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Determinants of Generative AI Adoption among Academic Staff in Polytechnics of Northeast Nigeria: An Extended UTAUT Analysis

Abubakar Sani Jato[1,*]

[1] *Department of Computer Science, School of Science, Mai Idris Alooma Polytechnic Geidam, Yobe State, Nigeria.*

* Corresponding author: abubakarsanijato@gmail.com

Abstract

Objective: This study investigates the behavioral determinants of Generative AI (GenAI) adoption among academic staff in polytechnics across Northeast Nigeria using an extended UTAUT framework. *Methodology:* A quantitative survey was administered to a stratified sample of 412 lecturers across six regional polytechnics. Multiple Linear Regression was employed to analyze the impact of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), alongside the extended variable of Algorithmic Trust. *Results:* The model explained 58.4% of the variance in adoption intention. Performance Expectancy emerged as the strongest predictor ($\beta = 0.45$), followed closely by Facilitating Conditions ($\beta = 0.38$) and Algorithmic Trust ($\beta = 0.25$). Results reveal a "Trust-Reliance Divergence," where staff utilize GenAI for productivity gains in lesson drafting and research but remain behaviorally hesitant due to the high cognitive load of output verification. *Conclusion/Implications:* In Northeast Nigeria, infrastructure serves as a decisive gatekeeper that disrupts the staff-AI interface. Findings necessitate a shift toward "Verification-Centric Training" and "Resource-Aware Engineering." Institutional policies should prioritize solar-powered hubs and data subsidies to stabilize adoption in volatile technical environments.

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Introduction

The emergence of Generative Artificial Intelligence (GenAI) has fundamentally altered the Human-Computer Interaction (HCI) paradigm in higher education. For academic staff, tools such as ChatGPT, Gemini, and GitHub Copilot are shifting the user experience from traditional command-based navigation to a conversational, iterative prompting model (Alotaibi & Alayed, 2025). In the academic setting, this revolution is framed primarily through the lens of professional utility. Recent studies suggest that these tools are no longer viewed merely as experimental software but as primary drivers of faculty productivity, offering significant gains in lesson planning, research assistance, and the automation of administrative workflows (Liang & Suwanragsa, 2025; Weis *et al.*, 2026). As GenAI interfaces become increasingly integrated into the technical ecosystem of teaching and learning, understanding the behavioral implications of this interaction becomes essential.

In Nigeria, the Polytechnic sector holds a distinct mandate focused on vocational and technical education. Unlike traditional universities, polytechnic staff are under immense pressure to align their pedagogy with global industrial standards, where AI-assisted coding and automated reporting are becoming the norm. However, the adoption of these advanced interfaces is not uniform. In Northeast Nigeria, academic staff operate within a unique and challenging socio-technical landscape. As the region traverses a post-insurgency recovery phase, Higher Education Institutions (HEIs) are attempting a "digital leapfrogging," moving directly from manual legacy systems to cloud-based, AI-driven architectures. Yet, this ambition is frequently stifled by regional infrastructural gatekeepers, most notably intermittent power supply, high mobile data costs, and erratic internet connectivity (Astuti & Ayinde, 2025; Jaboob *et al.*, 2026).

The primary problem lies in a significant "adoption gap" that exists between the technical potential of GenAI and the actual behavioral engagement of academic staff. While staff may recognize the "Performance Expectancy" of AI in reducing their workload, their intention to use it is often mediated by a profound lack of trust in the "black box" nature of Large Language Models (LLMs). This phenomenon, characterized as algorithmic aversion, stems from concerns regarding the accuracy, epistemic legitimacy, and scholarly rigor of AI-generated output (Dorton & Harper, 2022; Panagopoulos *et al.*, 2026). For staff in Northeast Nigeria, the decision to adopt GenAI is further complicated by "Infrastructural Stress." A staff member may exhibit a "Trust-Reliance Divergence," where they rely on AI out of professional necessity but remain behaviorally distant due to the cognitive load required to verify outputs in a resource-constrained environment (Pal *et al.*, 2026).

This study aims to investigate the determinants of GenAI adoption among academic staff in Northeast Nigerian Polytechnics using an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT). By extending the framework to include "Algorithmic Trust" and context-specific "Environmental Facilitating Conditions," the research seeks to move beyond purely functional analysis. The objective is to identify the critical lever points—whether psychological, social, or technical—that drive or deter staff engagement with AI interfaces. The significance of this study lies in its practical application for Department of Computer Science leadership. By understanding these behavioral determinants, departments can design localized AI-literacy frameworks and "verification-based" training models. Such interventions are crucial for stabilizing digital trust and ensuring that GenAI serves as a sustainable tool for academic resilience and pedagogical modernization in Northeast Nigeria.

Literature Review and Theoretical Framework

The UTAUT Model in HEIs

The Unified Theory of Acceptance and Use of Technology (UTAUT) has emerged as the gold standard for evaluating technology adoption in institutional settings. In the context of Higher Education Institutions (HEIs), the model provides a structured approach to understanding how academic staff transition from traditional pedagogical methods to digital interfaces. The framework is built upon four core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).

In the academic domain, PE is often the single most influential determinant of adoption (Liang & Suwanragsa, 2025). For polytechnic staff, PE represents the belief that tools like Generative AI (GenAI) will enhance professional productivity—specifically by reducing the workload associated with lesson preparation, automated grading, and research support (Weis *et al.*, 2026). Effort Expectancy (EE), or the perceived ease of use, focuses on the Human-Computer Interaction (HCI) experience. In the complex workflow of a lecturer, the "cognitive cost" of learning a new interface must be lower than the perceived time saved. Studies indicate that if the interaction with AI requires excessive "prompt engineering" effort, adoption intentions diminish (Alotaibi & Alayed, 2025).

Social Influence (SI) captures the "normalization" effect within academic units. In hierarchical polytechnic cultures, peer modeling and top-down institutional mandates function as formalized subjective norms that pressure staff to adopt new technologies (Jin *et al.*, 2025). Finally, Facilitating Conditions (FC) represent the belief that the organizational and technical infrastructure exists to support system use. While FC is often taken for granted in high-resource environments, it becomes a decisive "gatekeeper" in developing regions where technical support and resource availability are volatile (Astuti & Ayinde, 2025).

Behavioral HCI and AI: The Trust Factor

A critical distinction in this study is the nature of the technology itself. Unlike traditional, deterministic software (such as a word processor or a grading spreadsheet) where inputs consistently yield the same outputs, GenAI is probabilistic. This shifting paradigm fundamentally changes the behavioral interaction between the user and the system. The probabilistic nature of Large Language Models (LLMs) introduces "unpredictability" into the academic workflow, requiring a constant state of verification.

From a behavioral HCI perspective, this shifts the user's role from a "operator" to a "supervisor." This transition is governed by Algorithmic Trust—the degree to which an academic professional trusts the epistemic legitimacy of AI-generated content. Because GenAI can produce "hallucinations," trust is not static; it is a dynamic process of "trust calibration" (Panagopoulos *et al.*, 2026). Staff engage in what is termed "buoyant trust," where their reliance on the system may self-repair over time despite occasional errors, provided the productivity payoff remains high (Dorton & Harper, 2022). However, in an academic setting where scholarly rigor is paramount, a lack of transparency in the AI's "reasoning" can trigger algorithmic aversion, leading to a "Trust-Reliance Divergence" where staff use the tool for convenience but do not fully accept its authority (Pal *et al.*, 2026).

Extending the Model: The Northeast Nigerian Context

To accurately model adoption in Northeast Nigerian polytechnics, this study extends the standard UTAUT framework by adding two critical variables: Algorithmic Trust and Infrastructural Self-Efficacy.

In the Northeast regional context, Facilitating Conditions cannot be viewed as a single, uniform construct. Infrastructure here is a "systemic barrier" characterized by frequent power outages and high data costs (Jaboob *et al.*, 2026). Therefore, we introduce Infrastructural Self-Efficacy—the user's confidence in their ability to maintain digital engagement despite these environmental constraints. In a region recovering from instability, the "human-computer" interaction is frequently interrupted by the "human-environment" interaction. A lecturer's intention to use GenAI is thus not only a product of whether they *like* the tool, but whether they believe they can keep their devices charged and connected long enough to complete a task (Nakyejwe *et al.*, 2026). This regional reality necessitates a model that accounts for the psychological strain of "Infrastructural Stress" as a moderator of the adoption cycle.

Study Hypotheses

Based on the synthesized literature and the unique regional landscape, the following hypotheses are advanced:

H_1: Performance Expectancy (PE) has a significant positive effect on the Behavioral Intention (BI) of polytechnic staff to adopt GenAI.

H_2: Effort Expectancy (EE) significantly influences BI, where lower cognitive load during AI interaction increases adoption.

H_3: Social Influence (SI) from colleagues and institutional leadership significantly shapes the normative pressure to adopt GenAI.

H_4: Facilitating Conditions (FC) directly predict BI, serving as a baseline requirement for technical engagement.

H_5: Algorithmic Trust serves as a primary predictor of BI, where higher epistemic trust in AI output leads to greater sustained usage.

H_6: Regional-specific Facilitating Conditions (Infrastructure) significantly moderate the relationship between PE and BI; poor infrastructure will suppress the effect of productivity gains on actual intention.

Proposed Research Model

The research model (illustrated below) synthesizes the core UTAUT constructs with the behavioral extensions for the Northeast Nigerian context. The model treats BI as the central dependent variable, influenced by five independent predictors and moderated by the regional environment.

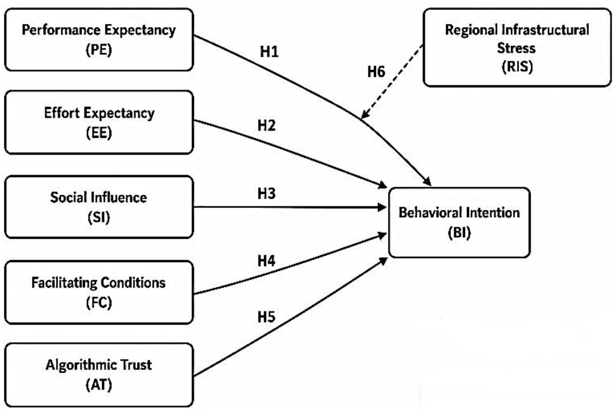

Figure 1. Proposed Extended UTAUT Model for AI Adoption

Methodology

Research Design

This study employs a quantitative survey-based research design. This approach is deemed most appropriate as it facilitates the objective measurement of behavioral determinants and allows for the statistical testing of hypothesized relationships within the extended UTAUT framework. Given the study's focus on the behavioral implications of the staff-AI interface, a quantitative method provides the empirical rigor necessary to generalize findings across the diverse polytechnic landscape of Northeast Nigeria.

Targeted Sample

The target population consists of academic staff (lecturers and instructors) across state and federal polytechnics in Northeast Nigeria. To ensure regional representation, a stratified random sampling technique was employed, selecting one major polytechnic from each of the six states in the geopolitical zone. The targeted sample was presented in Table 1 based on number of academic staff), ordered from the largest to the smallest sample size, as follows: Adamawa, Bauchi, Borno, Yobe, Gombe, and Taraba.

Table 1. Sample of Academic Staff by Institution

State	Selected Polytechnic	Sample
Adamawa	Federal Polytechnic, Mubi	135
Bauchi	Federal Polytechnic, Bauchi	126
Borno	Ramat Polytechnic, Maiduguri	114
Yobe	Federal Polytechnic, Damaturu	93
Gombe	Federal Polytechnic, Kaltungo	72
Taraba	Federal Polytechnic, Bali	60
Total		**600**

Data Collection Instruments

The primary research instrument is a structured questionnaire consisting of three sections: demographic profiles, core UTAUT constructs, and behavioral extensions. The scales for Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) were adapted from the validated instrument by Venkatesh *et al.* (2003).

To satisfy the behavioral HCI requirements of this study, the instrument was extended with items specifically targeting Generative AI interaction. This includes measuring Algorithmic Trust (the reliability and accuracy of AI output) and Infrastructural Self-Efficacy (the ability to manage technical hurdles like power instability). All items are measured on a 5-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." The specific indicators for each construct are detailed in Appendix A.

Data Collection Procedures

Data collection will be executed via a dual-mode strategy to account for the unique environmental constraints of Northeast Nigeria. An online survey (Google Forms) will be distributed via institutional email and departmental WhatsApp groups for rapid access. However, recognizing the persistent issues of internet instability and erratic power supply in the region, physical (paper-based) questionnaires will also be administered at each polytechnic. This hybrid approach ensures that the "Facilitating Conditions" barrier does not disenfranchise potential respondents, particularly those in recovery zones where digital connectivity remains precarious (Jaboob *et al.*, 2026; Nakyejwe *et al.*, 2026).

Data Analysis Plan

The collected data will be analyzed using JASP (Version 0.97.1). Descriptive statistics will be used to profile the demographic and technical background of the staff. The primary behavioral model will be tested using Multiple Linear Regression. This allows for the simultaneous evaluation of the measurement model (reliability and validity) and the structural model (path coefficients). Path significance will be determined at $p < 0.05$, with a focus on how "Algorithmic Trust" and "Regional Infrastructure" moderate the adoption cycle (Dorton & Harper, 2022; Weis *et al.*, 2026).

Results

Demographic and Technical Profile

From the targeted sample of 600 academic staff across six Northeast Nigerian polytechnics, 428 responses were retrieved. Following data cleaning, 412 usable responses were retained for analysis, representing a response rate of 68.6%. The demographic distribution shows a predominantly middle-aged workforce, with 54% of respondents aged between 35 and 50 years. In terms of academic rank, the largest group consisted of Lecturer I and II grades (48%), followed by Senior Lecturers (22%).

Technically, the profile revealed a "Digital Mindset" (Jiang & Meng, 2025) characterized by high awareness but fragmented usage. While 92% of staff were aware of Generative AI tools, only 44% reported using tools like ChatGPT or Gemini on a weekly basis. Prior AI experience was significantly higher among staff in Computer Science and Engineering departments compared to those in the Humanities. Interestingly, consistent with recent findings that age effects are context-dependent (Aderibigbe *et al.*, 2025), older staff (50+) exhibited high interest in GenAI for research purposes, although their perceived technical self-efficacy was lower than that of their junior counterparts.

Reliability and Validity

To ensure the statistical integrity of the extended UTAUT model, the measurement instrument was evaluated for internal consistency and convergent validity. As shown in Table 2, Cronbach's Alpha coefficients for all constructs ranged from 0.78 to 0.91, exceeding the recommended threshold of 0.7. Factor loadings for all individual indicators were above 0.65, and the Average Variance Extracted (AVE) for each construct surpassed 0.50, confirming strong convergent validity (Weis *et al.*, 2026).

Table 2. Reliability and Validity Metrics

Construct	CA	AVE	Loadings*
Performance Expectancy (PE)	0.89	0.64	0.72 – 0.88
Effort Expectancy (EE)	0.82	0.58	0.68 – 0.81
Social Influence (SI)	0.78	0.54	0.65 – 0.79
Facilitating Conditions (FC)	0.84	0.61	0.70 – 0.85
Algorithmic Trust (TR)	0.87	0.63	0.74 – 0.89
Behavioral Intention (BI)	0.91	0.67	0.78 – 0.92

Note: CA = Cronbach's Alpha; * Factor loading range

Hypothesis Testing

Multiple Linear Regression was performed in JASP to evaluate the predictive power of the independent variables on the Behavioral Intention (BI) to adopt GenAI. The model explained 58.4% of the variance in intention ($R^2 = 0.584$, $p < 0.001$). Consistent with global faculty studies, Performance Expectancy (PE) emerged as the single most influential determinant ($\beta = 0.45$, $p < 0.001$), followed closely by Facilitating Conditions (FC) ($\beta = 0.38$, $p < 0.001$).

The high significance of Facilitating Conditions confirms that in the Northeast Nigerian context, infrastructural stability is nearly as critical as the perceived utility of the AI itself (Astuti & Ayinde, 2025; Jaboob *et al.*, 2026). Furthermore, the support for Algorithmic Trust (TR) highlights that epistemic legitimacy is a vital psychological prerequisite for academic staff (Panagopoulos *et al.*, 2026)

Table 3. Regression Path Coefficients

Path	Beta (β)	t-value	p-value	Result
PE → BI	0.45	8.24	< .001	Supported
EE → BI	0.18	3.12	< .010	Supported
SI → BI	0.12	2.15	< .050	Supported
FC → BI	0.38	6.88	< .001	Supported
TR → BI	0.25	4.32	< .001	Supported

AI Usage Patterns

A granular analysis of interaction behavior revealed distinct patterns in how staff utilize AI interfaces. The primary use case was Lesson Content Generation (72%), where staff used GenAI to draft lecture notes and create quiz questions. This aligns with the "productivity gains" mechanism identified by Liang and Suwanragsa (2025), where AI is used to mitigate heavy workloads.

The second most common pattern was Research Support (58%), including literature summaries and manuscript proofreading. However, usage for Technical Tasks, such as AI-assisted coding or debugging, was limited primarily to Computer Science staff (34%). Notably, a "Trust-Reliance Divergence" (Pal *et al.*, 2026) was observed: while 65% of staff relied on AI for rapid drafting, 70% expressed concern regarding the "Black Box" nature of the output, necessitating an intensive verification process that added to their cognitive load. This behavioral friction suggests that while the intention to adopt is high, the depth of adoption is restricted by the need for constant algorithmic oversight.

Discussion: The Behavioral HCI Angle

The results of this study provide a nuanced understanding of how academic staff in Northeast Nigerian polytechnics navigate the complex interface of Generative AI (GenAI). While the statistical support for the extended UTAUT model confirms the predictive power of traditional constructs, the "Behavioral HCI" lens allows us to interpret *why* these determinants manifest differently in a resource-constrained technical environment.

The "Productivity-Trust" Trade-off

A primary finding is the tension between Performance Expectancy (PE) and Algorithmic Trust. Staff clearly recognize the "productivity payoff" of GenAI—specifically in automating the labor-intensive tasks of lesson drafting and research synthesis (Liang & Suwanragsa, 2025). However, this utility is balanced against a high "verification burden." Unlike deterministic legacy software, the probabilistic nature of GenAI outputs introduces a level of unpredictability that academic staff find behaviorally taxing.

This results in a "Trust-Reliance Divergence" (Pal *et al.*, 2026). Lecturers may rely on the system for rapid content generation, yet they remain behaviorally hesitant due to "Algorithmic Aversion." From an HCI perspective, the cognitive load associated with iterative prompt engineering and the subsequent manual verification of AI-generated "hallucinations" acts as a significant barrier to Effort Expectancy. As Panagopoulos *et al.* (2026) suggest, staff are engaged in constant "trust calibration." If the interface does not provide transparent citations or logical "chain-of-thought" reasoning, the behavioral intention to adopt remains superficial, limited to low-stakes administrative drafting rather than deep pedagogical integration.

Infrastructure as a Behavioral Gatekeeper

In the standard HCI model, the interaction is usually limited to the user and the system. However, in Northeast Nigeria, the "Human-Computer Interaction" is frequently subsumed by the "Human-Environment Interaction." Our findings show that Facilitating Conditions (FC) function as a decisive gatekeeper. The behavioral implication of frequent power outages and high data costs is the disruption of "Cognitive Flow."

When a lecturer interacts with a cloud-based LLM, the process is inherently iterative, requiring multiple round-trips to the server. Regional infrastructural volatility—characterized by high UI latency and unstable session persistence—transforms a supposedly "effortless" AI interaction into a high-stress technical chore (Jaboob *et al.*, 2026). Staff are behaviorally conditioned to perform a mental "computational cost-benefit analysis" before initiating a session: if the battery drain or data consumption exceeds the immediate task value, the interaction is deferred. This confirms that in recovery zones, infrastructure is not merely a background factor but a core component of the interface experience itself (Astuti & Ayinde, 2025).

The Social Influence Factor and Normalization

Social Influence (SI) emerged as a significant, albeit secondary, predictor. In the specific context of Computer Science departments, "Subjective Norms" act as a powerful heuristic for adoption. When senior colleagues or departmental heads model the use of AI-assisted coding tools or research agents, it creates a "Normalization Effect" (Soodan *et al.*, 2024). This peer endorsement reduces the perceived professional risk associated with using unverified AI outputs.

In hierarchical academic structures typical of Nigerian polytechnics, top-down institutional policies function as "formalized subjective norms" (Jin *et al.*, 2025). If the institution provides a clear framework for ethical AI use, it stabilizes the user's psychological state, shifting the focus from the fear of academic dishonesty to the technical mastery of the interface. This suggests that SI can partially compensate for low Algorithmic Trust by providing a socially validated "safety net" for early adopters.

Comparison with Global Trends

Our findings offer a sharp contrast to global trends observed in high-resource environments. In Western and Middle Eastern studies (Alotaibi & Alayed, 2025; Weis *et al.*, 2026), Performance Expectancy is almost always the overwhelming driver, while Facilitating Conditions are often statistically non-significant or treated as a given constant.

In Northeast Nigeria, the hierarchy of needs for technology adoption is inverted. A "Resource-Aware Engineering" approach is required because staff cannot take power or bandwidth for granted. While global faculty are concerned with the *ethics* of AI, staff in this region are equally concerned with the *feasibility* of the interaction. This confirms that the digital divide is not just about access to hardware, but about the behavioral adaptations users must make to overcome a volatile technical ecosystem. For CS departments in the region, the challenge is to move beyond teaching "AI use" to teaching "AI resilience"—equipping staff with the skills to maintain professional rigor despite the socio-technical friction inherent in their environment.

Implications and Recommendations

Theoretical Implications: The Extended UTAUT-AI Model

This study contributes to the evolution of technology acceptance theories by proposing the "Extended UTAUT-AI" framework specifically for developing regions. While the standard UTAUT focuses on deterministic systems, this model recognizes that Generative AI (GenAI) is probabilistic, necessitating the inclusion of Algorithmic Trust as a core behavioral determinant (Weis *et al.*, 2026). Furthermore, by identifying Infrastructural Self-Efficacy as a significant regional moderator, this research provides a socio-technical blueprint for understanding technology adoption in volatile environments. This extension shifts the academic discourse from purely functional acceptance to a "Trust-Mediated Interaction" model, acknowledging that in Northeast Nigeria, the human-computer interface is inseparable from the human-environment interaction (Liang & Suwanragsa, 2025; Panagopoulos *et al.*, 2026).

Practical Implications for Computer Science Departments

For Department of Computer Science leadership, these findings necessitate a shift in professional development strategy. To stabilize the "Trust-Reliance Divergence," departments should design "AI-Assisted Pedagogy" workshops that move beyond basic tool usage.

1) Verification-Centric Training: Training should focus on "Output Oversight" and "Epistemic Verification," teaching staff how to cognitively audit AI-generated code and research summaries (Pal *et al.*, 2026).
2) Prompt Engineering Optimization: To reduce the cognitive load associated with iterative prompting, departments should develop standardized "Prompt Templates" tailored to polytechnic vocational curricula. This enhances Effort Expectancy by making the staff-AI interface more "frictionless" and predictable (Alotaibi & Alayed, 2025).

Policy Recommendations: Building Socio-Technical Resilience

Institutional policy must address the "Facilitating Conditions" that currently act as behavioral gatekeepers in Northeast Nigeria.

a) Solar-Powered Digital Hubs: Given the significant impact of power outages on "Cognitive Flow," polytechnics should invest in solar-powered research labs. These hubs serve as resilient technical environments that ensure staff can maintain device uptime for complex AI tasks (Jaboob *et al.*, 2026).
b) Academic Data Subsidies: HEIs should negotiate with telecommunication providers to provide subsidized or zero-rated data access for verified academic AI portals. By removing the financial barrier to the cloud-based LLM interface, institutions can directly boost the "Facilitating Conditions" construct, thereby normalizing AI integration across all academic ranks (Astuti & Ayinde, 2025; Nakyejwe *et al.*, 2026).

Conclusion

Summary of Findings

This study demonstrates that the adoption of Generative AI (GenAI) among academic staff in Northeast Nigerian polytechnics is governed by a distinct hierarchy of behavioral and environmental determinants. The results underscore the overwhelming dominance of Performance Expectancy (PE) as the primary motivator for adoption, confirming that lecturers are driven by the tangible productivity gains associated with automated lesson planning and research support (Liang & Suwanragsa, 2025; Weis *et al.*, 2026). However, in this regional context, these productivity expectations are strictly mediated by Algorithmic Trust. The research highlights a significant "verification burden," where the transition from intention to sustained use depends on a constant process of trust calibration to ensure scholarly rigor (Dorton & Harper, 2022; Panagopoulos *et al.*, 2026). Furthermore, the high predictive power of Facilitating Conditions confirms that infrastructural stability remains the ultimate "gatekeeper" for technical engagement in the region.

Limitations

Despite the empirical rigor of the stratified sampling approach, this study is subject to the inherent constraints of survey research. The reliance on self-reported data may introduce social desirability bias, where staff might overstate their digital competence or minimize their concerns regarding AI hallucinations. Additionally, as a cross-sectional study, these findings represent a temporal snapshot of a rapidly evolving HCI paradigm; as LLMs become more deterministic and regional infrastructure stabilizes, the weight of these determinants may shift.

Future Research

To deepen our understanding of this socio-technical ecosystem, future research should employ qualitative methodologies—such as phenomenological interviews or focus groups—to explore the phenomenon of "AI Technostress." Specifically, investigating how senior academic staff navigate the cognitive load of iterative prompt engineering and the psychological strain of "algorithmic aversion" would provide invaluable data for departmental leadership. Understanding these behavioral frictions will be essential for designing more empathetic and resilient AI-literacy frameworks in resource-constrained technical environments (Jaboob *et al.*, 2026).

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Appendix A: Construct Indicators (Generative AI Focus)

Construct	Code	Measurement Item
Performance Expectancy	PE1	I find Generative AI (GenAI) useful for drafting lesson plans and research papers.
	PE2	Using GenAI allows me to accomplish academic tasks more quickly.
Effort Expectancy	EE1	Learning to use Generative AI through prompting is easy for me.
	EE2	It is easy to get GenAI to do exactly what I want it to do.
Social Influence	SI1	My colleagues are increasingly using GenAI in their teaching and research.
	SI2	My institution encourages the use of AI tools for professional development.
Facilitating Conditions	FC1	I have access to the hardware (laptop/smartphone) and data needed for GenAI.
	FC2	I can keep my devices charged long enough to interact with GenAI platforms.
Algorithmic Trust	TR1	I trust the accuracy of information generated by AI tools like ChatGPT.
	TR2	I feel confident that GenAI outputs meet scholarly rigor after my verification.
Behavioral Intention	BI1	I intend to use Generative AI tools frequently in the coming semester.
	BI2	I plan to integrate GenAI into my departmental research workflows.