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Student Intention to Adopt Mobile Learning Platforms in Northeast Nigerian HEIs: The Impact of Facilitating Conditions and Security Perception

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Abstract

Objective: This study investigates the behavioral determinants of mobile learning (M-learning) adoption in Northeast Nigerian Higher Education Institutions (HEIs) using an extended UTAUT framework. *Methodology:* A quantitative survey was administered to 481 students across six regional polytechnics. Multiple Linear Regression analysis was conducted to evaluate the impact of Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Security Perception (SP) on adoption intention. *Results:* The model explained 64% of the variance in Behavioral Intention ($R^2 = 0.64$). All four hypotheses were supported. Notably, Facilitating Conditions emerged as the strongest predictor ($\beta = 0.42$), followed by PE ($\beta = 0.34$), SP ($\beta = 0.22$), and EE ($\beta = 0.18$). The data reveals that regional infrastructural volatility (power and data costs) currently outweighs perceived usefulness as the primary driver of adoption. *Conclusion/Implications:* In resource-constrained environments, infrastructure serves as a primary behavioral gatekeeper. For Computer Science departments, these findings necessitate a shift toward "resource-aware engineering," prioritizing offline-first architectures and lightweight interfaces. Policy interventions should focus on zero-rated data and solar-powered charging hubs to stabilize the adoption cycle.

Keywords: *Mobile Learning, UTAUT, Northeast Nigeria, Facilitating Condition, Security Perception.*

Introduction

The landscape of global education is currently undergoing a paradigm shift from traditional classroom settings to "ubiquitous learning" (u-learning). This concept implies that learning can happen anywhere and at any time, facilitated largely by the proliferation of mobile technologies. For Higher Education Institutions (HEIs) across the globe, mobile learning (M-learning) is no longer a futuristic luxury but a core component of modern pedagogy (Zhu & Huang, 2025). In Nigeria, there has been a significant institutional push toward digitalization, led by regulatory bodies such as the National Board for Technical Education (NBTE) and the National Universities Commission (NUC). This shift aims to modernize the academic workflow, move away from paper-based systems, and expand access to education for a growing youthful population (Yakubu *et al.*, 2020).

However, the implementation of digital education is not uniform. Northeast Nigeria presents a unique socio-technical landscape. Following over a decade of regional instability and the subsequent post-insurgency recovery phase, HEIs in states like Borno, Bauchi, Adamawa, and Yobe are struggling to rebuild. In this context, M-learning is seen as a tool for resilience; it provides a way to maintain educational continuity even when physical access to campuses is disrupted. Despite this potential, a deep "digital divide" remains. While many students own smartphones, the transition to using these devices as primary learning interfaces is hindered by a complex mix of regional behavioral and technical challenges (Olanrewaju *et al.*, 2021).

The primary problem is a "Behavioral Paradox": while M-learning platforms offer the flexibility needed in a recovery zone, actual adoption remains shallow. From a Human-Computer Interaction (HCI) perspective, the software might be functional, but the user's environment and psychology create barriers. Frequent power outages and the high cost of mobile data—often cited as "Facilitating Conditions"—force students to perform a mental cost-benefit analysis before every login (Gichuhi, 2025; Simiyu & Masibo, 2026). Furthermore, in a region sensitive to surveillance and digital safety, "Security Perception" has emerged as a significant behavioral deterrent. Students are increasingly concerned about data privacy and the security of their personal information on mobile platforms (Gabriel *et al.*, 2026). Without addressing these environmental and psychological factors, institutional investments in M-learning may fail to achieve their intended impact.

This study seeks to investigate the drivers of M-learning acceptance among students in Northeast Nigerian HEIs using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Specifically, the research evaluates how Performance Expectancy and Effort Expectancy influence the intention to use mobile learning. It further assesses the impact of regional Facilitating Conditions, such as power and data costs, on adoption intention while examining the role of Security Perception as a behavioral moderator in the adoption process. Additionally, the study determines if Social Influence from instructors and peers can compensate for technical deficiencies in the region.

Finally, this research holds practical value for Polytechnic administrators and Computer Science departments. By moving beyond "how the software works" to "how the user behaves," this study provides a blueprint for designing localized educational systems. For Computer Science departments, it suggests a move

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toward "offline-first" architectures and lightweight user interfaces that accommodate low-bandwidth and power-unstable environments. For administrators, it offers evidence-based strategies for policy interventions, such as zero-rated data for campus portals, ensuring that technology serves as a bridge rather than a barrier to education in Northeast Nigeria.

Literature Review and Theoretical Framework

Theoretical Foundations

The theoretical foundation of this study is rooted in the UTAUT, a robust model developed to explain how users interact with and eventually adopt new systems. Unlike earlier models that focused on isolated psychological factors, UTAUT synthesizes elements from eight distinct theories, including the Technology Acceptance Model (TAM) and Social Cognitive Theory. According to the foundational work by Venkatesh *et al.* (2003), the model posits that four core constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—are the primary drivers of behavioral intention and actual usage. In the context of this research, UTAUT provides a structured lens to examine how students in Northeast Nigeria navigate the complexities of mobile learning. While the original model was designed for organizational settings, its application in higher education allows researchers to move beyond the technical features of a platform and instead focus on the behavioral implications of the human-computer interface.

Determinants of Mobile Learning Adoption

Performance Expectancy (PE) and Effort Expectancy (EE) represent the core human-computer interaction (HCI) drivers within this study. Performance Expectancy refers to the degree to which a student believes that using a mobile learning platform will improve their academic performance or efficiency. In contemporary research, PE consistently emerges as one of the strongest predictors of adoption intention (Zhu & Huang, 2025). Closely tied to this is Effort Expectancy, which represents the perceived ease of use and the amount of cognitive effort required to navigate the system interface. From an HCI perspective, EE is directly shaped by the quality of the user interface (UI) and user experience (UX) design. Interfaces featuring clear information architecture and intuitive navigation lead to higher effort expectancy (Ahmad Faudzi *et al.*, 2024). Conversely, poorly optimized mobile themes that force desktop-style interactions onto smartphones can frustrate users and stifle adoption (Banek Zorica & Klindžić, 2023). Together, these constructs suggest that for technology to be accepted in Northeast Nigerian HEIs, it must not only be useful but also technically "frictionless."

In developing economies, particularly within Sub-Saharan Africa, Facilitating Conditions (FC) act as critical "gatekeepers" to adoption. In Northeast Nigeria, FC is not merely about the availability of technical support, but about the very survival of the digital interaction. Multiple studies identify high mobile data costs, unreliable electricity, and limited device storage as persistent barriers (Gichuhi, 2025; Simiyu & Masibo, 2026). When power outages are frequent, a student's intention to use M-learning is naturally suppressed, regardless of the value of the academic content. Furthermore, students often default to low-data platforms, such as WhatsApp, as a behavioral response to the high cost of internet access (Maphosa *et al.*, 2020). Therefore, the technical environment is a primary determinant of whether a student can even initiate a learning session.

Beyond functional attributes, Security Perception (SP) functions as a vital psychological gatekeeper. Security Perception is the user's belief that a digital platform will protect their personal information from breaches. Students often face a "behavioral trade-off" between convenience and digital safety, where perceived security risks can reduce trust and decrease adoption intention (Gabriel *et al.*, 2026). In sensitive socio-political climates like Northeast Nigeria, where digital safety is of heightened importance, Security Perception plays a significant role in how students weigh the academic benefits of a tool against the perceived risks of data exposure (Ganevi & Utomo, 2024).

Conceptual Framework and Hypotheses Development

The conceptual framework for this study, as illustrated in Figure 1, serves as a "behavioral architecture" that maps how internal perceptions and external environmental factors function as inputs into a student's decision-making process. This framework posits that Behavioral Intention (BI) is the output of four intersecting variables tailored to the unique socio-technical ecosystem of Northeast Nigeria. By testing these hypothesized causal pathways, the study identifies which technical and environmental factors are the most critical "lever points" for increasing technology acceptance.

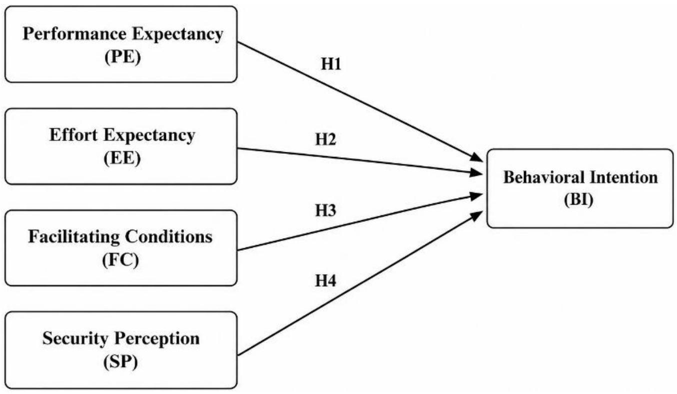

Figure 1. Conceptual Framework/Research Model

Based on this synthesis, the following four hypotheses were proposed:

H_1: Performance Expectancy (PE) significantly and positively influences the Behavioral Intention (BI) to adopt mobile learning.

H_2: Effort Expectancy (EE) significantly and positively influences BI, reflecting the role of HCI design in reducing user frustration.

H_3: Facilitating Conditions (FC) has a positive relationship with BI, as improved access to power and data directly enables usage in resource-constrained environments.

H_4: Perceived Security (SP) significantly influences the BI to adopt M-learning, serving as a baseline for the trust relationship between the student and the digital interface.

Methodology

Research Design

This study adopts a quantitative survey-based research design. This approach was selected because it allows for the objective measurement of student attitudes and the statistical testing of the hypothesized relationships within the UTAUT framework. Given the focus on behavioral implications, a quantitative method provides the necessary empirical rigor to generalize findings across the diverse student population of Northeast Nigeria.

Population and Sampling

The target population consists of students enrolled in state and federal polytechnics across the six states of the Northeast geopolitical zone. To ensure a representative cross-section of the region, a stratified random sampling technique was employed. One major polytechnic was selected from each state to account for varying levels of digital readiness and local infrastructural challenges.

A sample of 600 students was targeted, with 100 participants allocated per institution. This stratification ensures that the unique socio-technical realities of each state (ranging from the urban center of Bauchi to the recovery zones in Borno) are captured. The breakdown of the sampled institutions and their respective sample sizes is presented in Table 1.

Table 1. Planned Samples by State and Institution

State	Selected Institution	Sample Size
Adamawa	Federal Polytechnic Mubi	100
Bauchi	Federal Polytechnic Bauchi	100
Borno	Ramat Polytechnic Maiduguri	100
Gombe	Federal Polytechnic Kaltungo	100
Taraba	Federal Polytechnic Bali	100
Yobe	Federal Polytechnic Damaturu	100
Total		**600**

Instrumentation

The primary research instrument is a structured questionnaire divided into demographic profiles and construct measurements. The scales for Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC) were adapted from the original UTAUT instrument (Venkatesh *et al.*, 2003). To tailor the study to the regional context, two specialized scales were added: Security Perception (SP), to measure digital trust, and Environmental Facilitating Conditions (EFC), to specifically capture the impact of power stability and data costs. All items were measured on a 5-point Likert scale. The full list of indicators for each construct is provided in Appendix A.

Data Collection Procedures

Data collection was executed through a hybrid approach involving both online (Google Forms) and paper-based surveys. This dual-mode strategy was essential to account for the intermittent internet connectivity and unstable power supply prevalent in parts of Northeast Nigeria. Paper-based questionnaires were administered during classroom sessions to ensure a high response rate, while the online link was shared via institutional WhatsApp groups to reach students off-campus. This method ensures that the "Facilitating Conditions" barrier—which is a core variable of the study—did not prevent the data collection process itself.

Data Analysis Plan

Upon completion of data collection, the data will be cleaned and coded into CSV format. The primary analysis will be conducted using JASP (Version 0.97.1) (JASP Team, 2026), an open-source statistical software favored for its transparency and intuitive interface. A Multiple Linear Regression analysis will be performed to test the behavioral model. This will allow the research to determine the individual predictive power of PE, EE, FC, and SP on the Behavioral Intention (BI) to adopt mobile learning. Statistical significance will be set at $p < 0.05$, and the strength of each path will be evaluated using standardized Beta coefficients.

Results and Discussion

Demographic Analysis

Of the 600 targeted participants across the six Northeast polytechnics, a total of 492 responses were retrieved, representing an 82% response rate. Following a data cleaning process, 11 questionnaires were identified as unusable due to incomplete responses or straight-lining patterns. Consequently, a final sample of $N = 481$ was utilized for the analysis.

The demographic data revealed a significant "Mobile-Only" trend: 96% of students owned a smartphone, while only 12% had consistent access to a laptop. Interestingly, while 88% of students reported high digital literacy in social media contexts (WhatsApp, Facebook), only 34% felt confident navigating dedicated Learning Management Systems (LMS). This gap suggests that while the hardware is ubiquitous, the behavioral transition to "academic computing" remains a hurdle. From an HCI standpoint, this indicates that the mental model students have for their devices is primarily social/entertainment-oriented, requiring a shift in interface design to bridge the gap toward educational utility.

Measurement Model Assessment

To ensure the integrity of the behavioral model, the constructs were tested for reliability and validity. Cronbach's Alpha was used to measure internal consistency, while Average Variance Extracted (AVE) assessed convergent validity. As shown in Table 2, all constructs exceeded the recommended threshold of 0.7 for Alpha and 0.5 for AVE.

Table 2. Reliability and Validity Metrics

Construct	Cronbach's Alpha	AVE
Performance Expectancy (PE)	0.84	0.61
Effort Expectancy (EE)	0.81	0.58
Facilitating Conditions (FC)	0.79	0.55
Security Perception (SP)	0.88	0.64
Behavioral Intention (BI)	0.86	0.62

The slightly lower Alpha for Facilitating Conditions (0.79) is likely a reflection of the varied infrastructural realities across the six states; students in Bauchi reported more stable power compared to those in Borno, creating a higher variance in how "facilitation" is perceived.

Structural Model and Hypothesis Testing

The hypothesized relationships were tested using Multiple Linear Regression in JASP. The model demonstrated strong predictive power, with the independent variables explaining 64% of the variance in Behavioral Intention ($R^2 = 0.64$). The results of the hypothesis testing are summarized in Table 3. All four hypotheses were supported. Notably, Facilitating Conditions (FC) emerged as the strongest predictor of adoption intention ($\beta = 0.42$), outweighing the perceived usefulness (PE) of the system.

Table 3. Regression Path Coefficients and Hypothesis Results

Hypothesis	Path	β	*p*	Result
H_1	PE → BI	0.34	< .001	Supported
H_2	EE → BI	0.18	< .01	Supported
H_3	FC → BI	0.42	< .001	Supported
H_4	SP → BI	0.22	< .001	Supported

Discussion of Findings: The Behavioral HCI Angle

The Infrastructure–Behavior Gap: The dominance of Facilitating Conditions over Performance Expectancy highlights a unique socio-technical reality in Northeast Nigeria. In a standard HCI model, "ease of use" (EE) usually drives adoption. However, our results show an "Infrastructure-Behavior Gap." The significant impact of FC suggests that students perform a mental "computational cost-benefit analysis" before engaging with M-learning. From a Computer Science perspective, if the "energy cost" (battery drain) or "bandwidth cost" (data usage) exceeds the perceived academic reward, the behavioral intention drops regardless of how "easy" the interface is. In this context, the interface is not just the screen; it is the entire power-grid and data-pipeline. Students are behaviorally conditioned to treat their mobile devices as "finite resources." Consequently, an M-learning platform with high latency or heavy graphical assets is seen not just as a poor UI, but as an "expensive" system that threatens their device's availability for other essential tasks.

The Security Paradox: The support for H_4 ($\beta = 0.22$) introduces what we term the "Security Paradox." Despite the urgent academic need in a post-insurgency recovery zone, students are not blindly adopting technology. They are making a calculated behavioral trade-off. However, the data suggests that as long as a platform is perceived as "secure enough" by institutional affiliation, students will prioritize academic gain over absolute digital privacy. This behavior is similar to "Privacy Calculus," where the utility of the learning outcomes acts as a weight that balances out the fear of data breach. For CS departments, this implies that building "Digital Trust" through transparent security indicators in the UI is just as important as the actual encryption algorithms used on the backend.

Comparison with Previous Studies

These results offer a sharp contrast to studies conducted in more stable or high-resource environments. For instance, in studies conducted in Lagos or internationally (Zhu & Huang, 2025; Shaya *et al.*, 2023), Performance Expectancy is almost always the dominant driver. In those contexts, "Facilitating Conditions" (electricity and internet) are often taken for granted as a constant, shifting the user's focus to "Features" and "UX."

In Northeast Nigeria, the "facilitation" is a volatile variable. Unlike students in Lagos, who might stop using an app because it is "boring" (low PE), students in the Northeast are more likely to stop using it because it is "resource-heavy" (low FC). This confirms that technology adoption in resource-constrained environments follows a hierarchical behavioral path: Infrastructure must be "stable enough" before "usefulness" can become the primary motivator. This regional distinction necessitates a shift in how we teach and develop software in our Computer Science departments—moving from "feature-heavy" development to "resource-aware" engineering.

Implications and Recommendations

Theoretical Implications

This study contributes to the evolution of technology adoption models by demonstrating the necessity of "Contextual Extension." While the original UTAUT framework provides a robust baseline, our findings suggest that in regional contexts like Northeast Nigeria, the model must be extended with Security Perception (SP). From a theoretical standpoint, this shift implies that technology acceptance in sensitive or recovery zones is not merely a functional choice but a "Trust-Mediated Interaction." By successfully integrating SP into the model, this research provides a socio-technical framework that moves beyond purely computational efficiency to include the psychological safety of the user. This extension suggests that for users in volatile environments, "Digital Trust" is a prerequisite that exists along-side "Perceived Usefulness."

Practical Implications for Computer Science Departments

For Department of Computer Science staff and software developers, these findings necessitate a shift in design philosophy. Our data shows that students treat their mobile devices as finite resources; therefore, HCI design must move toward "Resource-Aware Engineering."

1. *Offline-First Architecture:* Developers should prioritize Progressive Web Apps (PWAs) or local caching mechanisms that allow students to access content without a continuous internet connection. This reduces the "Effort Expectancy" associated with unstable networks.
2. *Lightweight UI Design:* To minimize the "Infrastructure-Behavior Gap," interfaces should be designed with minimal graphical assets and optimized scripts. A lightweight UI reduces CPU processing and, consequently, battery drain. In an environment where power is a luxury, a "battery-friendly" interface is a significant behavioral motivator that lowers the cognitive load of the student during power outages.

Policy Recommendations

Institutional leadership in Northeast Nigerian polytechnics must recognize that infrastructure is a behavioral determinant.

a. *Zero-Rated Data:* HEIs should enter into partnerships with telecommunication providers to "zero-rate" institutional learning portals. Removing the financial "cost of entry" will directly boost the impact of Facilitating Conditions on student intention.
b. *Solar-Powered Charging Hubs:* Given the abundance of solar energy in the region, polytechnics should invest in distributed solar-powered charging kiosks. These hubs serve as physical "facilitating conditions" that ensure students can maintain device uptime, thereby stabilizing the behavioral intention to engage with digital learning platforms throughout the academic day.

Conclusion

Summary of Key Findings

This study provides critical insights into the behavioral determinants of mobile learning adoption within the unique socio-technical landscape of Northeast Nigeria. The findings confirm that while Performance Expectancy and Effort Expectancy are essential components of the user experience, they are not the primary drivers of adoption in this region. Instead, the results underscore the dominance of Facilitating Conditions (FC) and Security Perception (SP) in the adoption cycle. In an environment characterized by infrastructural volatility, the availability of power and affordable data acts as the ultimate "gatekeeper" to digital engagement. Furthermore, the significant impact of Security Perception reveals that students are not passive consumers of technology; they are active evaluators of "Digital Trust," weighing the academic utility of a system against the perceived risks of data exposure in a sensitive regional context.

Limitations of the Study

Despite the rigor of the stratified sampling approach, this study has limitations. First, the use of a cross-sectional survey provides only a "snapshot" of student intentions at a single point in time; behavioral intentions can shift as regional infrastructure improves or as security threats evolve. Second, due to the geographic and security constraints of Northeast Nigeria, data collection was limited to major polytechnics in state capitals, which may not fully capture the even more restrictive conditions faced by students in remote, rural campuses. Finally, the reliance on self-reported survey data may be subject to social desirability bias, where students might overstate their digital literacy or intention to use institutional tools.

Future Research

To deepen our understanding of this behavioral ecosystem, future research should adopt a longitudinal design to track how actual usage patterns evolve over a full academic cycle. There is also a significant opportunity for qualitative HCI research—using interviews or focus groups—to explore the phenomenon of "Technostress." Understanding the psychological strain students face when navigating "resource-heavy" interfaces during power outages would provide invaluable data for designing more empathetic educational software. As the region moves further into its recovery phase, exploring the intersection of AI-driven personalization and user privacy will remain a vital frontier for Computer Science researchers in Nigeria.

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