyond limits of time and space (Buabeng-Andoh, 2018). The mobile learning, delivery of educational contents through smartphones, tablets, iPads, and other portable devices has become a predominant scenario in the higher education sector since students are able to make learning flexible, ambulant, unrestricted, and inspiring anytime and anywhere (Wang, Wu & Wang, 2009; Tan et al., 2014; (Mubuke et al. 2017; Iqbal and Qureshi 2012). Mobile learning is a process in which mobile education activities are carried out using portable devices and wireless services. Learner and device both are capable of moving (El-Hussein & Cronje, 2010).

The most diversified benefits have evolved with this current transition to mobile learning. Mobile learning is the richest tool of activity-based learning (Shin 2012; Dobre 2015) where learners have access to real-time supplementing materials for varied interactive content in active engagement and personalized experience in learning (Huang et al., 2009; Al-Bashayreh, et al., 2022). As mobile devices become ubiquitous in student life, educational institutions are beginning to realize that there may be potential in mobile learning to strengthen engagement in and outcomes from learning activities (Bernacki et al., 2020; Criollo-C et al., 2021). In the context of Northeast India, it has diverse geography location, multi-ethnic demographics, and historical infrastructural challenges, mobile learning emerges as a vital equalizer. The rapid penetration of smartphones and mobile internet in recent years has created a paradigm shift, providing students in remote and rural areas of Northeast India with unprecedented access to educational resources (Gaurav, 2026). Despite this potential, the unique socio-cultural fabric and varying levels of digital infrastructure across the eight states of the region necessitate a localized investigation into the factors driving or hindering mobile learning adoption.

Nevertheless, several factors influence the adoption and use of mobile learning by students despite the multiple benefits it offers (Tan et al., 2012). Knowledge of these factors would be relevant to ensuring that mobile learning is maximally effective and that it is properly utilized as an instrument to facilitate deeper, more meaningful learning experiences (Moya & Camacho, 2024; Amaechi, 2024). The present study intends to examine the various determinants affecting the adoption and use of mobile learning among higher education students and will employ structural equation modeling to shed light on how these factors interact and the influence they exert on student behavior in terms of mobile learning.

Review of Related Literature

Mobile learning stands as an evolved form of e-learning that is made possible through the aid of mobile technologies (Almaiah & Almulhem, 2018). A major differentiator between the two is that mobile learning can, by design, provide instructions at any time and place. Traditional e-learning may require the user to be stationed at a particular computer, with limitations as to locations and situations where the use of portable computers may not be allowed (Behera, 2013; Wang et al., 2009). Mobile learning is thus understood in different ways. According to Almaiah and Alismaiel (2019), M-learning is, therefore, an advanced educational technology for engaging learners in educational activities through mobile devices, providing easy access to learning materials such as lectures, courses, assignments, quizzes, and examinations. Adejo et al. (2018) define M-learning as an educational methodology that delivers learning materials and content on mobile devices, allowing users to access them at any time and from anywhere. Park et al. (2012) define M-learning as "any educational provision where the sole or dominant technologies are handheld or palm-top devices." According to Chao (2019), it is a learning method whereby learners use mobile smart devices to access educational content anywhere, anytime, and in any environment. Learners of M-learning are freely enabled by Yousafzai et al. (2016) to access educational resources via smartphone devices regardless of location. The most widely accepted definition describes mobile learning as the acquisition of knowledge, skills, and attitudes with the use of mobile technologies,

thereby allowing learning to take place anywhere, anytime, and leading to behavioral change (Almaiah & Al Mulhem, 2019).

Mobile learning allows learners to use technology in any place and at any time (Ozdamli & Cavus, 2011; Sharples et al., 2010). This flexibility makes mobile learning an attractive mode for those in search of knowledge and information. With the combination of mobile communication networks and appropriate software and hardware, mobile learning stands ready to change the face of education (Bernacki, 2020). Mobile learning enhances and enlarges learners' potentials to communicate and access information through mobile and wireless devices (Martin & Ertzberger, 2013). The services offered by mobile learning have the possibility to immensely support formal education and provide both direct and indirect benefits to learning (Hao et al., 2017). The role of mobile learning technology is therefore crucial to learners (Abu-Al-Aish et al., 2013). For more than one reason, Sarraf et al. (2013) stated that mobile learning has advantages such as being able to learn anywhere and anytime, access to all sorts of sources across the globe, flexibility in choosing what time to learn and at what pace, and staying focused on learning activities. Mobile learning, as stated by Shin et al. (2015), is a good means of engaging learners with minimal face-to-face interaction in distance learning.

The adoption of mobile learning (M-learning) keeps getting bigger in universities for use in governance and learning. The change that mobile telecommunications have brought in with the support of wireless technologies has been tremendous (Althunibat, 2015). In contrast, M-learning creates educational systems across higher education institutions by setting the right path for learners' attitudes toward learning and accelerated and smooth access toward the learning activities (Almaiah & Alismaiel, 2019). As a technological innovation, M-learning carries a lot of promise for the enhancement of higher education. It encourages the creation of an educational experience divorced from consideration of time and space, thereby improving learning efficiency and effectiveness (Senaratne et al., 2019). The M-learning could bring about several opportunities and challenges for teachers as well as students. It permits academics to deliver information at any chosen time and location; for students, it provides the opportunity to exercise more independence by accessing online learning resources (Al-Emran et al., 2016). M-learning carries several advantages: it gives learners freedom of movement, ease of access to educational materials, promotion of self-directed learning, and smooth interaction between learners and instructors. M-learning also enhances the availability of information and participation (Almaiah & Alismaiel, 2019). M-learning serves to provide channels of communication between students and educators through use of mobile devices, promoting the learning process most beneficently. Its use enhances academic performance while reducing personal cost and enhancing time management, and its multimedia applications instill positive attitudes toward learning (Park et al., 2012). In addition, M-learning helps students with special needs by giving their support in attending lectures through the mobile devices (Buabeng-Andoh, 2020).

While existing literature extensively covers m-learning adoption in Western and metropolitan Indian contexts, there remains a conspicuous gap in research focusing on Northeast India. Previous studies indicate that technology adoption is heavily influenced by localized socio-economic and

infrastructural realities (Isa et al., 2019; Nyirongo, 2009). In Northeast India, where community bonds are exceptionally strong and digital infrastructure is still evolving, understanding how social influence and system quality dictate technology acceptance is critical. This study addresses this gap by contextualizing the UTAUT and IS Success models within the Northeast Indian higher education landscape.

Theoretical Framework and Conceptual Framework

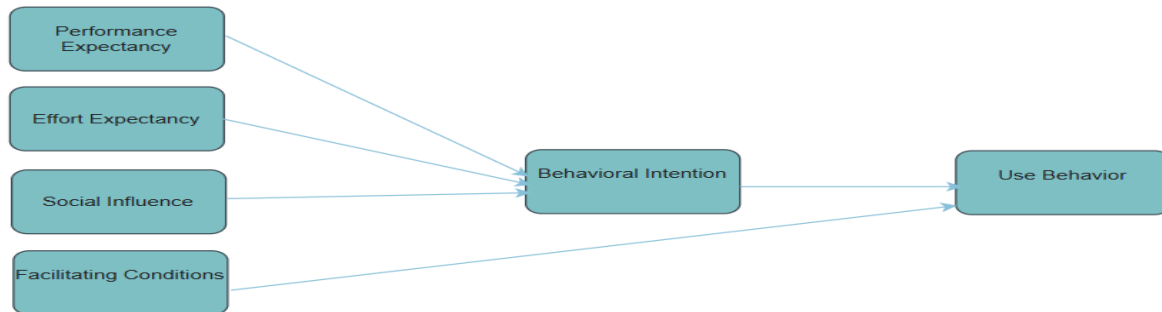


Fig-1: Unified Theory of Acceptance and Use of Technology (UTAUT).

(Source : Venkatesh et al., 2003)

The Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al., 2003] attempts to merge multiple theoretical frameworks with respect to similar variables predicting IS acceptance according to different models with different vocabularies (Min et al., 2008). Figure 1 shows that UTAUT posits four basic constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions are associated with users' behavioral intention and actual usage behavior.

Within the UTAUT framework, the constructs of performance expectancy and effort expectancy align with the concepts of perceived usefulness and perceived ease of use, respectively. Additional constructs within UTAUT encompass social influence, which directly influences the behavioral intention to utilize the information system, and enabling factors, which directly affect usage behavior. For the current study, which focuses on the direct determinants of behavioral intention, facilitating conditions have been excluded from the proposed model as it does not directly influence behavioral intention to use (Venkatesh et al., 2003). Age and gender were removed for simplicity, and UTAUT variables of experience and voluntariness were excluded since mobile learning use in this study is voluntary and experience mainly acts as a moderator. As the study focuses on students' behavioral intention, behavioral constructs from UTAUT (Venkatesh et al., 2003) and the DeLone and McLean model (1992; 2003) were also omitted.

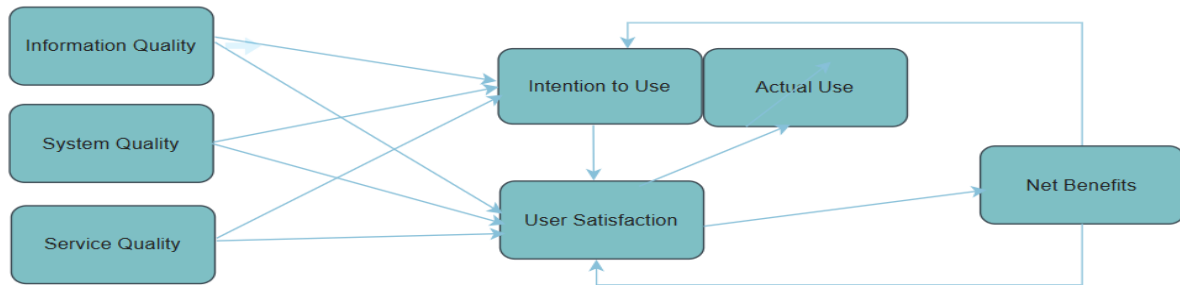


Fig-2: Modified IS Success Model (DeLone et al., 2003)

DeLone and McLean (D&M) (DeLone et al., 1992) created a model for evaluating the success of Information Systems (IS). Following a comprehensive examination of pertinent literature, D&M determined that IS success may be assessed through a multidimensional framework comprising six unique categories: system quality, information quality, usage, user satisfaction, individual impact, and organizational effect (Fig. 2). System Quality and Information Quality affect both Usage and User Satisfaction. User satisfaction may also be affected by the degree of usage, and conversely. Both Use and User Satisfaction exert direct influences on Individual Impact. Moreover, Individual Impact directly influences Organizational Impact.

The D&Ms model lays down a strong foundation for measuring IS success as it describes the temporal and causal relationships among these categories: system quality (quality characteristics), information quality (IS output quality), use (output consumption), user satisfaction (users' response), and individual impact (behavioral effects on users) as well as organizational impact (effects on organizational performance) (McGill et al., 2003; Seddon, 1997). Researchers have interrogated those relationships extensively; among them, McGill et al. (2003), Seddon (1997), Etezadi-Amoli & Farhoomand (1996) and Goodhue & Thompson (1995). The researchers have introduced a revised IS-success model in response to the literature review findings and empirical evidence, which added "service quality" to the range of measurement categories and consolidated the two former categories, individual and organizational impacts, into a new category termed "net benefits" (Fig-2). This study uses the dimensions included in the new model of IS Success as thus modified by DeLone et al. (2003). These categories are explained within the research model section.

The Rationale of the Study

The educational environment is increasingly reshaped by the evolution of M-learning, effectively modifying the conventions of how students interact with learning materials and carry out academic activities (Al-Rahmi et al., 2021; Abduljawad & Ahmad, 2023). The growth of smartphone tablets and internet access allowed opportunities for higher learning students regarding the enhancement of learning activities to support mobile technologies (Aithal & Aithal, 2023). Mobile learning allows students to access learning resources from wherever they are and whenever they want, thus allowing them independence of ways and times of engaging with their studies (Camilleri & Camilleri, 2023; Husnita et al., 2023). This variability can lead to more personalized learning experiences that can be tailored to the unique needs and preferences of students. However, while mobile learning technology does create new opportunities and advantages, these opportunities and

advantages are difficult for both the practitioners and the academia to bring into acceptance and adoption.

Unlike most educators and institutions finding it hard to integrate mobile learning into their teaching, some are merrily doing so because they recognize and resample through their own experiences to get the maximum benefits in an educational setting (Cobcroft et al., 2006; Ishtaiwa et al., 2015; Dolawattha et al., 2019). The enthusiasm of students to embrace mobile learning varies: some highly enthusiastic students are using mobile technologies for learning purposes, while others remain hesitant or resistant to applying the use of such tools (Moorthy et al., 2017; Lee et al., 2019; Maketo et al., 2023). The arguments about what factors influence the use and acceptance of mobile learning are still alive. Different studies have suggested different sets of determinants for mobile learning adoption.

Adoption levels of mobile learning could actually determine the students and educators who would probably have gone toward or away from it. Some students have a predisposition to availability of mobile learning due to their high technology familiarity and preference for flexible learning environments (Cheon et al., 2012; Hamidi & Chavoshi, 2018). Also, some teachers may tend to use mobile learning technology in their teaching just because they have a positive attitude toward technology and innovation (Mac Callum et al., 2014; Dolawattha et al., 2019). So, it's important to find out the determinant factors that influence the adoption and use of mobile learning at higher education level. Therefore, it's important to find out the determinant factors that influence the adoption and use of mobile learning at the higher education level, particularly in the context of Northeast India. Students in this region often face intermittent internet connectivity and varying levels of digital literacy, making their technology acceptance behavior distinct from their urban counterparts. By focusing on higher education students from this region, this study aims to provide actionable insights that reflect the ground reality of learners operating in an environment transitioning from digital scarcity to digital integration.

Objective of the study

To study the factors that influence the adoption and use of mobile learning among higher education students.

Hypotheses of the study

H1: Performance expectancy will significantly influence students' decision to utilize mobile learning tools.

H2: Effort expectancy will significantly influence students' intention to utilize mobile learning technologies.

H3: Social influence will significantly impact students' inclination to utilize mobile learning tools.

H4: The quality of the system will positively influence students' happiness with mobile learning solutions.

H5: The quality of information will positively influence students' happiness with mobile learning systems.

H6: The pleasure of students will positively influence their inclination to utilize mobile learning

solutions.

H7: The quality of information will positively influence students' happiness with mobile learning systems.

H8: The quality of the system will have a favorable impact on students' satisfaction with mobile learning technologies.

H9: Information satisfaction will have a beneficial impact on performance expectancy.

H10: System satisfaction will have a beneficial impact on effort expectation.

The attitudes of lecturers towards the utilization of mobile devices would positively influence students' intention to engage with mobile learning systems.

Methodology

Participants and data collection

In the current study, 460 students were purposefully taken to collect a varied array of viewpoints on mobile learning adoption. The participants were primarily drawn from Tezpur University, Assam, a central university that attracts students from all eight states of Northeast India, thereby providing a highly representative sample of the region's diverse demographic. The participants were apprised of the study's objective before to completing the questionnaire and were guaranteed that any information submitted would be kept confidential and utilized exclusively for research reasons. Informed permission was secured to guarantee ethical adherence. The data gathering process entailed the administration of a structured questionnaire aimed at evaluating multiple aspects affecting the uptake and utilization of mobile learning. Each participant, on average, required approximately 30 to 40 minutes to complete the questionnaire.

Tool

The tool was created based on elements derived from and verified by the previous study. Participants taking the survey responded to the 43 items across the 10 constructs. These constructs included Performance Expectancy (four items), Effort Expectancy, Social Influence, and Behavioral Intention to Use [Venkatesh, Morris, Davis, & Davis (2003)]; Information Quality and System Quality [DeLone & McLean (1992,2003)]; User Satisfaction, Information Satisfaction, and System Satisfaction [Alharbi & Drew, 2014] as a part of the modified IS Success framework [Seddon and Kiew (2007)]; and Lecturers' Attitude [Alharbi & Drew, 2014]. Each of the items was rated on a 7-point scale, with the scores of 1 signifying 'strongly disagree' and 7 signifying 'strongly agree.'

Data Analysis

The data obtained were subjected to analysis using Partial Least Squares (PLS) Structural Equation Modelling (SEM). SEM has several advantages, such as the ability to study multiple dependent relationships simultaneously, especially those that include direct and indirect effects among constructs (Hair et al., 2010); to study the relationships between latent and observed variables; and to measure latent variables using multiple indicators while testing hypotheses at the construct level instead of the item level (Holden and & Rada, 2011). The two-step methodology of SEM (Schumacker and Lomax, 2010) commences with the evaluation of the measurement model, which assesses how well the observed indicators reflect the latent constructs. The second step is the

structural component of SEM, which analyzes the relationships between exogenous and endogenous latent variables. SMART PLS4 (Ringle et al., 2024) was used to analyze the models.

Results

Convergent Validity

This section lists the data reliability and validity gathered in this study. Fornell and Larcker (1981) proposed three ways to assess the validity of convergence; these are item reliability, composite reliability (CR), and average variance extracted (AVE). The reliability of an item is measured through the index factor loading, which was stated by Hair et al. (2006) to be acceptable when loading is above 0.5. Here, Table I reports the factor loading of the array of items ranging from 0.73 to 0.93, exceeding the cut-off criterion set by Hair et al. (2006). According to Nunnally and Bernstein (1994), a CR between 0.7 and 0.9 is regarded as satisfactory. Composite reliability for the constructs in the present study, as presented in Table I, ranged from 0.74 to 0.90. AVE is described as "the grand average value of the squared loadings of the indicators associated with the construct" (Hair et al., 2014). Convergent validity is adequate if AVE values 0.5 or above (Fornell and Larcker, 1981). Cronbach's alpha thus was used to measure the internal consistency of the items. Hair et al. (2014) recommended CA values of 0.60 and 0.70 as acceptable. In the table above, all CA values were above the 0.7 threshold, thus giving a good indication of internal consistency because all the AVE values are over the 0.5 threshold. Convergent validity in respect of the proposed constructs, as reported in Table I, was found to be satisfactory.

Table I Convergent validity for the measurement model

Construct	Items	Factor Loading	Cronbach Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
BIU	BIU1	0.866	0.806	0.810	0.721
	BIU2	0.849			
	BIU3	0.831			
EE	EE1	0.886	0.867	0.872	0.717
	EE2	0.770			
	EE3	0.854			
	EE4	0.872			
IQ	IQ1	0.843	0.930	0.932	0.642
	IO2	0.841			
	IQ3	0.819			
	IO4	0.840			
	IQ5	0.807			
	IO6	0.739			
	IQ7	0.753			
	IO8	0.782			
	IQ9	0.779			

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IS	IS1	0.877	0.740	0.747	0.793
	IS2	0.904			
LA	LA1	0.856	0.843	0.847	0.761
	LA2	0.889			
	LA3	0.872			
PE	PE1	0.776	0.812	0.820	0.637
	PE2	0.794			
	PE3	0.829			
	PE4	0.793			
SI	SI1	0.934	0.847	0.848	0.867
	SI2	0.929			
SQ	SQ1	0.783	0.943	0.945	0.638
	SQ2	0.794			
	SQ3	0.800			
	SQ4	0.789			
	SQ5	0.804			
	SQ6	0.803			
	SQ7	0.801			
	SQ8	0.820			
	SQ9	0.829			
	SQ10	0.796			
	SQ11	0.768			
SS	SS1	0.926	0.830	0.830	0.854
	SS2	0.923			
US	US1	0.791	0.781	0.792	0.695
	US2	0.879			
	US3	0.829			

Discriminant validity

The extent to which a construct is differentiated from the other constructs experimentally is called discriminant validity. Discriminant validity has two techniques: the Fornell and Larcker approaches, which stipulate the square root of the average variance extracted (AVE) for each latent construct. According to it, this should surpass the highest squared correlation with any other construct (Fornell and Larcker, 1918), and the requirement that the loadings of each indicator must exceed all corresponding cross-loadings (Chin, 1998). This is shown in Table I, which means that every indication is granted its highest loading on its designated build, and no indicator has a loading more significant than that for any other construct. Table II indicates that the square root of AVE for each construct surpasses the cross-correlations with the other constructs. At the level of concepts, discriminant validity is considered to be sufficient for all constructs.

Discriminant validity discloses extent of experimental difference between constructs. Two techniques were used by which discriminant validity was assessed; the first was using the Fornell and Larcker criteria with the specification that the square root of the AVE (average variance extracted) for each latent construct would surpass the highest squared correlation with any other construct (Fornell and Larcker, 1918) and the second criterion held by Chin (1998) that the loadings of each indicator must exceed all corresponding cross-loadings. Thus, it is visible in Table I, wherein each indication shows its maximum loading on its designated build without loading significantly on any other construct other than that assigned by it. As indicated in Table II, the square root of AVE for each construct exceeds the cross-correlations with the other constructs to determine discriminant validity on the conceptual level for all constructs.

Table II Discriminant validity for the measurement model

	BIU	EE	IQ	IS	LA	PE	SI	SQ	SS	US
BIU	0.849									
EE	0.325	0.847								
IQ	0.328	0.289	0.801							
IS	0.180	0.210	0.156	0.891						
LA	0.299	0.136	0.187	0.182	0.872					
PE	0.316	0.338	0.487	0.225	0.301	0.798				
SI	0.361	0.419	0.176	0.177	0.177	0.229	0.931			
SQ	0.278	0.239	0.288	0.220	0.247	0.316	0.224	0.799		
SS	0.216	0.225	0.188	0.253	0.210	0.267	0.152	0.269	0.924	
US	0.265	0.216	0.285	0.335	0.223	0.267	0.195	0.302	0.314	0.834

Hypothesis Testing

Bootstrapping with 5,000 resamples (Ringle et al., 2024) was used to estimate path coefficients and test hypotheses. Perceived usefulness significantly predicted attitude ($\beta = 0.227$, $p = 0.001$), and attitude predicted intention to use ($\beta = 0.407$, $p = 0.000$). Perceived ease of use affected both perceived usefulness ($\beta = 0.447$, $p = 0.000$) and attitude ($\beta = 0.429$, $p = 0.000$). Subjective norm significantly influenced perceived usefulness ($\beta = 0.249$, $p = 0.000$), attitude ($\beta = 0.202$, $p = 0.000$), and behavioral intention ($\beta = 0.132$, $p = 0.032$), supporting all hypotheses (H1-H7). The model explained 23.0% of variance in behavioral intention, 33.8% in perceived usefulness, and 47.6% in attitude, with good model fit (SRMR = 0.054).

Table III results of hypotheses testing

Hypotheses	Path	Path coefficient (β)	T statistics	P values	Results
H1	EE -> BIU	0.138	2.482	0.013**	Supported
H2	IQ -> IS	0.156	3.339	0.001**	Supported
H3	IQ -> US	0.216	4.091	0.000***	Supported
H4	IS -> PE	0.225	4.583	0.000***	Supported
H5	LA ->BIU	0.175	3.704	0.000***	Supported

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<i>H6</i>	PE -> BIU	0.136	2.809	0.005**	Supported
<i>H7</i>	SI -> BIU	0.218	3.919	0.000***	Supported
<i>H8</i>	SQ -> SS	0.269	5.347	0.000***	Supported
<i>H9</i>	SQ -> US	0.240	4.311	0.000***	Supported
<i>H10</i>	SS -> EE	0.225	4.292	0.000***	Supported
<i>H11</i>	US -> BIU	0.118	2.449	0.014**	Supported

Notes: PE, Performance Expectancy; EE, Effort Expectancy; SI, Social Influence; BIU, Behavioural Intention to Use; IQ, Information Quality; SQ, System Quality; US, User Satisfaction; IS, Information Satisfaction; SS, System Satisfaction; LA, Lecturers' Attitude. SRMR=0.047, **P< 0.05, *** P< 0.001

Path Analysis:

Table IV Direct, indirect, and total effect of the research model

Endogenous variables	Coefficient of determination (R ²)	Determinant	Direct effect	Indirect effect	Total effect
BIU	0.25	EE	0.138	--	0.138
		IQ	--	0.03	0.03
		IS	--	0.03	0.03
		LA	0.175	--	0.175
		PE	0.136	--	0.136
		SI	0.218	--	0.218
		SQ	--	0.037	0.037
		SS	--	0.031	0.031
		US	0.118	--	0.118
EE	0.051	SQ	--	0.061	0.061
		SS	0.225	--	0.225
IS	0.024	IQ	0.156	--	0.156
PE	0.05	IQ	--	0.035	0.035
		IS	0.225	--	0.225
SS	0.072	SQ	0.269	--	0.269
US	0.134	IQ	0.216	--	0.216
		SQ	0.24	--	0.24

Notes: PE, Performance Expectancy; EE, Effort Expectancy; SI, Social Influence; BIU, Behavioural Intention to Use; IQ, Information Quality; SQ, System Quality; US, User Satisfaction; IS, Information Satisfaction; SS, System Satisfaction; LA, Lecturers' Attitude

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Table IV presents direct, indirect, and total effects on Behavioral Intention to Use (BIU). Direct effects show immediate influence, indirect effects occur through mediators, and total effects are their sum. Based on Cohen (1988), effects are small (0.02), medium (0.15), and large (0.35). BIU ($R^2 = 0.25$) is mainly influenced by Social Influence (0.218), Lecturers' Attitude (0.175), Effort Expectancy (0.138), and Performance Expectancy (0.136), while Information and System factors contribute indirectly. Effort Expectancy ($R^2 = 0.051$) depends on System Support (0.225 direct) and System Quality (0.061 indirect). Information Satisfaction ($R^2 = 0.024$) is driven by Information Quality (0.156), and Performance Expectancy ($R^2 = 0.05$) by Information Satisfaction (0.225 direct). System Satisfaction ($R^2 = 0.072$) is affected by System Quality (0.269), and User Satisfaction ($R^2 = 0.134$) by Information Quality (0.216) and System Quality (0.240).

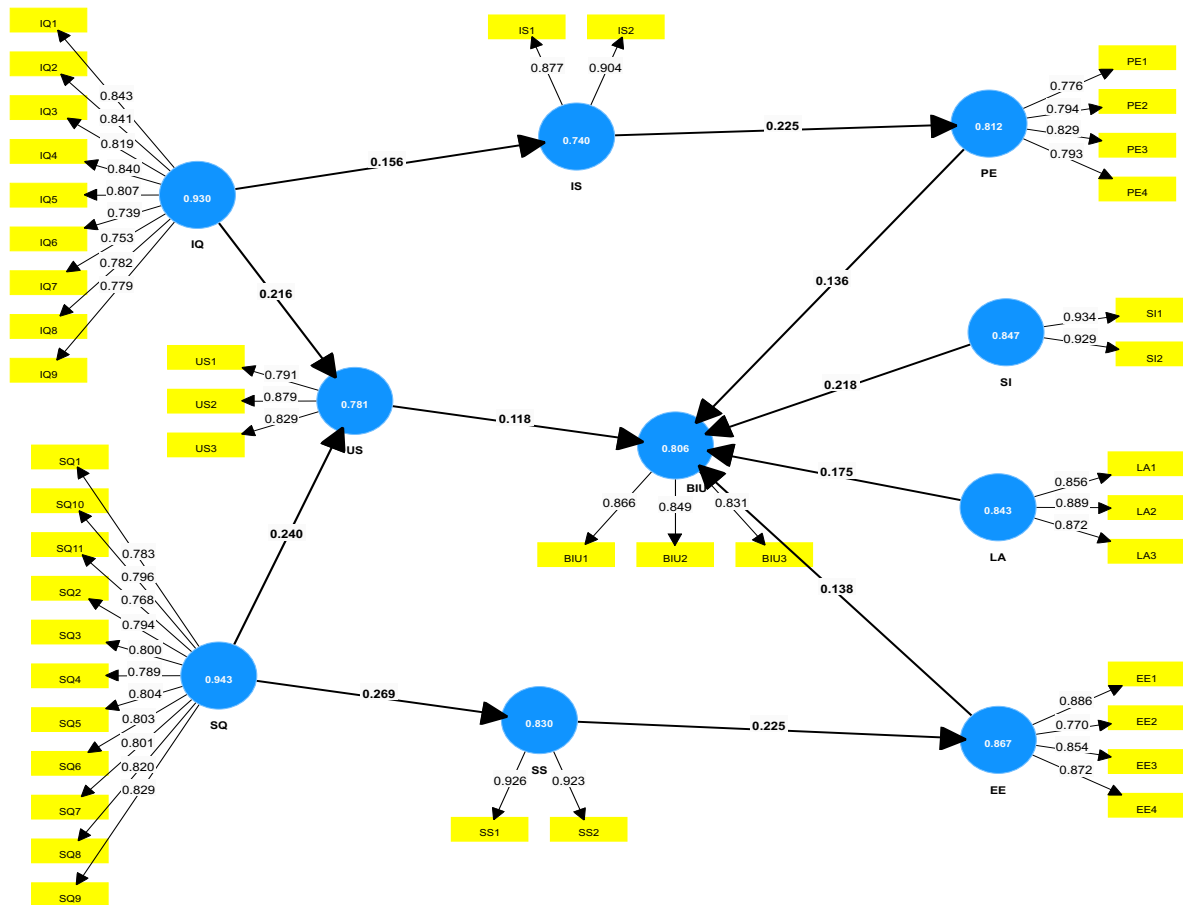


Fig-3 The results of path coefficients of the research model

Discussion

The model depicted in Figure 3 indicates that attitude exerted the most substantial significant influence on behavioral intention (BI). Perceived usefulness exerted an indirect influence on behavioral intention. The variables such as attitude toward m-learning, subjective norm, perceived usefulness, and perceived ease of use accounted for 23 percent of the variance in students' intention to utilize m-learning. This indicates that the resultant model was rather effective in predicting and elucidating BI among students.

The study aimed to explore factors that influence mobile learning among higher education students using UTAUT and IS Success Model to predict and explain university students' intention to use mobile learning (m-learning). The study found that behavioral intention to use a system was significantly influenced by several factors, including how easy users expect the system to be, lecturers' attitudes, how well the system performs, social influence, and user satisfaction. Information quality also played an important role, impacting both how satisfied users were with the information and their overall satisfaction with the system. Additionally, users' satisfaction with the information affected their expectations of how the system would perform. The quality of the system itself had a strong impact on both system satisfaction and user satisfaction. Lastly, satisfaction with the system influenced how easy users expected it to be.

The results of this model emanate from the study on the key attributes that shape Behavioral Intention to Use (BIU) in learning and technology domains. Thus, Effort Expectancy (EE), Lecturers' Attitude (LA), Performance Expectancy (PE), and Social Influence (SI) are of interest in shaping the users' intentions to adopt educational technologies (Nandwani & Khan, 2016; Bayaga & du Plessis, 2024). The most significant attribute is SI, indicating that in the perceptions of what peers, teachers, and the entire educational community think about the use of technology, students may derive attitudes that lead to the adoption or not acceptance of the technology (Ifinedo, 2016; Hamid et al., 2015). The prominence of Social Influence (SI) as a major determinant of Behavioral Intention to Use (BIU) is particularly noteworthy in the context of Northeast India. The region is known for its strong community structures and collectivistic cultural fabric, where peer opinions and the attitudes of respected figures (such as lecturers) play a pivotal role in individual decision-making. Furthermore, the strong impact of System Quality (SQ) and Information Quality (IQ) on user satisfaction highlights the challenges students face with intermittent internet connectivity in the region. Students in Northeast India are highly sensitive to systems that consume excessive data or fail to perform under low-bandwidth conditions, which explains why robust system quality directly dictates their ease of use and overall satisfaction. Therefore, for m-learning to be successfully integrated into this region, developers must ensure that platforms are optimized for low-data consumption and offline capabilities.

Such a finding has a significance in all forms of educational institutions, namely primary, secondary, and higher educational institutions, as where and to what extent social influence in the form of teachers and peers affects students' adoption of new technologies. Positive norms in the use of technology, through peer-led workshops or teacher-driven tech integration strategies, could increase BIU use among students (Theobald et al., 2018; Scarlett, 2022).

Nonetheless, challenges are likely to arise in an environment with limited resources where either the system quality or the support infrastructure is inadequate (Frehywot et al., 2013). An access to reliable technology and the strengthening of support systems in educational institutions are very crucial in the effective adoption of technology (Nyirongo, 2009; Isa et al., 2019; Susilawati et al., 2023). Findings such as these give some hope that context-specific interventions such as improving infrastructure, technical support centres, and teacher capacity building can be key in overcoming barriers.

Previous supportive finding of such studies is that the factors such as Performance Expectancy and Effort Expectancy are usually very strong predictors of technology adoption behavior in educational scenarios (Brown et al., 2010; Magsamen-Conrad et al., 2015). Furthermore, research studies have reiterated that teacher attitudes toward technologies might make a substantial difference in regard to students' interaction with and willingness to use technology (Luo, & Murray, 2018; Chhibber et al., 2024). Thus, foster culture of enthusiasm on technology among teachers would be important for the smooth process of implementing technology.

This research calls for taking multifaceted approaches toward technology integration in educational environments. To boost intention to use among students, a school and a university should enhance its technical infrastructure and improve social aspects, for example, strengthening positive attitudes toward technology along with developing stronger social supports (Park, 2009; Park et al., 2012; Nikou & Economides, 2017). The benefit of this, among other things, would render technology a seamless and beneficial aspect of the learning process, thereby contributing positively to educational outcomes.

Conclusion

The study really sheds light on the factors that lead to Behavioral Intention to Use of educational technologies by university students in Northeast India. Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), and Lecturers' Attitude (LA) and system-related aspects such as Information Quality (IQ) and System Quality (SQ) play similar roles in affecting students' BIU within this specific regional context. Results presented do indicate that there are social influences and technical factors towards creating a good environment in which students can accept and use technology effectively.

The above factors are significant for an educational institution, particularly a university in Northeast India, in determining technology adoption in the institution as well as making the learning experience more dynamic. Programs for improving system quality such as establishing robust campus Wi-Fi and offline digital repositories to combat regional connectivity issues, establishing a strong technical support system, and empowering positive attitudes toward technology amongst students and teachers would improve adoption rates. Such findings may thus be generalized to other levels of education across the region, that is, secondary schools or medical institutions, as the importance of technology adoption becomes ever more considerable.

Notwithstanding the sample used, the method as limited in this study, it adds to the burgeoning understanding of technology adoption in education and builds the groundwork for future inquiries into this critical area. Research across a variety of educational environments and through longitudinal perspectives will lead to future studies creating more richer methods for addressing effective technology integration in different contexts of learning, especially across varying topographies and digital infrastructures.

Declarations

Informed Consent Declaration:

Informed consent was obtained from all participants before data collection. Participation was voluntary, and confidentiality and anonymity were ensured.

Conflict of Interest:

The author(s) declare that there is no conflict of interest regarding the research, authorship, or publication of this study.

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