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ARE SCHOOL STUDENTS READY FOR MOBILE LEARNING? INSIGHTS FROM A DEVELOPING COUNTRY

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Abstract

In today's world, where mobile technologies are transforming education, this study explores the behavioral intentions of secondary and higher secondary students in Bangladesh to adopt mobile learning (m-learning). The unified theory of acceptance and use of technology 2 (UTAUT2) framework was adopted as the theoretical foundation of this study. This study introduced two new concepts, perceived negative consequences and learning value, to identify the main factors that drive the students' acceptance of m-learning. Convenience and snowball sampling techniques were applied to collect data from respondents through a structured questionnaire. Advanced partial least squares structural equation modeling (PLS-SEM) was used to analyze 517 respondents' data and test the hypothetical model. The results of this study indicate that the most important factors that impact students' intention to adopt m-learning are performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and learning value. However, the study finds that perceived negative consequences such as diversions or health concerns do not influence the decisions of the students. The findings of the study expand the UTAUT2 model and convey useful ideas for legislators, teachers, and tech developers to create innovative and effective m-learning platforms.

Keywords: Mobile Learning, Student's Adoption, Usage Behavior, UTAUT2, Learning Value, Perceived Negative Consequences.

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Introduction

A new era of innovative education has been ushered in by the explosive growth of mobile technologies, which are changing how people access, exchange, and acquire knowledge. Al-Emran, Mezhuyev, and Kamaludin (2018) define mobile learning as using portable electronics, such as tablets and mobile phones, for educational objectives. It has become a potent tool to improve learning experiences, especially in areas with insufficient traditional educational infrastructure. M-learning has enormous potential to address issues including restricted access to high-quality education, packed classrooms, and resource constraints in Bangladesh, a developing nation with a rapidly expanding young population and rising mobile penetration (Islam & Grönlund, 2016). The fact that secondary and higher secondary students' use of m-learning is still inconsistent, despite the growing prevalence of smartphones and online access, raises the question of what factors affect their willingness to accept and use this technology. Although mobile devices are becoming more and more common among Bangladeshi secondary and higher secondary students, their use is frequently restricted to social and recreational purposes rather than academic endeavors (Khan et al., 2012). This begs the question of what barriers prevent this group from embracing m-learning. Secondary and higher secondary students, especially those in poor nations, have received little attention in the literature on m-learning uptake, which has mostly concentrated on higher education or business environments (Al-Emran et al., 2018).

Additionally, although the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model has been extensively used to investigate technology adoption, its applicability to m-learning among young children in resource-limited settings remains poorly understood. By examining the behavioral intention of secondary and higher secondary students in Bangladesh to embrace m-learning, this study aims to close the gaps. The study attempts to offer a more thorough understanding of the factors influencing m-learning adoption in this particular environment by expanding the UTAUT2 model to incorporate two new constructs: perceived negative consequences and learning value.

While perceived negative implications include prospective downsides like distractions or health difficulties, learning value pertains to the perceived academic advantages of m-learning, such as information retention and engagement. These additions are meant to highlight the distinct dynamics of Bangladeshi students' adoption of mobile learning.

Since secondary and higher secondary students are at a pivotal point in their academic development, their adoption of m-learning is very noteworthy. Their future academic and professional success is based on the abilities and information they gain throughout this time.

However, these students are frequently not adequately engaged by standard instructional techniques, which results in indifference and subpar academic achievement (Islam & Grönlund, 2016). These issues could be resolved by m-learning, which is interactive and adaptable and can make learning more interesting, accessible, and customized. Notwithstanding its potential, a number of obstacles stand in the way of m-learning's adoption in Bangladesh, such as low levels of digital literacy, ignorance of educational applications, and worries about the detrimental effects of mobile device use, such as distractions and health problems (Cheon et al., 2012). Finding the elements that affect students' behavioral intention to embrace m-learning and creating plans to encourage its efficient use are crucial to overcoming these obstacles.

The need to comprehend the particular elements that promote or impede the use of m-learning among Bangladeshi secondary and higher secondary students serves as justification for this study. The study intends to offer a more comprehensive knowledge of the factors driving m-learning adoption in this environment by expanding the UTAUT2 model and adding the notions of learning value and perceived negative effects. The development and deployment of m-learning platforms that are suited to the requirements and preferences of Bangladeshi students can then be guided by this.

The study's conclusions have significant theoretical and practical implications. By extending the UTAUT2 model and confirming its suitability for use in secondary and postsecondary education in a developing nation, the study theoretically adds to the body of knowledge on m-learning. A gap in the research is filled by adding learning value and perceived negative repercussions as extra constructs, which offer a more comprehensive understanding of the factors influencing the adoption of m-learning. From a practical standpoint, the study provides insightful information for technology developers, educators, and legislators. The findings can help guide the design and implementation of m-learning platforms that are intuitive, engaging, and aligned with students' educational needs by identifying the primary characteristics that influence students' intention to use m-learning.

The study emphasizes for policymakers the significance of tackling obstacles to m-learning uptake, like low digital literacy and ignorance, with focused interventions and programs. Furthermore, the study has wider ramifications for the international education community, especially in developing nations dealing with comparable issues. The study highlights the need for increased investment in digital infrastructure and mobile technologies by showcasing how m-learning may improve educational performance. The study's ultimate goal is to help build more effective and inclusive learning settings that enable students to reach their greatest potential in a world that is becoming more and more digital.

2. LITERATURE REVIEW

2.1 The UTAUT2 Model

Rapid developments in information systems as well as information technology have led to significant study on consumer acceptability and usage patterns, especially for new technologies (Hasan et al., 2021). To address the difficulties of technology adoption, scientists have created a variety of theoretical models for describing and forecasting user behavior (Kijsanayotin et al., 2009; Madigan et al., 2016). Among these, Venkatesh et al. (2003) introduced the UTAUT 2 model the Unified Theory of Acceptance and Use of Technology (UTAUT), which stands out as a strong and comprehensive paradigm. The original UTAUT model describes four main factors that influence people's intention to use technology: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These dimensions are modified by contextual characteristics such as age, gender, experience, and voluntary use, which improve the model's predictive accuracy (Venkatesh et al., 2003). However, as technology advances at an unparalleled rate, the necessity to broaden the UTAUT framework becomes increasingly clear. To close this gap, UTAUT2 was presented as an extension of the original model, adapted specifically to consumer contexts and mobile technology uptake (Venkatesh et al., 2012). UTAUT2 includes additional constructs such as Hedonic Motivation (HM) and Habit (HT), which represent the intrinsic delight and automaticity that come with technology use. These modifications improve the model's capacity to describe user behavior in modern circumstances, particularly mobile apps and digital platforms.

By incorporating these characteristics, UTAUT2 provides a more nuanced and precise study of the determinants of technology adoption, making it an invaluable tool for both researchers and practitioners. The UTAUT2 model's versatility and comprehensiveness have established it as a cornerstone in technology acceptance research, particularly in educational contexts where mobile learning is gaining ground. Its capacity to account for both inner and extrinsic incentives, as well as contextual and habitual elements, makes it an effective paradigm for understanding the complexities of technology adoption. As the digital landscape evolves, the UTAUT2 model provides an important theoretical framework for investigating the dynamics of user acceptance and behavior in the face of new technologies.

2.2 Mobile Learning

Mobile learning is a game-changing approach to education that uses portable handheld devices like cellphones, tablets, netbooks, and e-readers to extend learning outside of traditional classrooms (Joan, 2013). M-learning, a subset of e-learning, is described as the acquisition of knowledge and skills via mobile devices, allowing learners to overcome geographical and temporal constraints (Kumar Basak et al., 2018; Yeap et al., 2016). This flexibility enables students to learn at any time and from any location, resulting in a more personalized and accessible educational experience (Sharples et al., 2009).

Investigations into m-learning have predominantly concentrated on adoption factors, employing frameworks such as UTAUT 2 to examine user behavior (García Botero et al., 2018; Venkataraman & Ramasamy, 2018). Although these studies have illuminated the factors affecting m-learning adoption, further research is required to explore the wider implications of mobile learning, including its pedagogical, institutional, and infrastructural aspects (Cheng et al., 2020; Hao et al., 2017; Kumar & Chand, 2019).

Implementing and maintaining effective m-learning programs necessitates significant institutional commitment, including financial investments, human resources, and the creation of strong technology infrastructure (Chen & Keng, 2019). Beyond the technical features, m-learning is a comprehensive educational method that encompasses a variety of stakeholders, including teachers, students, and technical support teams. It also involves the development of personalized instructional content, novel learning activities, and techniques to excite and motivate students (Borup et al., 2020).

Unlike the common notion of m-learning as a passive medium for material delivery, it provides a dynamic and interactive platform that encourages both educators and learners to reconsider established teaching and learning paradigms. Adopting m-learning enables educational institutions to create adaptable, engaging, and efficient learning environments that cater to the diverse needs of students in the digital era.

2.3. Conceptual Framework and Hypotheses Development

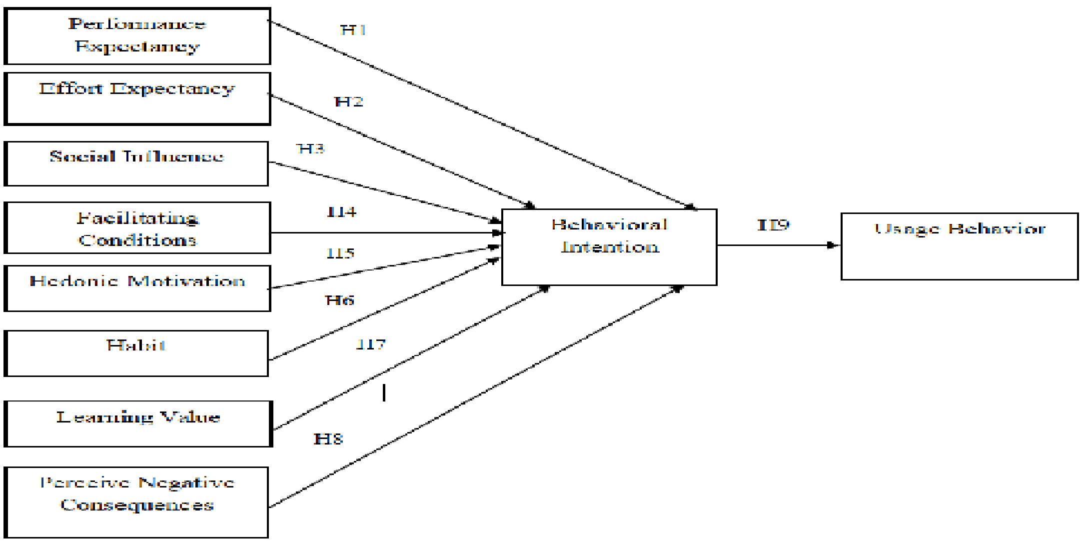

Figure 1: Conceptual Framework

2.3.1 Performance Expectancy

Performance expectation, or PE, refers to the extent to which individuals believe that employing a technology would enhance their performance (Venkatesh et al., 2003; Zwain, 2019). PE records students' opinions about how mobile platforms can enhance their learning outcomes, academic performance, and overall educational experience in the context of mobile learning. In models that study how people adopt technology, like UTAUT and UTAUT2, research often highlights that perceived ease of use (PE) is an important part of why students decide to use mobile learning (Hoi, 2020; Mehta et al., 2019; Venkatesh et al., 2012). A major factor influencing the adoption of mobile learning is the degree to which students view it as advantageous for their academic achievements.

H1: Performance expectancy significantly influences students' behavioral intention to accept and use mobile learning.

2.3.2 Effort Expectancy

The perceived usability of a technology is reflected in Effort Expectancy (EE) (Venkatesh et al., 2003; Wang & Wang, 2010). EE serves as a strong indicator of technology adoption, especially in educational contexts, and is based on characteristics such as perceived ease of use (TAM/TAM2), complexity (MPCU), and ease of use (IDT) (Venkatesh et al., 2012). Students' opinions of the platform's ease of use and intuitiveness are reflected in EE for mobile learning. Adoption rates are expected to increase if adopting mobile learning tools is seen as requiring less effort.

H2: Effort expectancy has a major impact on students' desire to embrace and use mobile learning.

2.3.3 Social Influence

Social influence (SI) is the degree to which people feel that important others classmates, teachers, or family members expect them to embrace a particular technology (Venkatesh et al., 2003). In the framework of mobile learning, SI reflects how social networks including classmates, teachers, and university tutors influence students' adoption choices (García Botero et al., 2018; Nikolopoulou et al., 2020). SI plays a crucial part in educational settings, since student behavior is frequently influenced by the judgments of peers and mentors.

H3: Social influence greatly affects students' behavioral intention to adopt and use mobile learning.

2.3.4 Facilitating Conditions

According to Venkatesh et al. (2003), the facilitating conditions (FC) are the extent to which individuals believe that organizational and technological infrastructure is in place to support the deployment of a technology. Nikolopoulou et al. (2020) state that students' perceptions of the availability of resources, technological support, and institutional backing for using mobile platforms are all included in FC in mobile learning. Strong supportive settings can lower adoption barriers, making mobile learning more appealing and accessible.

H4: Facilitating conditions significantly influence students' desire to adopt and utilize mobile learning.

2.3.5 Hedonic Motivation

Venkatesh et al. (2012) define hedonic motivation (HM) as the pleasure or happiness derived from utilizing a technology. The intrinsic joy that students have when using mobile platforms, like interactive content or gamified learning experiences, is captured by HM in mobile learning. Research highlights that enjoying technology is important for getting people to use it more, as it greatly increases user engagement and acceptance (Nikolopoulou et al., 2020; Wang & Wang, 2010).

H5: Hedonic motivation significantly influences students' behavioral intention to adopt and use mobile learning.

2.3.6 Habit

Habit (HT) refers to how much individuals perceive an action as automatic due to frequent use (Venkatesh et al., 2012). In mobile learning, HT is influenced by students' prior experiences with mobile technologies and their familiarity with utilizing cellphones for educational reasons. The habitual use of mobile devices might facilitate a smooth transition to mobile learning platforms, encouraging adoption intentions.

H6: Habit has a major impact on students' behavioral intention to accept and make use of mobile learning.

2.3.7 Learning Value

Learning value (LV) is the perceived instructional utility of a technology (Sitar-Taut & Mican, 2021). In mobile learning, LV refers to the amount to which students believe mobile platforms improve their learning experiences, knowledge acquisition, and academic performance. By including LV into the UTAUT2 paradigm, this study emphasizes the importance of intrinsic educational gains in promoting adoption, in addition to typical extrinsic reasons.

H7: Learning value significantly impacts the intention of students to accept and use mobile learning.

2.3.8 Perceived Negative Consequences

Perceived Negative Consequences (PNC) are the prospective downsides or negative results of adopting technology (Zheng & Lee, 2016). PNC in mobile learning can include concerns about distractions, privacy, or over-reliance on mobile devices. While ubiquitous technologies like cellphones provide convenience, their abuse can have negative consequences, impacting students' attitudes and behaviors toward mobile learning.

H8: The perception of negative consequences significantly influences students' intention to adopt and use mobile learning.

2.3.9 Behavioral Intention

Behavioral intention (BI) serves as a significant predictor of actual technology use, indicating an individual's readiness to participate in a specific behavior (Ajzen & Fishbein, 1977; Venkatesh et al., 2003). In the context of mobile learning, BI evaluates students' readiness to engage with mobile platforms for educational purposes. Strong behavioral intents are essential for turning adoption intentions into actual usage, hence BI is a key feature in technology adoption models (Sitar-Taut & Mican, 2021; Venkatesh et al., 2012).

H9: Using mobile learning is greatly affected by behavioral intention.

3. Research Methods

3.1 Population and sample of the study

The study population comprised secondary and higher secondary students in Bangladesh. The respondents were chosen using convenience and snowball sampling techniques. A self-administered questionnaire was employed to gather data from the respondents. All responses were maintained anonymously to ensure the respondents' confidentiality. In the end, the final data analysis incorporated the responses of 517 students.

3.2 Measures

The constructs used in this study were derived from well-established scales in prior research, which ensures reliability and validity. Performance expectancy (PE) and effort expectancy (EE) were assessed using the metrics established by Venkatesh et al. (2003) while social influence (SI), facilitating conditions (FC), hedonic motivation (HM), and behavioral intention (BI) were taken from Venkatesh et al. (2012). Additionally, the assessment of learning value (LV) was conducted utilizing the measures established by Sitar-Taut and Mican (2021), and perceived negative consequences (PNC) were taken from the study of Zheng and Lee (2016). Minor alterations were made to these scales to fit the context of mobile learning services. To ensure consistency and ease of interpretation for respondents, all components were evaluated using a five-point Likert scale, which ranged from strongly disagree (1) to strongly agree (5).

3.3 Data collection procedure

This study used a mixed-method approach to ensure robust and thorough data gathering, combining in-person contacts with online surveys. Initially, participants were engaged in person to administer self-administered surveys, allowing for direct interaction and explanation of any questions. To increase the study's reach and inclusion, online surveys were sent via Google Forms, allowing individuals who were unable to participate in person to respond. This dual strategy not only increased the sample's diversity but also allowed respondents to select their preferred manner of involvement. By combining both methodologies, the study acquired a diverse spectrum of viewpoints and experiences about mobile learning uptake among secondary and higher secondary students in Bangladesh, resulting in a rich and representative dataset.

3.4 Data analysis

This study used Smart PLS-4 software to analyze the data, with an emphasis on demographic distribution, internal consistency reliability, convergent validity, discriminant validity, and structural model evaluation, which included hypothesis testing. Smart PLS-4 was used to enable robust and precise analysis by exploiting its sophisticated capabilities for partial least squares structural equation modeling (PLS-SEM).

4. Results

4.1 Respondents' Demographics

The demographic profile of the respondents provides useful information on the characteristics of mobile learning users in Bangladesh. As shown in Table 1, the study included 517 participants, with 203 (39.26%) males and 314 (60.74%) females, demonstrating a higher prevalence of mobile learning adoption among female students. The age distribution of respondents was 14.51% ≤ 15 years old, 55.32% 15-20 years old, and 30.17% 20-25 years old, indicating a significant representation of younger learners. Academically, 14.51% of the participants were secondary-level students, with the majority (85.49%) being upper secondary-level students. This demographic split demonstrates the increased interest in mobile learning among younger, primarily female students, emphasizing its potential as a transformational educational tool in Bangladesh.

4.2 Measurement Model

Table 1. Socio-demographic Information of Students of Mobile Learning Users

Demographic Information	Category	Frequency (N=517)	%
Gender	Male	203	39.26
	Female	314	60.74
Age	<=15 years old	75	14.51
	15-20 years old	286	55.32
	20-25 years old	156	30.17
Educational Qualification	Secondary	75	14.51
	Higher Secondary	442	85.49

The measurement model's analysis examined the internal consistency, discriminant, and convergent reliability of 46 items across nine distinct latent variables. The cutoff values for composite dependability must all be more than 0.70 to confirm the internal consistency of the reliabilities. (Gefen et al., 2000; J. Hair et al., 2017). Table 2 demonstrates that the calculated composite reliability values were higher than the minimum cut-off values of 0.70 (Fornell and Larcker, 1981), confirming the statistical significance of the items. The threshold value of Average Variance Extracted (AVE) should be at least .50 and the cut-off values of each indicator should be greater than 0.70 (Fornell and Larcker, 1981), however occasionally they can be between 0.50 and 0.60, to evaluate convergent validity; (Chin, 1998; J. F. Hair et al., 2019). According to Table 2, all items' indicator loadings are higher than 0.60, and all constructs' AVE scores are higher than the intended threshold value of 0.50. This confirms the accuracy and convergent validity of the data.

4.3 Heterotrait-Monotrait Ratio of Correlations

Table 2. Construct Reliability and Validity

Constructs	Indica-tors	Indicator Loadings	Cron-bach's α	Composite reliability (rho_a)	Composite reliability (rho_c)	Average Variance Extracted AVE
Behavioral Intention	BI1	0.858	0.801	0.819	0.881	0.712
	BI2	0.839				
	BI3	0.835				
Effort Expectancy	EE1	0.778	0.801	0.809	0.861	0.555
	EE2	0.672				
	EE3	0.747				
	EE4	0.769				
	EE5	0.754				
Facilitating Conditions	FC1	0.745	0.872	0.888	0.903	0.609
	FC2	0.791				
	FC3	0.791				
	FC4	0.841				
	FC5	0.87				
	FC6	0.769				
Hedonic Motivation	HM1	0.883	0.862	0.867	0.916	0.784
	HM2	0.926				
	HM3	0.847				

Habit	HT1	0.877	0.879	0.897	0.916	0.732
	HT2	0.853				
	HT3	0.853				
	HT4	0.839				
Learning Value	LV1	0.764	0.879	0.936	0.907	0.664
	LV2	0.851				
	LV3	0.915				
	LV4	0.829				
	LV5	0.7				
Performance Expectancy	PE1	0.875	0.909	0.911	0.936	0.785
	PE2	0.909				
	PE3	0.898				
	PE4	0.862				
Perceive Negative Consequences	PNC1	0.744	0.886	0.914	0.905	0.579
	PNC2	0.717				
	PNC3	0.729				
	PNC4	0.68				
	PNC5	0.803				
	PNC6	0.829				
	PNC7	0.811				
Social Influence	SI1	0.799	0.839	0.839	0.893	0.675
	SI2	0.876				
	SI3	0.777				
	SI4	0.832				
Usage Behavior	UB1	0.73	0.899	0.906	0.926	0.715
	UB2	0.868				
	UB3	0.867				
	UB4	0.9				
	UB5	0.854				

(HTMT) Criterion

The discriminant validity was examined using the Heterotrait-Monotrait (HTMT) ratio of correlations technique, according to Table 3. This analysis of discriminant validity is more robust and popular. (Henseler et al., 2015). The discriminant validity analysis is satisfied when all of the estimated values of HTMT are less than the cut-off value of 0.90 (Gold et al., 2001). All of the HTMT values listed in Table 3 are less than 0.90. As a result, the HTMT criterion confirms the discriminant validity of the study's findings.

The Fornell and Larcker criteria is the

Table 3. Heterotrait-Monotrait Ratio of Correlations (HTMT) Criterion

	BI	EE	FC	HM	HT	LV	PE	PNC	SI	UB
BI										
EE	0.418									
FC	0.602	0.381								
HM	0.597	0.303	0.571							
HT	0.402	0.266	0.761	0.629						
LV	0.401	0.218	0.434	0.36	0.317					

PE	0.456	0.385	0.761	0.51	0.646	0.477				
PNC	0.289	0.388	0.585	0.437	0.624	0.286	0.607			
SI	0.677	0.305	0.734	0.446	0.617	0.57	0.722	0.471		
UB	0.875	0.321	0.702	0.581	0.523	0.467	0.525	0.339	0.759	

Table 4: Discriminant Validity-Fornell-Larcker Criterion

	BI	**EE**	**FC**	**HM**	**HT**	**LV**	**PE**	**PNC**	**SI**	**UB**
BI	0.844									
EE	0.333	0.745								
FC	0.545	0.306	0.781							
HM	0.512	0.212	0.509	0.886						
HT	0.374	0.175	0.656	0.556	0.856					
LV	0.405	0.138	0.395	0.351	0.322	0.815				
PE	0.415	0.338	0.672	0.456	0.577	0.435	0.886			
PNC	0.29	0.331	0.515	0.421	0.578	0.257	0.561	0.761		
SI	0.575	0.231	0.625	0.385	0.542	0.533	0.63	0.423	0.822	
UB	0.757	0.276	0.631	0.526	0.478	0.485	0.473	0.335	0.655	0.846

method most frequently employed. It compares the square root of the value of each average variance extracted (AVE) in the diagonal with the coefficient of correlation of the latent variable (off-diagonal) for each variable in the related columns and rows. A variable must provide a better explanation for the variation of its indicators than do other latent variables. A measure of discriminant validity known as the Fornell-Larcker criterion states that "a factor's AVE must be larger than its squared correlations with all other factors comprised in the model (Fornell and Larcker, 1981; Henseler, 2017; Voorhees et al., 2016)," adding that "the Fornell-Larcker criterion compares the square root of the AVE values with the latent variable correlations." Mostly, each construct's square root should have a larger value than its maximum reliability with any other construct (Mahmud et al., 2021). Each of the constructs in Table 4 shows that they satisfy the requirements.

5. Discussion

This study aimed to augment the UTAUT2 framework by incorporating two new constructs learning value (LV) and perceived negative consequences (PNC) to examine the determinants affecting students' behavioral intentions for mobile learning uptake. Eight of the nine presented hypotheses were validated, whereas one, perceived negative consequences, exhibited no significant impact on behavioral intention (BI). The results indicated that performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), and habit (HT) significantly positively influenced behavioral intention, aligning with prior research by Venkatesh et al. (2012). Notably, the addition of learning value (LV) as a new construct increased the model's explanatory power, emphasizing the importance of intrinsic educational advantages in promoting mobile learning uptake. This research demonstrates that students prioritize the perceived educational utility of mobile learning platforms, emphasizing the need of institutions designing content that maximizes learning outcomes and engagement. Interestingly, contrary to expectations, perceived negative consequences (PNC) had no significant influence on Behavioral Intention. Several things may have contributed to this result. First, students appear to value the learning value and practical benefits of mobile learning more than possible negatives like distractions or privacy concerns. Second, the normalization of technological hazards among digital-native students may reduce the perceived severity of unfavorable outcomes. Third, strong institutional support, technological competency, and social influence may alleviate fears about negative outcomes. Finally, effective communication about the advantages of mobile learning may outweigh perceived hazards, lowering their impact on adoption intentions.

These findings have substantial implications for theory as well as practice. This study theoretically enhances the UTAUT2 framework by demonstrating the significance of learning value in educational contexts and highlighting the intricate role of perceived negative consequences. Practically, the findings imply that educators and governments should prioritize improving the learning value of mobile platforms, providing technical and institutional support, and using social influence to boost uptake. Addressing potential downsides through tailored interventions, such as digital literacy training and privacy measures, can also help students feel more confident with mobile learning.

5.1 Theoretical Implications

Table 5: Hypothesis Results

Hypothesis	Relationships	Standard deviation (STDEV)	T statistics	P values	Decision
H1	PE -> BI	0.044	3.009	0.003	Supported
H2	EE -> BI	0.035	4.998	0.000	Supported
H3	SI -> BI	0.046	8.402	0.000	Supported
H4	FC -> BI	0.039	6.665	0.000	Supported
H5	HM -> BI	0.052	6.320	0.000	Supported
H6	HT -> BI	0.056	2.196	0.028	Supported
H7	LV -> BI	0.033	2.159	0.031	Supported
H8	PNC -> BI	0.042	1.923	0.055	Not Supported
H9	BI -> UB	0.023	33.067	0.000	Supported

The incorporation of learning value and perceived negative consequences significantly enhances the theoretical implications of the UTAUT2 framework, offering a more thorough comprehension of mobile learning adoption among high school and college students. The incorporation of learning value strengthens the UTAUT2 model by highlighting the intrinsic educational benefits and motivational elements that influence students' behavioral intentions. This aligns with the findings of Venkatesh et al. (2012), who emphasize the significance of intrinsic motivation in technology adoption and suggest that students are more inclined to embrace mobile learning when they perceive it as advantageous to their academic growth. This study addresses a notable deficiency in the UTAUT2 framework, which has traditionally prioritized extrinsic factors such as performance expectancy and effort expectancy, by emphasizing learning value. Second, the inclusion of perceived drawbacks offers a more complex viewpoint on the obstacles to the adoption of mobile learning, including technological difficulties, privacy issues, and diversions. Kukulska-Hulme et al. (2017) found that addressing these impediments is key to increasing confidence in mobile learning tools. This extension validates their findings. The enlarged UTAUT2 model provides a more balanced perspective of the adoption process by recognizing and addressing these issues, allowing researchers and educators to create interventions that take into account both the advantages and disadvantages of mobile learning. Overall, by adding contextual elements that are important to students' decision-making, this study not only confirms the UTAUT2 framework's robustness but also broadens its applicability to the educational setting. According to Al-Emran et al. (2020), comprehending these elements is essential to creating customized tactics that increase the uptake of mobile learning. This study offers a thorough theoretical framework for next research and real-world projects targeted at advancing mobile learning in educational contexts by combining perceived negative effects with learning value. Researchers and educators may use this enlarged model as a guide to fully realize the promise of mobile learning and make sure it becomes a game-changing tool in the digital age.

5.2 Practical Implications

This study provides valuable information for educational institutions, policymakers, and technology companies to promote mobile learning among high school and college students.

First, by incorporating mobile technology into curricula in ways that complement students' interests and academic goals, institutions can maximize the learning potential of these tools and increase student motivation and engagement. According to research, learning results are greatly improved by customized, student-centered content (Liu et al., 2010). Second, to allay worries about privacy and distractions, educational institutions should provide focused training programs that give students the tools they need to protect their data and deal with digital distractions. This will enhance students' confidence in utilizing mobile learning resources

(Kukulska-Hulme et al., 2017). Third, legislators can enact progressive legislation that fosters the ethical utilization of mobile devices in educational settings, ensuring equitable access and advancing digital literacy. Research highlights how policies can help close the digital divide and establish inclusive classrooms (Selwyn, 2016). Fourth, in order to create user-friendly and efficient solutions, technology suppliers must work together with educators to give priority to accessibility, security, and user experience in mobile learning platforms. Research indicates that systems that are easy to use greatly increase adoption rates (Al-Emran et al., 2020). Fifth, by starting communication campaigns that emphasize the advantages of mobile learning like its flexibility, ease, and enhanced academic performance parents, teachers, and students can change their perspectives, overcoming opposition and promoting acceptance (Traxler, 2018). Lastly, in order to improve mobile learning projects and make sure they stay effective and relevant, institutions should embrace a culture of ongoing review, collecting input from educators and students. Maintaining long-term success requires this iterative process (Kirkwood & Price, 2014). Stakeholders may realize the full potential of mobile learning and build a more inventive, inclusive, and technologically advanced educational ecosystem by implementing these proactive and cooperative measures.

6. Conclusion

This study demonstrates the transformative potential of mobile learning for secondary and higher secondary students in Bangladesh, indicating that adoption is significantly influenced by factors such as performance expectancy, effort expectancy, and perceived learning value. The overwhelming advantages such as flexibility, ease, and enhanced academic performance underline the importance of mobile learning in enabling students to succeed, even though anticipated negative effects were found to have minimal effect. Teachers and legislators may create a more inventive, inclusive, and technologically advanced educational environment by adopting these insights. Mobile learning is more than just a tool; it's a means of enabling students to reach their full potential and determining their success in the digital age.

Future studies on mobile learning for secondary and higher secondary students should focus on filling in the gaps and overcoming the obstacles that currently exist while also expanding our knowledge of its transformative potential, especially in countries like Bangladesh. Longitudinal studies are crucial to assess the long-term effects of mobile learning on academic success, student engagement, and retention rates. Furthermore, cross-cultural comparisons may help clarify how socioeconomic, cultural, and infrastructure elements affect the uptake and efficacy of mobile learning in various nations and areas. Examining how professional development and teacher training contribute to the efficient integration of mobile learning resources into classrooms and guarantee that teachers are prepared to use these tools is another exciting avenue. Research should also look into ways to make mobile learning more accessible and inclusive for students with disabilities and underserved groups, as well as creating culturally and contextually relevant content that is adapted to local curriculum. Further research is necessary to fully understand how parental participation supports mobile learning at home, as well as how gamification and adaptive learning technologies affect student motivation and individualized learning. To address ethical and practical issues, research on data privacy, security issues, and the environmental sustainability of mobile learning systems is also crucial. Lastly, policy-oriented research may elucidate how infrastructure investments and governmental regulations might promote the widespread use of mobile learning, ensuring it becomes a cornerstone of an innovative, inclusive, and technologically advanced educational framework. Researchers may actualize the complete potential of mobile learning as a tool for equipping students for success in the digital age by pursuing these avenues.

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