JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Determinants of University Students' Intention to Use Mobile Learning: An Integrative TAM–UTAUT–TTF Approach in Bangladesh

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Abstract
The rapid adoption of mobile technologies has transformed higher education, enabling mobile learning that provides flexible, personalized, and ubiquitous access to educational resources. Despite its growing prevalence, empirical research on the factors influencing students' intention to use mobile learning in developing countries, particularly Bangladesh, remains limited. This study addresses this gap by proposing and empirically testing an integrative research framework that combines the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), motivational theory, and Task-Technology Fit (TTF). The model examines the effects of attitude toward mobile learning, social influence, perceived skill, perceived resources, perceived enjoyment, perceived ease of use, perceived usefulness, habit, intrinsic motivation, and task-technology fit on undergraduate students' intention to use mobile learning (IUML). Data were collected from 349 undergraduate students in Dhaka, Bangladesh, using a structured questionnaire and analyzed through partial least squares structural equation modeling (PLS-SEM). Results indicate that cognitive, motivational, habitual, and contextual factors collectively influence students' IUML, with attitude, perceived usefulness, and task-technology fit emerging as the most significant predictors. Social influence and intrinsic motivation also demonstrated meaningful, though smaller, effects. These findings highlight the importance of designing mobile learning systems that are not only user-friendly and useful but also aligned with academic tasks and supported by adequate technological and institutional resources. The study contributes to the theoretical literature by validating an integrative adoption model in a developing-country context and offers practical guidance for educators, policymakers, and designers seeking to enhance mobile learning adoption and sustainability in higher education.

Keywords: Mobile learning, Technology Acceptance Model, UTAUT2, Task-Technology Fit, Bangladesh.

Introduction

The rapid advancement of mobile technologies has fundamentally transformed higher education, enabling new forms of mobile learning (m-learning) that provide flexible, personalized, and ubiquitous access to educational resources (Ahmad et al., 2025; Fan & Wang, 2025). Mobile learning refers to the use of portable digital devices, such as smartphones and tablets, to facilitate learning anytime and anywhere, transcending the constraints of traditional classroom environments (Crompton, 2013; Khan et al., 2019; Zhang et al., 2025). In recent years, mobile learning has gained significant attention due to its potential to enhance learner engagement, improve academic performance, and support sustainable education systems (Al-Rahmi et al., 2021; Alias & Razak, 2025). The global shift toward digital education was further accelerated by the COVID-19 pandemic, which compelled higher education institutions to adopt mobile and online learning solutions at an unprecedented scale (Dhawan, 2020; Roy & Sarkar, 2025). Even in the post-pandemic period, mobile learning continues to play a critical role in supporting blended and hybrid instructional models, particularly in developing countries where access to conventional educational infrastructure remains uneven (James et al., 2025; Zhu & Huang, 2025). As a result, understanding the factors that influence students' intention to use mobile learning technologies has become a pressing research priority.

From a theoretical perspective, scholars have extensively employed technology acceptance models to explain individuals' adoption of educational technologies. The Technology Acceptance Model (TAM) emphasizes perceived usefulness and perceived ease of use as the primary determinants of behavioral intention (Davis, 1989; Roy et al., 2025). Similarly, the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended version, UTAUT2, incorporate additional factors such as social influence, facilitating conditions, and habit to explain technology adoption behaviors (Venkatesh et al., 2003, 2012). While these frameworks have demonstrated strong explanatory power, recent studies argue that mobile learning adoption is a multifaceted phenomenon that cannot be fully captured by a single theoretical lens (Alghazi et al., 2021; Roy et al., 2025).

To address this limitation, researchers have increasingly integrated TAM and UTAUT with motivational theories and the Task-Technology Fit (TTF) model. Motivational theory highlights the importance of intrinsic drivers, such as enjoyment and interest, in shaping technology use behaviors (Ahsan, 2025; Deci & Ryan, 1985), whereas TTF emphasizes the alignment between technological features and task requirements as a critical determinant of performance and adoption (Goodhue & Thompson, 1995; Roy et al., 2025). Empirical evidence suggests that mobile learning adoption is more likely when learners perceive the technology as enjoyable, useful, easy to use, and well-suited to their academic tasks (Voicu & Muntean, 2023).

Despite the growing body of research on mobile learning, several critical gaps remain. First, most existing studies have been conducted in developed or technologically mature contexts, limiting the generalizability of findings to developing countries with different infrastructural, cultural, and institutional characteristics. Second, research on South Asian contexts remains fragmented, with relatively few empirical studies examining mobile learning adoption in Bangladesh, despite rapid expansion in mobile internet usage and higher education enrollment. Bangladesh represents a particularly compelling context, as mobile devices are widely accessible among university students, yet disparities persist in digital infrastructure, institutional support, and pedagogical integration.

Moreover, prior studies often rely on single-theory approaches, which may overlook the complex interplay between cognitive beliefs, motivational factors, habitual behavior, and contextual support mechanisms. There is therefore a need for integrative research frameworks that combine multiple theoretical perspectives to provide a more comprehensive understanding of mobile learning adoption in developing higher education systems. Addressing this gap is essential not only for advancing theory but also for informing policy and practice aimed at promoting sustainable digital learning initiatives.

In response to these gaps, the present study proposes and empirically tests an integrated research framework grounded in TAM, UTAUT/UTAUT2, motivational theory, and TTF to examine the determinants of intention to use mobile learning (IUML) among undergraduate students in Bangladesh. Specifically, the study investigates the effects of attitude toward mobile learning, social influence, perceived skill, perceived resources, perceived enjoyment, perceived ease of use, perceived usefulness, habit, intrinsic motivation, and task-technology fit on IUML using partial least squares structural equation modeling (PLS-SEM).

By focusing on the Bangladeshi higher education context, this study makes three key contributions. First, it extends mobile learning adoption theory by validating an integrative model in an under-researched developing-country setting. Second, it provides empirical insights that are comparatively relevant to neighboring South Asian countries, such as India, Pakistan, and Sri Lanka, which share similar educational and technological challenges. Third, it offers practical implications for educators, policymakers, and system designers seeking to leverage mobile learning as a sustainable solution for improving higher education access and quality.

Literature review and hypothesis development

Mobile Learning in Higher Education

Mobile learning (m-learning) has emerged as a transformative modality in higher education, enabling learners to access instructional resources anytime, anywhere on portable digital devices (Crompton & Burke, 2018; Khan & Hossain, 2016). Advances in mobile technologies, combined with increased internet penetration, have accelerated the integration of mobile learning into university teaching and learning processes, particularly in developing economies where traditional infrastructure may be constrained (Al-Rahmi et al., 2021). In South Asian contexts, including Bangladesh, mobile learning plays a critical role in expanding access to education, supporting flexible learning arrangements, and complementing institutional learning management systems (Islam et al., 2021; Roy & Musfika, 2025).

Despite its growing adoption, students' intentions to use mobile learning systems remain uneven, suggesting that technological availability alone does not guarantee sustained usage. Prior research emphasizes that learners' behavioral intentions are shaped by a combination of cognitive evaluations, affective responses, contextual conditions, and habitual behaviors (Venkatesh et al., 2012; Roy et al., 2024). Consequently, an integrative theoretical approach is required to comprehensively explain mobile learning acceptance, particularly in underexplored developing-country settings such as Bangladesh.

Attitude toward mobile learning and use intention

Attitude toward mobile learning (ATML) reflects learners' overall evaluative judgment regarding the use of mobile technologies for educational purposes. Rooted in the Technology Acceptance Model (TAM), attitude has consistently been identified as a proximal determinant of behavioral intention (Davis, 1989). Empirical evidence suggests that students who hold favorable attitudes toward mobile learning are more likely to adopt and continue using such systems (Al-Rahmi et al., 2021; Khan & Roy, 2023). In developing-country contexts, attitudes toward mobile learning are often shaped by perceived academic value, system reliability, and alignment with instructional practices (Sarrab et al., 2022). Given the rapid digitalization of Bangladeshi higher education and students' increasing reliance on smartphones for academic tasks, a positive attitude toward mobile learning is expected to translate into stronger intentions to use mobile learning.

H1: Attitude toward mobile learning positively influences intention to use mobile learning.

Social influence and use intention

Social influence (SI) refers to the extent to which individuals perceive that important other, such as peers, instructors, or institutions, expect them to use a particular technology (Venkatesh et al., 2012). Prior studies in mobile and e-learning contexts have produced mixed findings regarding the role of social influence. While some research reports a significant effect, particularly in collectivist societies (Alanazi et al., 2024; Roy et al., 2021), others find that its influence diminishes as users gain experience and autonomy (Zhou et al., 2025). In university settings, especially among digitally literate undergraduates, technology adoption decisions may be increasingly driven by personal evaluations rather than normative pressure. Nevertheless, given the collaborative learning culture prevalent in Bangladeshi universities, social influence remains theoretically relevant.

H2: Social influence positively influences intention to use mobile learning.

Perceived skill and use intention

Perceived skill (PS) captures students' self-assessment of their ability to effectively use mobile technologies for learning. Drawing from self-efficacy theory, prior research suggests that learners with higher perceived competence are more confident and willing to adopt educational technologies (Voicu & Muntean, 2023). However, as mobile devices have become ubiquitous, especially among young adults in South Asia, basic operational skills may no longer differentiate users' intentions. This raises questions about the continued salience of perceived skill in contexts where mobile literacy is widespread, such as urban Bangladesh.

H3: Perceived skill positively influences intention to use mobile learning.

Perceived resources and use intention

Perceived resources (PR) refer to learners' perceptions of having adequate technological, institutional, and infrastructural support to engage in mobile learning. This construct aligns with facilitating conditions in UTAUT and has been shown to be critical in developing-country contexts, where disparities in internet access, device quality, and institutional readiness persist (Venkatesh et al., 2012; Al-Rahmi et al., 2021). In Bangladesh, variations in campus infrastructure and internet reliability may directly affect students' willingness to use mobile learning platforms. When learners perceive sufficient resources and institutional support, adoption barriers are reduced.

H4: Perceived resources positively influence intention to use mobile learning.

Perceived enjoyment and use intention

Perceived enjoyment (PE) reflects the intrinsic pleasure derived from using mobile learning systems, independent of performance outcomes. Motivational theories suggest that enjoyment enhances engagement and sustained usage, particularly in digital learning environments (Deci & Ryan, 2000). Empirical studies consistently demonstrate that enjoyable mobile learning experiences increase students' willingness to adopt and continue using such technologies (Al-Rahmi et al., 2021). In technology-rich yet academically demanding environments like Bangladeshi universities, enjoyment may serve as a critical differentiator between occasional and sustained use.

H5: Perceived enjoyment positively influences intention to use mobile learning.

Perceived ease of use and use intention

Perceived ease of use (PEU) denotes the degree to which students believe that mobile learning systems are free of effort. TAM posits PEU as a fundamental antecedent of technology acceptance, influencing both perceived usefulness and behavioral intention (Davis, 1989; Roy & Khatun, 2023). In mobile learning contexts, usability is particularly salient due to small screen sizes, interface complexity, and varying levels of system integration. Prior studies in South Asia confirm that intuitive and user-friendly mobile learning platforms significantly enhance adoption intentions (Islam et al., 2025).

H6: Perceived ease of use positively influences intention to use mobile learning.

Perceived usefulness and use intention

Perceived usefulness (PU) represents learners' beliefs that mobile learning enhances academic performance and productivity. Extensive evidence across educational technologies identifies PU as the strongest predictor of usage intention (Venkatesh et al., 2012; Zhou et al., 2025). In performance-oriented educational systems such as Bangladesh's, students are particularly sensitive to technologies that demonstrably improve learning outcomes. Mobile learning applications that facilitate exam preparation, content accessibility, and academic efficiency are therefore more likely to be adopted.

H7: Perceived usefulness positively influences intention to use mobile learning.

Habit and use intention

Habit (H) reflects the extent to which mobile learning usage becomes automatic due to repeated prior behavior. UTAUT2 emphasizes habit as a critical determinant of continued technology use (Venkatesh et al., 2012). Given the pervasive use of smartphones among Bangladeshi undergraduates, habitual engagement with mobile applications may naturally extend to learning-related activities (Roy et al., 2021). As mobile learning becomes embedded in daily academic routines, habit is expected to exert a significant influence on users' intention to use.

H8: Habit positively influences intention to use mobile learning.

Intrinsic motivation and use intention

Intrinsic motivation (IM) refers to engaging in mobile learning for inherent satisfaction, curiosity, or personal growth. Although motivation-based models highlight their importance, empirical findings remain inconsistent, particularly in formal education settings where extrinsic outcomes dominate (Voicu & Muntean, 2023). In examination-driven systems like Bangladesh's, intrinsic motivation may be secondary to utilitarian considerations, raising questions about its direct effect on mobile learning intention.

H9: Intrinsic motivation positively influences intention to use mobile learning.

Task-Technology Fit and Use Intention

Task-Technology Fit (TTF) theory posits that technology adoption depends on how well system functionalities align with users' task requirements (Goodhue & Thompson, 1995). In mobile learning, TTF captures the extent to which mobile technologies support academic tasks such as content review, collaboration, and assessment preparation. Prior studies demonstrate that strong task-technology alignment enhances both perceived usefulness and adoption intention (Zhou et al., 2025). In Bangladeshi universities, where students increasingly rely on mobile devices for coursework, TTF is expected to play a decisive role.

H10: Task–technology fit positively influences intention to use mobile learning.

Integrative research framework

Drawing on TAM, UTAUT2, motivational theory, and TTF, this study proposes an integrative framework to explain undergraduate students' intention to use mobile learning in Bangladesh. See figure 1. By synthesizing cognitive, affective, contextual, and behavioral perspectives, the model addresses gaps in prior research that examined these factors in isolation or within technologically mature contexts. The framework advances understanding of mobile learning adoption in developing higher education systems and offers a robust basis for empirical testing.

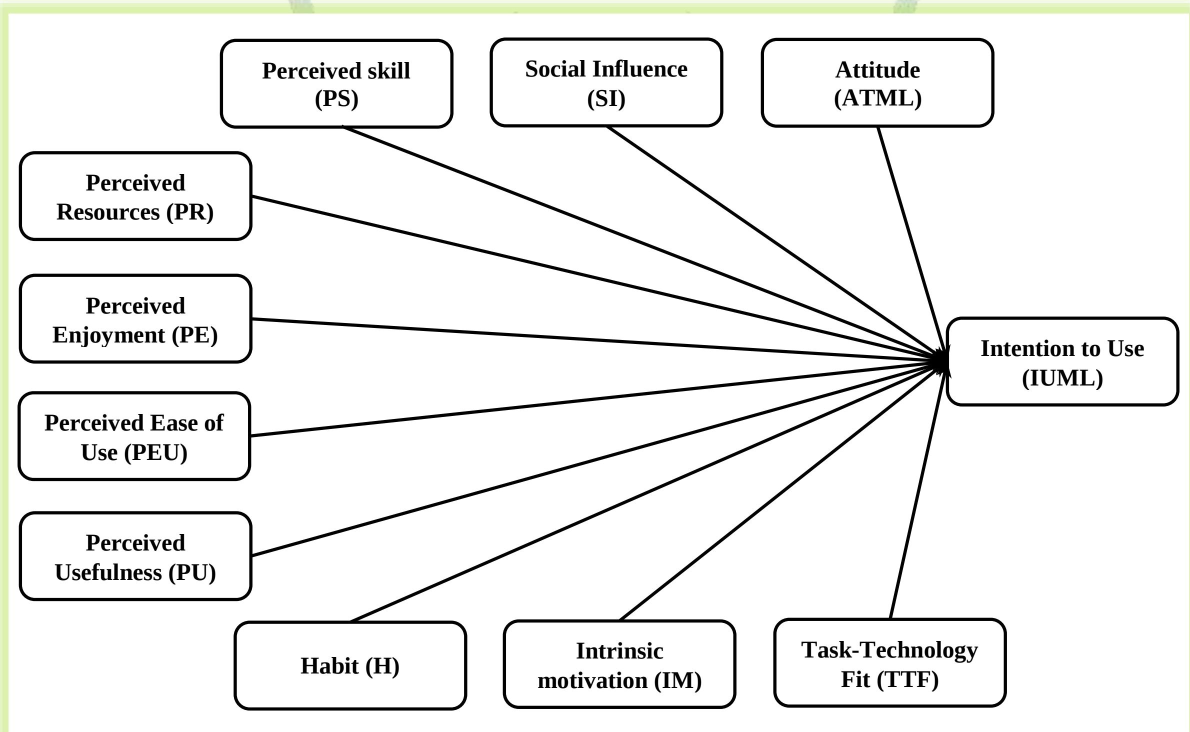

Figure 1: Conceptual research framework

Research methodology

Participants

This study is based on primary data collected to ensure methodological rigor and enhance the credibility of the empirical findings. Data were collected through a structured, systematically designed questionnaire administered to undergraduate students enrolled in higher education institutions in Dhaka, Bangladesh. Dhaka was selected as the study context due to its high concentration of public and private universities and the widespread adoption of smartphones and mobile internet services among students, making it an appropriate setting for investigating mobile learning intentions. The target population comprised undergraduate students from diverse academic disciplines, thereby capturing a broad range of learning experiences and technological engagement. Participation was entirely voluntary, and respondents were informed of their right to withdraw at any stage of the survey. After data screening and removal of incomplete responses, the final dataset comprised 349 valid questionnaires, suitable for subsequent statistical analysis.

Sampling Technique

A nonprobability sampling approach combining convenience and purposive sampling was used to recruit participants. Non-probability sampling was selected for its efficiency in terms of time and cost, particularly appropriate for technology adoption studies conducted in academic environments. Convenience sampling facilitated rapid access to respondents, while purposive sampling ensured that all participants had prior experience with mobile learning, a critical criterion for examining intention to use mobile learning systems (Chowdhury et al., 2019). To validate the survey instrument and assess item clarity, a pilot study involving 40 undergraduate students was conducted, and minor refinements were made accordingly. The main survey was subsequently distributed via an online questionnaire using widely adopted mobile communication platforms such as Messenger and WhatsApp, which are commonly used by Bangladeshi university students. After excluding incomplete and invalid responses, a total of 349 usable questionnaires were retained for analysis. Although this dual sampling strategy enhances accessibility while maintaining relevance to the research objective, potential biases associated with non-probability sampling, such as self-selection bias, are acknowledged and addressed in the limitations section.

Sample Size

The adequacy of the sample size was evaluated using both statistical power analysis and methodological guidelines. The minimum required sample size was calculated using G*Power software (version 3.1.9.4). Following established recommendations, an effect size of 0.05 and a statistical power of 0.95 were specified, yielding a minimum sample size of 262 respondents. The final sample of 349 participants exceeds this threshold, thereby providing sufficient power to detect statistically significant effects. In addition, the sample size is appropriate for the complexity of the proposed research model, which includes eleven latent constructs and multiple structural paths. Consistent with PLS-SEM guidelines, which recommend a minimum sample size of ten times the largest number of structural paths directed at any construct, the obtained sample size substantially surpasses the minimum requirement (in this study, ten direct paths suggest a minimum of 100, well below 349). Consequently, the sample size enhances the robustness, reliability, and internal validity of the findings and supports their generalizability within the Bangladeshi undergraduate context and to comparable higher education settings in developing economies.

Measurement instrument

This study incorporates eleven latent constructs, namely attitude toward mobile learning (ATML), social influence (SI), perceived skill (PS), perceived resources (PR), perceived enjoyment (PE), perceived ease of use (PEU), perceived usefulness (PU), habit (H), intrinsic motivation (IM), task–technology fit (TTF), and intention to use mobile learning (IUML). Most measurement items were adopted from well-established and widely validated scales used in prior mobile learning and technology adoption research. To ensure contextual relevance and clarity for the Bangladeshi higher education setting, minor wording modifications were made without altering the conceptual meaning of the items.

Specifically, five measurement items for ATML, PR, PE, PEU, PU, TTF, and IUML were adapted from the validated instrument developed by Al-Rahmi et al. (2021). In addition, the measurement items for habit (5 items), perceived skill (3 items), and intrinsic motivation (4 items) were adapted from Voicu and Muntean (2023). Furthermore, five items measuring social influence were drawn from the scale proposed by Alghazi et al. (2021).

All constructs were measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Higher scores indicate stronger agreement with the corresponding statements and reflect a higher level of the underlying construct. The use of a seven-point Likert scale enhances response sensitivity and is consistent with best practices in structural equation modeling and mobile learning research.

Description of the sample

The study sample comprised undergraduate students from multiple higher education institutions in Dhaka, representing a wide range of academic disciplines. Male students accounted for 59.90% of the sample, while 40.10% were female. Participants' ages ranged from 19 to 26 years, with a mean age of 22.98 years (SD = 1.387). In terms of academic standing, the majority of respondents were third-year students (51.30%), while first-year students accounted for 14.60% of the sample. Additionally, more than 57.00% of the participants reported having at least two to three years of experience using mobile technologies for learning purposes, indicating substantial prior exposure to mobile learning. A detailed summary of the respondents' demographic characteristics is presented in Table 1.

Table 1: Profile of the participants

Variables	Items	Frequency	Percentage
Gender	Male	209	59.90
	Female	140	40.10
Academic year	1st year	51	14.60
	2nd year	58	16.60
	3rd year	179	51.30
	4th year	61	17.50
Experience of mobile learning	1 year	56	16.00
	2 years	97	27.80
	3 years	103	29.50
	4 years	48	13.80
	5 years	29	8.30

	6 years	13	3.70
	7 years	3	0.90
	Total	349	100.00

Analysis method

This study employed partial least squares structural equation modeling (PLS-SEM) for data analysis, using SmartPLS, in line with established methodological recommendations (Ringle et al., 2015). Compared with covariance-based SEM techniques (e.g., AMOS), PLS-SEM offers several methodological advantages, particularly for complex, prediction-oriented research models (Hair & Sarstedt, 2019; Khatun et al., 2025). Specifically, PLS-SEM is well-suited for estimating models involving multiple latent constructs and interrelated structural paths, making it appropriate for the present research framework (Sarstedt et al., 2016).

Given the study's predictive focus, PLS-SEM was selected for its superior ability to maximize explained variance and assess predictive relationships (Sharma et al., 2018; Chowdhury & Roy, 2015). In addition, PLS-SEM does not require strict distributional assumptions, such as multivariate normality, and is therefore robust when analyzing data collected through Likert-scale surveys (Hair et al., 2019). Another important justification for adopting PLS-SEM is its effectiveness in estimating predictive effects while explicitly accounting for measurement error, thereby overcoming limitations commonly associated with regression-based approaches and factor-based SEM techniques, including PROCESS macro analyses (Nitzl et al., 2016; Nahar et al., 2023). PROCESS-based methods typically estimate structural relationships in isolation and do not fully incorporate measurement model assessment, which may lead to biased parameter estimates (Hussain & Papastathopoulos, 2022).

In contrast, PLS-SEM simultaneously evaluates the measurement and structural models, accounts for measurement error, and offers greater flexibility in model specification (Sarstedt et al., 2020). Taken together, these methodological strengths justify the use of PLS-SEM as the most appropriate analytical technique for this study. Accordingly, a two-stage analytical procedure was followed: the measurement model was assessed first to establish reliability and validity, followed by the evaluation of the structural model to test the proposed hypotheses, consistent with the guidelines of Hair and Sarstedt (2019).

Data analysis and results

Normality analysis

The results of the Shapiro-Wilk normality test, presented in Table 2, indicate that the assumption of univariate normality was violated for all measurement items. Consistent with these findings, the assessment of multivariate normality using Mardia’s skewness and kurtosis statistics also led to the rejection of the null hypothesis, confirming substantial deviations from multivariate normality. Given these results, the application of PLS-SEM is methodologically appropriate, as this approach does not require adherence to univariate or multivariate distributional assumptions and is well-suited for analyzing non-normally distributed data.

Table 2

Item-wise normality and multivariate normality tests

Factors	Name	Mean	SD	Shapiro-Wilk Statistic
Attitude Towards mobile learning (ATML)	ATML1	4.871	0.953	0.890***
	ATML2	4.923	1.093	0.882***
	ATML3	4.854	1.032	0.907***
	ATML4	4.957	1.010	0.888***
	ATML5	4.937	0.976	0.857***
Social Influence (SI)	SI1	4.848	0.888	0.852***
	SI2	5.083	0.823	0.864***
	SI3	5.109	0.779	0.836***
	SI4	4.817	0.915	0.850***
	SI5	4.897	0.961	0.870***
Perceived skill (PS)	PS1	5.358	1.171	0.876***
	PS2	5.413	1.103	0.899***
	PS3	5.393	1.042	0.885***
Perceived Resources (PR)	PR1	4.794	1.020	0.893***
	PR2	5.052	0.956	0.817***
	PR3	4.888	0.979	0.889***
	PR4	5.057	0.907	0.863***
	PR5	5.095	0.951	0.852***
Perceived Enjoyment (PE)	PE1	5.037	0.937	0.865***
	PE2	4.900	1.083	0.868***
	PE3	5.066	1.073	0.852***
	PE4	5.106	1.006	0.889***

	PE5	5.083	0.931	0.844***
Perceived Ease of Use (PEU)	PEU1	5.040	1.150	0.879***
	PEU2	5.140	0.990	0.862***
	PEU3	5.135	1.039	0.878***
	PEU4	5.132	1.107	0.901***
	PEU5	5.052	1.020	0.886***
Perceived Usefulness (PU)	PU1	5.037	1.008	0.897***
	PU2	5.083	1.002	0.867***
	PU3	5.123	0.998	0.878***
	PU4	4.957	0.970	0.877***
	PU5	5.057	0.950	0.856***
Habit (H)	H1	4.989	0.945	0.873***
	H2	5.117	0.880	0.811***
	H3	5.140	0.949	0.815***
	H4	5.115	0.960	0.877***
	H5	5.235	0.956	0.865***
Intrinsic motivation (IM)	IM1	5.006	0.912	0.830***
	IM2	5.106	0.916	0.844***
	IM3	4.911	0.990	0.873***
	IM4	4.966	0.895	0.857***
Task-Technology Fit (TTF)	TTF1	5.120	1.077	0.900***
	TTF2	5.229	1.001	0.866***
	TTF3	5.229	0.951	0.831***
	TTF4	5.132	0.856	0.780***
	TTF5	5.063	1.002	0.874***
Intention to Use Mobile Learning (IUML)	IUML1	5.330	1.172	0.835***
	IUML2	5.289	1.128	0.818***
	IUML3	5.209	1.168	0.869***
	IUML4	5.344	1.134	0.801***
	IUML5	5.404	1.163	0.884***
Tests for multivariate normality				
Mardia's multivariate skewness = 892.8582***				
Mardia's multivariate kurtosis = 3759.9686***				

Notes: *p < 0.05; **p < 0.01; ***p < 0.001, SD = Standard deviation.

Assessment of the measurement model

In line with established methodological guidelines (Hair, 2021; Roy et al., 2023), all reflective measurement constructs were evaluated for reliability as well as convergent and discriminant validity. As reported in Table 3, the values of Cronbach's alpha (α) and composite reliability (CR) for all constructs exceeded the recommended threshold of 0.70, thereby confirming satisfactory internal consistency and construct reliability (Mohaimen et al., 2025; Nunnally & Bernstein, 1994). Furthermore, all measurement items exhibited standardized factor loadings above 0.708, indicating strong indicator reliability (Hair et al., 2023; Kawser et al., 2023; Roy, 2023f). See Figure 2.

Convergent validity was further established, as the average variance extracted (AVE) values for all reflective constructs exceeded the recommended minimum criterion of 0.50, demonstrating that each construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981; Roy, 2023a).

Table 3
Evaluation of the measurement model

Indicators	Loadings	Average variance extracted (AVE)	Cronbach's alpha	Composite reliability (CR)
ATML1	0.826	0.715	0.900	0.926
ATML2	0.831			
ATML3	0.870			
ATML4	0.851			
ATML5	0.849			
H1	0.844	0.699	0.892	0.921
H2	0.870			

H3	0.807			
H4	0.822			
H5	0.836			
IM1	0.847	0.743	0.885	0.920
IM2	0.849			
IM3	0.895			
IM4	0.855			
IUML1	0.872	0.732	0.908	0.932
IUML2	0.856			
IUML3	0.842			
IUML4	0.848			
IUML5	0.861			
PE1	0.872	0.713	0.899	0.925
PE2	0.820			
PE3	0.812			
PE4	0.837			
PE5	0.877			
PEU1	0.823	0.709	0.897	0.924
PEU2	0.853			
PEU3	0.858			
PEU4	0.853			
PEU5	0.823			
PR1	0.833	0.715	0.900	0.926
PR2	0.866			
PR3	0.877			
PR4	0.829			
PR5	0.820			
PS1	0.910	0.808	0.881	0.927
PS2	0.889			
PS3	0.897			
PU1	0.850	0.728	0.907	0.931
PU2	0.850			
PU3	0.865			
PU4	0.853			
PU5	0.849			
SI1	0.816	0.632	0.855	0.896
SI2	0.799			
SI3	0.770			
SI4	0.805			
SI5	0.784			
TTF1	0.870	0.740	0.912	0.934
TTF2	0.865			
TTF3	0.857			
TTF4	0.851			
TTF5	0.858			

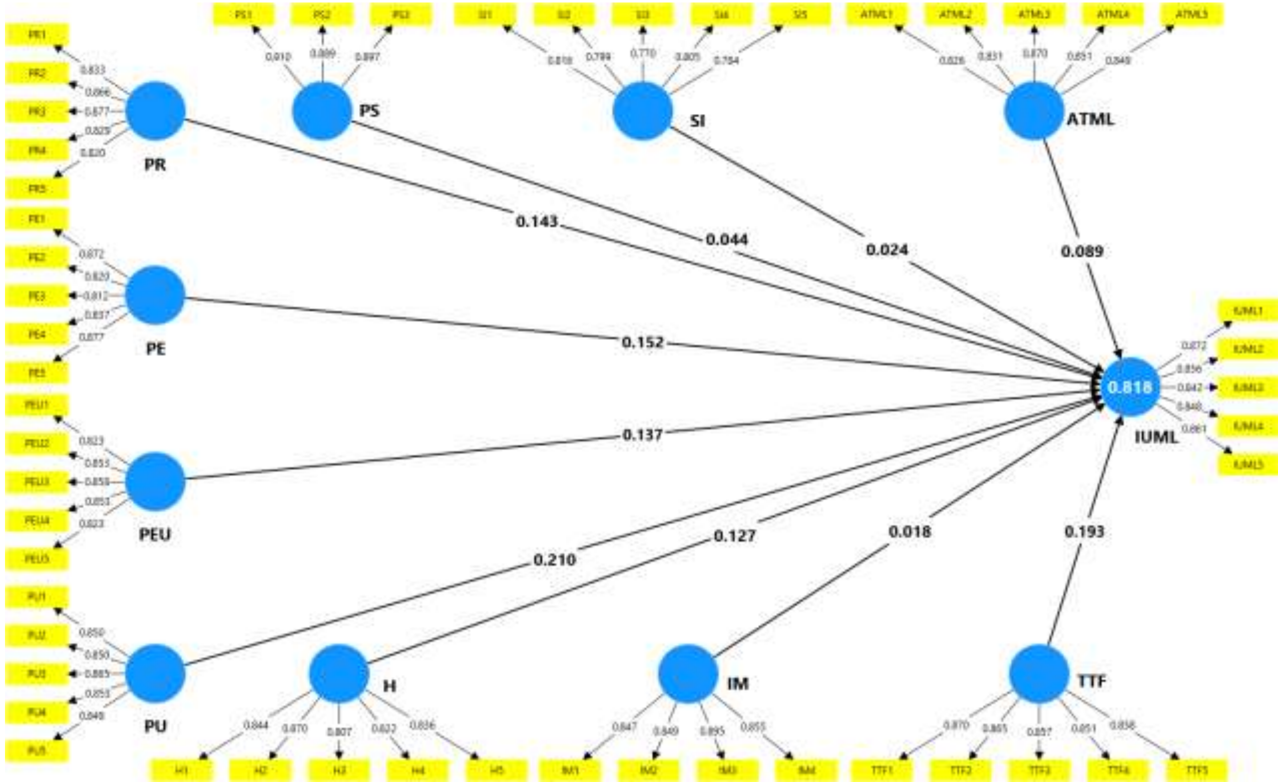

Figure 2: Results of the measurement model

Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait-monotrait ratio of correlations (HTMT), following established recommendations (Fornell & Larcker, 1981; Roy, 2023b). As shown in Table 4, the square roots of the average variance extracted (AVE) for all reflective constructs, represented by the bold diagonal values, exceed the corresponding inter-construct correlation coefficients, thereby satisfying the Fornell-Larcker criterion (Farrell, 2010). In addition, all HTMT values are well below the conservative threshold of 0.85, indicating adequate discriminant validity and the absence of multicollinearity or construct overlap concerns (Henseler et al., 2016; Khatun & Roy, 2022).

Table 4
Discriminant validity estimation

	ATML	H	IM	IUML	PE	PEU	PR	PS	PU	SI	TTF
Fornell–Larcker criterion											
ATML	**0.846**										
H	0.502	0.8**36**									
IM	0.483	0.506	**0.862**								
IUML	0.665	0.709	0.581	**0.856**							
PE	0.616	0.572	0.523	0.743	**0.844**						
PEU	0.588	0.615	0.521	0.757	0.640	**0.842**					
PR	0.596	0.587	0.541	0.767	0.658	0.658	**0.845**				
PS	0.088	0.235	0.274	0.244	0.156	0.225	0.199	**0.899**			
PU	0.577	0.603	0.492	0.765	0.603	0.672	0.695	0.158	**0.853**		
SI	0.471	0.374	0.393	0.539	0.542	0.474	0.539	0.141	0.525	**0.795**	
TTF	0.555	0.655	0.532	0.762	0.650	0.652	0.663	0.197	0.595	0.396	**0.860**
HTMT Ratio											
ATML											
H	0.557										
IM	0.537	0.567									
IUML	0.735	0.785	0.647								
PE	0.681	0.632	0.580	0.816							
PEU	0.654	0.685	0.585	0.838	0.708						
PR	0.662	0.652	0.604	0.847	0.727	0.731					
PS	0.101	0.265	0.313	0.272	0.172	0.252	0.224				
PU	0.636	0.669	0.550	0.842	0.663	0.744	0.767	0.177			
SI	0.531	0.420	0.444	0.605	0.620	0.536	0.610	0.165	0.594		

TTF	0.613	0.724	0.591	0.836	0.713	0.721	0.731	0.219	0.654	0.441

Notes: The bold diagonal elements in the table represent the square roots of the average variance extracted (AVE) for each construct, while the off-diagonal values indicate the correlations among the constructs.

Common method bias (CMB)

Given the self-reported nature of the data, the potential presence of common method bias (CMB) was carefully considered (Malhotra et al., 2006; Roy, 2023c). To minimize the risk of CMB, a combination of a priori procedural remedies and post-hoc statistical assessments was implemented, following established methodological guidelines (Podsakoff et al., 2003). First, respondent anonymity and confidentiality were assured by avoiding the collection of personally identifiable information, thereby reducing evaluation apprehension and social desirability bias. Second, a pre-test was conducted with a convenience sample of 40 undergraduate students to assess item clarity, content validity, and questionnaire comprehensibility (Perneger et al., 2015). Based on the feedback received, minor revisions, primarily related to wording, were made before administering the finalized survey.

In addition, several post-hoc statistical techniques were employed to assess the potential impact of CMB. Initially, Harman's single-factor test was conducted, revealing that the largest factor accounted for 43.346% of the total variance, which is below the recommended threshold of 50%, indicating that CMB is unlikely to be a serious concern (Ahmed et al., 2025; MacKenzie & Podsakoff, 2012). Furthermore, a full collinearity assessment, including the use of a random marker variable (Kock & Lynn, 2012) and a full collinearity test (Kock, 2015; Roy & Islam, 2023), was performed. As reported in Table 5, all variance inflation factor (VIF) values were below the conservative cutoff of 3.3, providing additional evidence that common method bias does not materially affect the study results.

Table 5:

Collinearity estimates (VIF scores)

	Full collinearity test	Full collinearity test with a random variable
	IUML	Random
ATML	2.002	2.022
SI	1.643	1.539
PS	1.122	1.112
PR	2.803	1.175
PE	2.531	2.362
PEU	2.585	1.067
PU	2.558	1.569
H	2.166	2.095
IM	1.715	1.692
TTF	2.565	2.456
IUML		2.101

Structural model assessment

The structural model was evaluated to test the proposed hypotheses and examine the relationships among the latent constructs. Consistent with prior methodological recommendations, PLS-SEM was employed to estimate the effects of the predictor variables on intention to use mobile learning (IUML) (Roy, 2023d). The evaluation of the structural model focused on the significance and magnitude of the path coefficients (β). The results indicate that most of the hypothesized direct relationships were supported, except for H2, H3, and H9. A summary of the structural model results is presented in Table 6.

The findings reveal significant positive relationships between IUML and attitude toward mobile learning (ATML) ($\beta = 0.089$, $p < 0.05$), perceived resources (PR) ($\beta = 0.143$, $p < 0.001$), perceived enjoyment (PE) ($\beta = 0.152$, $p < 0.001$), perceived ease of use (PEU) ($\beta = 0.137$, $p < 0.01$), perceived usefulness (PU) ($\beta = 0.210$, $p < 0.001$), habit (H) ($\beta = 0.127$, $p < 0.01$), and task–technology fit (TTF) ($\beta = 0.193$, $p < 0.001$). Accordingly, hypotheses H1, H4, H5, H6, H7, H8, and H10 were supported.

In contrast, social influence (SI) ($\beta = 0.024$, $p > 0.05$), perceived skill (PS) ($\beta = 0.044$, $p > 0.05$), and intrinsic motivation (IM) ($\beta = 0.018$, $p > 0.05$) did not exhibit statistically significant effects on IUML, leading to the rejection of H2, H3, and H9. These relationships are illustrated in Figure 3. Among all predictor variables, perceived usefulness (PU) emerged as the strongest determinant of IUML, demonstrating the largest standardized path coefficient ($\beta = 0.210$, $p < 0.001$).

Table 6

Results of the hypotheses testing

H	Relationships	Coefficient	Standard deviation	T statistics	P values	Supported?
H1	ATML -> IUML	0.089	0.037	2.448	0.015	Yes
H2	SI -> IUML	0.024	0.029	0.847	0.397	No
H3	PS -> IUML	0.044	0.024	1.826	0.068	No
H4	PR -> IUML	0.143	0.040	3.596	0.000	Yes
H5	PE -> IUML	0.152	0.042	3.643	0.000	Yes
H6	PEU -> IUML	0.137	0.039	3.487	0.001	Yes

H7	PU -> IUML	0.210	0.040	5.191	0.000	Yes
H8	H -> IUML	0.127	0.043	2.972	0.003	Yes
H9	IM -> IUML	0.018	0.030	0.586	0.558	No
H10	TTF -> IUML	0.193	0.042	4.565	0.000	Yes

Coefficient of Determination
$R^2_{IUML} = 0.818$

Predictive Relevance
$Q^2_{IUML} = 0.590$

Effect Sizes
$f^2_{ATML} = 0.022$; $f^2_{SI} = 0.002$; $f^2_{PS} = 0.009$; $f^2_{PR} = 0.040$; $f^2_{PE} = 0.051$; $f^2_{PEU} = 0.040$; $f^2_{PU} = 0.095$; $f^2_{H} = 0.041$; $f^2_{IM} = 0.001$; $f^2_{TTF} = 0.080$

Items	PLS-SEM_RMSE	LM_RMSE	Differences	Predictive power
IUML1	0.738	0.798	-0.060	
IUML2	0.729	0.767	-0.040	High
IUML3	0.761	0.804	-0.040	
IUML4	0.737	0.823	-0.090	
IUML5	0.744	0.811	-0.070	

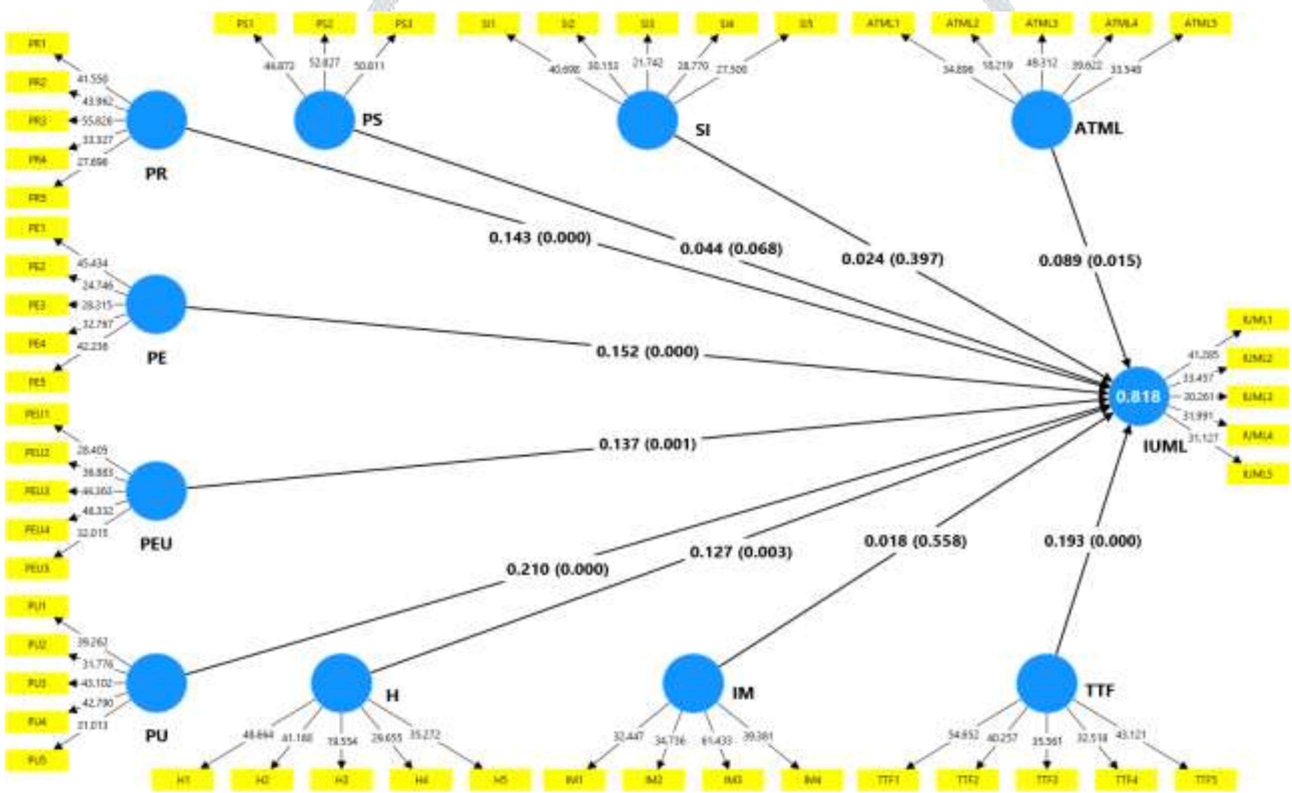

Figure 3: Results of the structural model

The in-sample explanatory power of the structural model was evaluated using the coefficient of determination (R^2) and effect size (f^2) statistics to assess the proportion of variance explained by the predictor constructs. As reported in Table 6, the model explains 81.8% of the variance in intention to use mobile learning (IUML), indicating substantial explanatory power, particularly given the inclusion of multiple exogenous constructs. According to Hair et al. (2020), the f^2 effect size reflects the relative contribution of each independent construct to the endogenous variable. In the present study, most predictors exhibited small but meaningful effect sizes, while social influence (SI), perceived skill (PS), and intrinsic motivation (IM) demonstrated negligible effects, consistent with Cohen's (2013) classification criteria (see Table 6).

Because R^2 and f^2 assess only the model's in-sample predictive performance and do not provide insight into its out-of-sample predictive performance, additional predictive validity measures were employed. Specifically, Stone-Geisser's Q^2 and PLSpredict were used to evaluate the model's predictive relevance (Hair, 2021; Roy, 2023e). The blindfolding procedure was applied to compute Q^2 values for IUML (Chin et al., 2020). As shown in Table 6, the Q^2 value for IUML was 0.590, exceeding zero and surpassing the threshold of 0.35, thereby indicating strong predictive relevance (Shmueli et al., 2019). However, Q^2 has known limitations, as it combines in-sample and out-of-sample information and does not rely on holdout samples, which may obscure true predictive performance (Shmueli et al., 2016, 2019).

To address these limitations and provide a more rigorous assessment of out-of-sample predictive power, PLSpredict was conducted following the recommendations of Shmueli et al. (2016) and Hair (2021). A 10-fold cross-validation procedure was employed, using root mean square error (RMSE) as the prediction error metric. As presented in Table 6, all IUML indicators exhibited lower RMSE values than those of the naïve linear regression benchmark, thereby confirming the model's strong predictive accuracy and robustness (Hair et al., 2020).

Discussion

This study investigated the determinants of intention to use mobile learning (IUML) among undergraduate students in Bangladeshi higher education by integrating constructs from TAM, UTAUT/UTAUT2, motivational theory, and the TTF framework. Overall, the findings provide strong empirical support for the proposed model, explaining a substantial proportion of variance in IUML and highlighting the relative importance of technological, cognitive, and contextual factors in a developing-country setting. The discussion below interprets the results for each hypothesis in light of prior research and the Bangladeshi context.

The results confirm H1, demonstrating that attitude toward mobile learning (ATML) has a significant positive effect on IUML. This finding is consistent with the core propositions of TAM, which posit attitude as a proximal determinant of behavioral intention (Davis, 1989). In Bangladesh, where mobile devices are deeply embedded in students' daily academic and social lives, positive attitudes toward mobile learning likely reflect perceived convenience, flexibility, and alignment with learning preferences. Similar findings have been reported in studies conducted in India and Pakistan, where favorable attitudes toward mobile technologies significantly predicted adoption intentions (Abdelwahed & Soomro, 2023; Jabeen et al., 2025; Roy, 2023g). The result suggests that fostering positive perceptions of mobile learning remains essential for sustaining its use in Bangladeshi universities.

Contrary to expectations, H2 was not supported, as social influence (SI) did not significantly affect IUML. While UTAUT posits social influence as a key determinant of technology adoption (Venkatesh et al., 2003), its non-significance in this study may reflect the increasing autonomy of Bangladeshi university students in technology-related decisions. As mobile devices are already ubiquitous, students may rely more on personal experience than on peer or instructor opinions. Similar non-significant effects of social influence have been observed in Sri Lanka and Nepal, where mobile learning adoption was driven more by perceived usefulness and personal competence than by social norms (Dissanayake & Velananda, 2020; Adhikari et al., 2023).

H3 was not supported, indicating that perceived skill (PS) does not significantly influence IUML. This finding suggests that most undergraduate students in Dhaka possess a baseline level of digital competence sufficient for engaging with mobile learning systems, rendering perceived skill as a differentiating factor less salient. Comparable results have been reported in studies from urban India, where digital literacy among university students is high, and skill-related concerns no longer constrain mobile learning adoption (Chatterjee et al., 2020; Khan & Roy, 2023). In Bangladesh, the widespread use of smartphones and mobile internet may have normalized basic technical proficiency, thereby reducing its explanatory power.

The results support H4, revealing a significant positive relationship between perceived resources (PR) and IUML. This finding underscores the importance of infrastructure, internet accessibility, and institutional support in shaping mobile learning adoption. Despite high mobile penetration, disparities in connectivity and learning resources persist across Bangladeshi universities. Similar patterns have been observed in Pakistan and Sri Lanka, where perceived availability of technical and institutional resources strongly influenced students' intentions to use mobile learning platforms (Akour et al., 2021; Beneragama et al., 2021). The result highlights the continued need for institutional investment in digital infrastructure to support equitable adoption of mobile learning.

Consistent with prior research, H5 was supported, indicating that perceived enjoyment (PE) positively influences IUML. This aligns with extensions of TAM that emphasize intrinsic motivation and hedonic value as key drivers of technology acceptance (Davis et al., 1992; Roy & Ahmed, 2016). In the Bangladeshi context, where traditional pedagogical approaches still dominate many classrooms, the interactive and engaging nature of mobile learning may enhance students' learning experiences. Similar findings have been reported in India and Malaysia, where enjoyment significantly predicted mobile learning continuance intentions (Al-Rahmi et al., 2021; Kumar & Bervell, 2019).

The findings confirm H6, showing that perceived ease of use (PEU) has a significant positive effect on IUML. This result is consistent with TAM and extensive empirical evidence indicating that user-friendly systems facilitate adoption (Davis, 1989). In Bangladesh, where students often rely on mobile devices due to limited access to laptops or desktops, ease of use becomes particularly critical. Comparable results have been reported in Nepal and India, where system simplicity and intuitive interfaces significantly influenced mobile learning intentions (Adhikari et al., 2023; Roy et al., 2023).

Among all predictors, perceived usefulness (PU) exerted the strongest effect on IUML, thereby supporting H7. This finding reinforces PU as the most robust determinant of technology acceptance across contexts (Davis, 1989). Bangladeshi students are likely to adopt mobile learning when they perceive it as enhancing academic performance, efficiency, and access to learning materials. A similar dominance of PU has been documented in studies from India, Pakistan, and Sri Lanka, highlighting its universal relevance to mobile learning adoption (Akour et al., 2021; Beneragama et al., 2021; Khan et al., 2022).

The results support H8, indicating that habit (H) significantly influences IUML. This finding aligns with UTAUT2, which emphasizes habitual behavior as a key driver of continued technology use (Venkatesh et al., 2012). In Bangladesh, where smartphones are integral to daily life, repeated use of mobile devices for academic purposes may naturally lead to sustained mobile learning intentions. Similar effects of habit have been observed in India and Malaysia, suggesting that habitual engagement strengthens long-term adoption (Alghazi et al., 2021).

H9 was not supported, as intrinsic motivation (IM) did not significantly influence IUML. This result may reflect the instrumental orientation of Bangladeshi higher education, where students prioritize performance outcomes over intrinsic enjoyment. Comparable findings have been reported in Pakistan and Nepal, where extrinsic and utility-driven factors outweighed intrinsic motivation in predicting mobile learning adoption (Adhikari et al., 2023).

Finally, H10 was supported, confirming that task-technology fit (TTF) positively influences IUML. This result highlights the importance of aligning mobile learning functionalities with academic tasks, such as accessing materials, collaborating with peers, and completing assignments. In the Bangladeshi context, mobile learning is more likely to be adopted when it clearly supports curriculum-related activities. Similar findings from India and Sri Lanka further validate the relevance of TTF in mobile learning research across South Asia (Chatterjee et al., 2020; Jabeen et al., 2025; Roy, 2022).

Theoretical Implications

This study makes several important theoretical contributions to the mobile learning and technology adoption literature. First, by integrating constructs from TAM, UTAUT/UTAUT2, motivational theory, and TTF into a single predictive framework, the study advances existing models by demonstrating that mobile learning adoption in developing-country contexts is best explained through a multi-theoretical lens. The model's high explanatory power underscores the value of combining cognitive, behavioral, and contextual perspectives when examining mobile learning intention in higher education. Second, the findings reaffirm the central role of perceived usefulness as the strongest determinant of mobile learning intention, thereby reinforcing TAM’s core proposition in a Bangladeshi context. This result extends prior research by confirming that, even in environments characterized by infrastructural constraints, students prioritize technologies that demonstrably enhance academic performance. This aligns with evidence from neighboring South Asian countries, suggesting the cross-contextual robustness of perceived usefulness in mobile learning adoption.

Third, the study contributes to UTAUT2 theory by validating the significance of habit in predicting intention to use mobile learning. This highlights the importance of habitual technology use in contexts where smartphones are deeply embedded in daily life. At the same time, the non-significant effects of social influence and perceived skill suggest a contextual boundary condition for UTAUT constructs, indicating that in technologically mature student populations, normative pressure and basic digital competence may lose explanatory relevance. This insight refines existing theoretical assumptions and encourages scholars to reassess the role of these constructs in similar emerging economies. Fourth, the significant effects of task-technology fit and perceived resources extend TTF theory by demonstrating that institutional and infrastructural readiness remain critical theoretical considerations in developing countries. The findings suggest that technology acceptance theories must account not only for user perceptions but also for system-task alignment and environmental support, particularly in contexts where resource disparities persist.

Finally, the non-significant influence of intrinsic motivation challenges assumptions derived from self-determination theory and highlights a potential instrumental orientation toward learning among Bangladeshi undergraduates. This finding contributes to theory by suggesting that extrinsic, performance-oriented factors may dominate intrinsic motives in highly competitive educational environments, a pattern that may also apply to other South Asian contexts.

Practical Implications

The findings of this study offer several actionable insights for policymakers, university administrators, educators, and educational technology developers in Bangladesh and similar developing economies. First, given the dominant role of perceived usefulness, higher education institutions should emphasize how mobile learning platforms directly support academic performance, assessment preparation, and access to learning resources. Clearly linking mobile learning tools to measurable learning outcomes can significantly enhance students’ adoption intentions. Second, the significant influence of perceived ease of use and task-technology fit underscores the need for intuitive, task-oriented mobile learning systems. Universities should prioritize platforms that align closely with curriculum requirements, such as accessing lecture materials, submitting assignments, and participating in collaborative learning activities. Training programs for faculty should focus on designing mobile-compatible learning tasks that integrate seamlessly with students’ academic workflows.

Third, the importance of perceived resources highlights the continued need for institutional investment in digital infrastructure, including reliable internet connectivity, technical support, and access to learning management systems optimized for mobile devices. Policymakers in Bangladesh should consider expanding public-private partnerships to improve digital access across universities, particularly for students from resource-constrained backgrounds. Fourth, the significant role of habit suggests that early and consistent exposure to mobile learning can foster long-term adoption. Universities can encourage habitual use by embedding mobile learning into routine academic activities, such as attendance tracking, formative assessments, and peer discussions. Such strategies are particularly relevant in Bangladesh, where students already use mobile technologies extensively in their daily lives.

Fifth, the non-significant effects of social influence and perceived skill imply that awareness campaigns alone may be insufficient to promote mobile learning adoption. Instead, practical efforts should focus on system quality, usability, and tangible academic benefits, rather than relying on peer or instructor endorsement. Similarly, as basic digital skills are already widespread among students, training initiatives should move beyond technical proficiency and instead emphasize effective academic use of mobile learning tools. Finally, the limited role of intrinsic motivation suggests that mobile learning initiatives in Bangladesh should be framed in terms of career relevance, academic efficiency, and performance enhancement, rather than solely emphasizing enjoyment or personal interest. This performance-oriented framing may be particularly effective in competitive higher education systems across South Asia, including India, Pakistan, and Sri Lanka.

Limitations and Future Research Directions

Despite its theoretical and empirical contributions, this study has several limitations that should be acknowledged, and that also offer meaningful avenues for future research. First, the study employed a cross-sectional research design, which restricts the ability to infer causal relationships among the examined constructs. Although the proposed model demonstrates strong predictive power, future studies should adopt longitudinal or panel designs to capture changes in mobile learning intentions over time and to better understand how habitual usage and perceptions evolve with prolonged exposure. Second, the sample was drawn exclusively from undergraduate students in Dhaka, which may limit the generalizability of the findings to other regions of Bangladesh or to different educational contexts. While Dhaka represents a technologically advanced academic environment within the country, future research should include students from rural areas, public universities outside the capital, and private institutions with varying levels of digital infrastructure. Expanding the sampling frame would allow for more robust comparisons and improve the external validity of the findings.

Third, the study relied on self-reported data, which may be subject to common method bias and social desirability effects, despite the implementation of multiple procedural and statistical remedies. Future research could mitigate these limitations by incorporating objective usage data, such as system log files or learning analytics, as well as multi-source data from instructors or institutional records to triangulate student responses. Fourth, although the model integrates several well-established theoretical frameworks, it does not account for certain context-specific variables that may influence mobile learning adoption in developing countries. Future studies could extend the model by incorporating factors such as economic constraints, language preferences, cultural learning norms, data affordability, and institutional policy support, which are particularly salient in Bangladesh and neighboring South Asian countries.

Fifth, the non-significant effects of social influence, perceived skill, and intrinsic motivation suggest the presence of potential moderating variables that were not examined in this study. Future research could explore moderators such as gender, academic discipline, prior mobile learning experience, type of institution (public vs. private), or digital inequality to better understand under what conditions these constructs become influential. Comparative studies across South Asian countries, including India, Pakistan, Nepal, and Sri Lanka, would further enrich theoretical insights by identifying cross-cultural similarities and differences in mobile learning adoption. Finally, this study focused on intention to use mobile learning, rather than actual usage or learning outcomes. While intention is a strong predictor of behavior, future research should investigate actual adoption behavior, learning engagement, and academic performance outcomes to provide a more comprehensive understanding of mobile learning effectiveness. Experimental or quasi-experimental designs could be particularly valuable in assessing the causal impact of mobile learning interventions on student achievement.

Conclusion

This study examined the determinants of IUML among undergraduate students in Bangladesh by proposing and empirically validating an integrated research framework grounded in TAM, UTAUT/UTAUT2, motivational theory, and TTF. The findings demonstrate that the proposed model possesses strong explanatory and predictive power, offering robust insights into mobile learning adoption within a developing-country context.

The results reveal that perceived usefulness is the most influential predictor of mobile learning intention, underscoring students' strong preference for technologies that directly enhance academic performance and learning efficiency. In addition, attitude toward mobile learning, perceived resources, perceived enjoyment, perceived ease of use, habit, and task–technology fit were found to significantly influence IUML, highlighting the combined importance of cognitive evaluations, infrastructural support, intrinsic experiences, and system-task alignment. Conversely, social influence, perceived skill, and intrinsic motivation did not exhibit significant effects, suggesting that Bangladeshi university students' mobile learning adoption decisions are increasingly shaped by personal evaluations and functional value rather than social pressure or basic digital competence.

By situating the analysis within the Bangladeshi higher education landscape, this study extends the mobile learning literature by providing empirical evidence from an underrepresented context and offering comparative insights relevant to neighboring South Asian countries with similar technological and educational characteristics. The findings contribute to theory by validating and refining established technology acceptance models and by offering practical guidance for universities and policymakers seeking to promote sustainable mobile learning adoption.

Overall, this study concludes that the successful integration of mobile learning in Bangladeshi higher education requires a strategic focus on usability, usefulness, institutional readiness, and task alignment, rather than relying solely on normative influence or technical skill development. By addressing these critical factors, higher education institutions can better leverage mobile technologies to enhance learning experiences, support academic achievement, and advance digital transformation in developing-country contexts.

"Statements and Declarations"

Acknowledgment

Thanks to all participants.

Declaration of competing interest

The authors declare no conflict of interest.

Funding
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability
The data that support the findings of this study are not openly available due to securing the anonymity of the respondents and their institutions. However, anonymized data sets are available from the corresponding author upon reasonable request.

Informed consent
Informed consent was obtained from all participants in this study.

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