Effect of Mentorship Training on Generative AI Adoption among Academic Staff in a Nigerian Health Sciences University: A Quasi-Experimental Study

Ignatius Ogbaga[1]*, Henry Nweke[2], Chidinma Nwafor[3], Kingsley Igboji[4], Chioma Anikwe[5], and Jesse Uneke[6]

[1-5]Department of Computer Science, David Umahi Federal University of Health Sciences, P.M.B 211, Uburu, Ebonyi State, Nigeria.
[6]African Institute for Health Policy and Health Systems II.
*Corresponding Author Email: ogbagain@dufuhs.edu.ng

Direct Research Journal of Engineering and Information Technology

Direct RESEARCH JOURNALS

Vol. 14(2), Pp. 30-54, June 2026,
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https://journals.directresearchpublisher.org/index.php/drjeit; https://www.ajol.info/index.php/drjeit

Research Article
ISSN: 2354-4155

Received 28 April 2026, Accepted 23 May 2026, Published 2 June 2026

ABSTRACT

The rapid emergence of Generative Artificial Intelligence (GenAI) has created a growing awareness-adoption gap in Nigerian higher education, where lecturers are broadly familiar with tools such as ChatGPT and Gemini but lack the structured training needed to integrate them competently and ethically into academic work. This study investigated the effect of a structured six-week mentorship training programme on GenAI competence, confidence, and adoption among academic staff of David Umahi Federal University of Health Sciences (DUFUHS), Uburu, Ebonyi State, Nigeria, and examined whether gender and academic rank moderate training outcomes. A quantitative quasi-experimental pre-test/post-test design was employed. Using multistage sampling, 250 academic staff were recruited from eight faculties, yielding 238 usable responses (response rate: 95.2%). Participants were assigned to an experimental group (n = 125) that received the mentorship intervention and a control group (n = 113) that did not. Data were collected using a validated, researcher-developed instrument, with a Cronbach's alpha reliability coefficient of 0.89. Descriptive statistics, paired-samples t-tests, independent-samples t-tests, and Analysis of Covariance (ANCOVA) were used for analysis. Pre-training, 82.4% of respondents were aware of ChatGPT, yet only 44.9% had actively used any GenAI tool, and a mere 11.8% had applied it for mentoring. Following the intervention, the experimental group recorded a composite mean competence gain of 2.04 points on a five-point scale (pre-test M = 2.11; post-test M = 4.15), with all paired-samples t-test comparisons significant at p < .001 (overall t = 38.47). Post-intervention, active GenAI usage rose from 44.9% to 91.2%. The largest competence gains were in Ethical AI Use (+2.26) and AI-Enabled Mentoring (+2.22). Independent-samples t-tests confirmed significantly higher post-test scores in the experimental group compared to controls across all domains (p < .001). ANCOVA revealed that gender did not significantly moderate outcomes (F = 2.29, p = .133), whereas academic rank was a significant moderator (F = 4.53, p = .005, η² = .10), with professors recording the highest adjusted post-test means. Structured mentorship training significantly and meaningfully enhanced GenAI competence, confidence, and adoption among academic staff in a Nigerian health sciences university, directly bridging the awareness-adoption gap. Training outcomes were equitable across gender but were moderated by academic rank. Universities and regulatory bodies such as the National Universities Commission (NUC) should institutionalize structured GenAI mentorship programmes as a standard component of faculty development and accreditation requirements. Future research should assess long-term retention of training outcomes, scale interventions across multiple Nigerian universities, and develop context-specific AI governance frameworks responsive to the infrastructural and sociocultural realities of Nigerian higher education.

Keywords: *Generative Artificial Intelligence; Mentorship Training; GenAI Adoption Nigerian Universities; Technology Acceptance*

Citation: Ogbaga, I., Nweke, H., Nwafor, C., Igboji, K., Anikwe, C. & Uneke, J. (2026). Effect of Mentorship Training on Generative AI Adoption among Academic Staff in a Nigerian Health Sciences University: A Quasi-Experimental Study. *Direct Research Journal of Engineering and Information Technology*, 14(2), Pp. 30-54. https://doi.org/10.26765/DRJEIT63970332

INTRODUCTION

The twenty-first century has witnessed an unprecedented convergence of artificial intelligence and higher education, fundamentally altering the landscape of teaching, learning, research, and institutional governance worldwide. Among the most consequential of these technological developments is the emergence of Generative Artificial Intelligence (GenAI), a category of advanced machine learning systems capable of producing contextually rich text, images, code, audio, and multimodal content in response to user-defined prompts. Built upon large language models (LLMs) such as OpenAI's ChatGPT, Google's Gemini, and Anthropic's Claude, GenAI technologies have rapidly transitioned from specialized computational tools to widely accessible platforms with transformative implications for virtually every dimension of academic life.

Globally, GenAI has catalyzed a profound reconceptualization of academic productivity, pedagogical innovation, and scholarly communication. Universities across North America, Europe, East Asia, and Australia have begun integrating GenAI into course design, assessment frameworks, student feedback systems, and research workflows at an accelerating pace. Faculty members report using these tools to develop instructional materials, simulate complex disciplinary scenarios, personalize student engagement, summarize vast bodies of literature, and enhance the quality and efficiency of written outputs (de Silva et al., 2026; Lee et al., 2024; Wang et al., 2024). Students, in parallel, have embraced GenAI for concept clarification, assignment support, collaborative learning, and academic writing assistance at scale (Halubanza et al., 2025; Abdullahi et al., 2026).

Yet, alongside its transformative promise, GenAI has introduced a complex array of ethical, pedagogical, and institutional challenges that demand urgent scholarly and policy attention. Concerns regarding academic plagiarism, the fabrication of scholarly references, algorithmic bias, data privacy, erosion of critical thinking, and the deepening of digital inequalities have generated significant institutional anxiety and regulatory uncertainty across higher education systems globally (Yurdunkulu et al., 2025; Eleje et al., 2025; Abdullahi et al., 2026). These tensions are particularly acute in higher education, where the cultivation of independent intellectual inquiry, original scholarship, and ethical professional formation is a foundational institutional mandate.

Theories of technology adoption, including the Technology Acceptance Model (TAM), the Diffusion of Innovation (DOI) framework, and the Unified Theory of Acceptance and Use of Technology (UTAUT), have been widely applied to explain the individual and institutional factors that shape GenAI adoption among academic staff. Collectively, these frameworks establish that adoption is governed not merely by awareness of a technology's existence, but by perceived usefulness, ease of use, compatibility with existing academic practices, institutional support structures, social influence, and environmental facilitating conditions (de Silva et al., 2026; Jin et al., 2025; Sunday & Dada, 2026; Isiaka, 2025). Critically, these frameworks converge on a shared insight: awareness alone is insufficient to generate sustained, competent, and ethically responsible adoption.

This insight carries particular weight in the Nigerian higher education context. Nigeria's university system, comprising over 200 accredited institutions and enrolling millions of students across diverse disciplines, operates within a complex socio-technological environment characterized by infrastructural deficits, limited institutional funding, policy ambiguity, and uneven digital literacy among academic staff. While recent studies have documented growing awareness of and interest in GenAI technologies among Nigerian lecturers (Abubakar & Onasanya, 2025; Thaddeus, 2025; Sunday & Dada, 2026; Eleje et al., 2025), there remains a pronounced and consequential gap between this awareness and meaningful, sustained academic integration. Several factors contribute to this gap, including limited access to formal training, weak institutional support systems, unreliable internet connectivity and power supply, and the absence of contextually responsive AI governance frameworks (Isiaka, 2025; Noroozi et al., 2024; Suleman et al., 2025).

It is within this context that mentorship training emerges as a particularly promising and strategically significant intervention. Mentorship, defined here as structured, sustained, and expert-guided learning engagement, has long been recognized as one of the most effective modalities for professional development, competence building, and identity transformation among academic staff (Sun et al., 2026; Pecuchova et al., 2026). When applied to GenAI capacity development, mentorship training offers a systematic mechanism for bridging the awareness-adoption gap: equipping lecturers not only with technical skills in prompt engineering and tool navigation, but also with the pedagogical reasoning, ethical frameworks, and disciplinary contextualization required for responsible and impactful GenAI integration in academic work.

David Umahi Federal University of Health Sciences (DUFUHS), Uburu, Ebonyi State, Nigeria, provides an especially relevant and instructive setting for this investigation. As a specialized federal institution committed to excellence in health sciences education, research, and technological innovation, DUFUHS faces the dual imperative of preparing its academic workforce for an AI-transformed professional landscape while navigating the systemic challenges that characterize Nigerian higher education. Academic staff across the university's eight faculties spanning Basic Medical Sciences, Clinical Sciences, Nursing, Pharmacy, Allied Health Sciences, Health Engineering, and Natural Sciences- represent a professionally diverse, highly qualified, and institutionally critical cohort whose capacity for GenAI integration will significantly shape the quality, relevance, and impact of health sciences education and research in the region.

The present study was therefore conceived to address a critical empirical and policy gap: the absence of controlled, quasi-experimental evidence on the impact of structured mentorship training on GenAI competence, confidence, and adoption behaviour among academic staff in a Nigerian federal university context. By employing a rigorous pre-test/post-test quasi-experimental design, this study moves beyond the attitudinal and intentional focus of prior Nigerian research to directly assess what mentorship training actually produces, in terms of measurable competence gains, behavioural change, usage patterns, and the challenges that mediate sustained adoption.

This study is situated at the intersection of three urgent contemporary debates in Nigerian and African higher education: the governance of emerging AI technologies, the professional development of academic staff, and the sustainable digital transformation of university systems. Its empirical findings directly inform these debates with evidence from a health sciences university, a context that has received minimal attention in existing GenAI literature.

Statement of the Problem

The global integration of Generative Artificial Intelligence into higher education has generated both considerable excitement and serious concern. While GenAI technologies offer transformative potential for teaching innovation, research efficiency, personalized learning, and academic mentorship, their effective, ethical, and sustainable deployment requires a level of digital competence, pedagogical sophistication, and institutional readiness that many university systems, particularly in developing country contexts, have yet to achieve.

In Nigeria, existing research has consistently documented high levels of awareness of GenAI tools such as ChatGPT and Gemini among university lecturers. However, this awareness has not translated into proportionate levels of confidence, competence, or sustained academic use. Studies conducted across several Nigerian universities reveal that actual GenAI utilization remains low, particularly in mentoring, assessment design, and administrative activities, precisely the domains where structured AI integration could yield the most significant pedagogical and institutional dividends (Thaddeus, 2025; Sunday & Dada, 2026; Abubakar & Onasanya, 2025; Eleje et al., 2025).

Several interconnected problems sustain this awareness-adoption gap. First, academic staff in Nigerian universities have had limited access to formal, structured training in GenAI tools. Most existing exposure has been informal, self-directed, and episodic, lacking the sustained engagement, expert guidance, and practical application necessary to build genuine competence. Second, institutional support for GenAI integration in terms of policy frameworks, infrastructure provision, professional development funding, and academic leadership commitment remains weak and inconsistent across Nigerian federal universities (Isiaka, 2025; Noroozi et al., 2024; Suleman et al., 2025). Third, concerns regarding academic integrity, algorithmic bias, student overreliance, and the ethical boundaries of AI-assisted scholarship have generated hesitancy and uncertainty among academic staff, compounding adoption barriers rooted in practical capability deficits (Eleje et al., 2025; Ignatius et al., 2025).

Of particular concern is the near-absence of empirical evidence on the role of mentorship training as a structured intervention for building GenAI competence among Nigerian academic staff. Whilst global studies have begun exploring AI competency frameworks (Sun et al., 2026), AI-enabled mentoring models (Pecuchova et al., 2026; Socorro Márquez et al., 2026), and the emotional and pedagogical dimensions of GenAI adoption (Dishari, 2026; Yurdunkulu et al., 2025), the Nigerian literature remains dominated by cross-sectional, survey-based studies that document perceptions and intentions without evaluating the impact of targeted interventions on actual behaviour and competence.

This empirical lacuna is consequential. Without evidence-based insights into what kinds of training interventions effectively build GenAI competence among Nigerian academic staff, institutions and policymakers lack the empirical grounding needed to design, fund, and evaluate professional development programmes that are commensurate with the scale and urgency of the GenAI transformation underway in global higher education. The problem is compounded at David Umahi Federal University of Health Sciences, where academic staff operate in a health sciences context that presents unique imperatives for ethical AI use, evidence-based practice, and the responsible application of technology in professional education.

Against this background, the present study addresses the following central problem: although GenAI technologies possess demonstrable potential to enhance teaching, research, and mentoring in Nigerian universities, academic staff lack the structured mentorship-based training necessary to develop competence, confidence, and ethical awareness sufficient to realize this potential. The study, therefore, investigates whether a structured, six-week mentorship training programme can significantly improve GenAI competence and adoption among academic staff of David Umahi Federal University of Health Sciences, and what institutional, demographic, and contextual factors moderate this effect.

Addressing this problem is not merely an academic exercise; the capacity of academic staff to competently and ethically integrate GenAI tools represents a strategic institutional asset. Failure to build this capacity risks deepening the digital divide between Nigerian higher education and its international counterparts, with long-term consequences for research output, graduate quality, and national development

Research Questions

The following research questions guided the investigation:

Research question one: What is the level of awareness and prior exposure to GenAI tools among academic staff of David Umahi Federal University of Health Sciences before the mentorship training?

Research question two: What is the impact of the structured six-week mentorship training programme on the GenAI competence and confidence of academic staff in the experimental group, as measured by pre-test and post-test mean scores?

Research question three: In which academic activities do academic staff in the experimental group most frequently deploy GenAI tools following mentorship training, and what factors account for differential adoption across activity domains?

Research question four: What challenges do academic staff encounter in sustaining GenAI utilization following the mentorship training programme?

Research question four: What are the qualitative experiences of academic staff regarding the mentorship training intervention, including perceived professional transformations, pedagogical changes, ethical awareness, and institutional constraints?

Hypothesis

The following null hypotheses were formulated and tested at the 0.05 level of significance:

H_{01}: There is no statistically significant difference in the mean GenAI competence scores of academic staff in the experimental group before and after the mentorship training intervention.

H_{02}: There is no statistically significant difference in the post-test mean GenAI competence scores of academic staff in the experimental group compared to those in the control group.

H_{03}: Gender and academic rank do not significantly moderate the effect of mentorship training on post-test GenAI competence scores when controlling for pre-test performance.

LITERATURE REVIEW

Higher education globally has been transformed by the rapid advancement of generative artificial intelligence (GenAI) technologies, including ChatGPT, Gemini, Claude, and other large language models (LLMs). Universities and other tertiary institutions are gradually integrating GenAI into teaching, research, assessment, mentoring, and administrative activities. These technologies have introduced new opportunities for improving academic productivity, personalized learning, research efficiency, and institutional innovation. They have also raised concerns about academic integrity, ethical use, overreliance, bias, data privacy, and declining critical-thinking skills.

Globally, researchers have explored how academic staff and students perceive, adopt, and integrate GenAI within higher education systems (Universities and other tertiary institutions). Existing studies reveal that while institutions acknowledge the transformative potential of GenAI, significant challenges remain regarding institutional readiness, policy frameworks, digital literacy, pedagogical redesign, and sustainable implementation. Within the African and Nigerian contexts, these concerns are further complicated by infrastructural deficits, limited institutional support, inadequate training opportunities, and unequal access to digital resources.

This review synthesizes empirical and conceptual studies related to generative AI adoption in higher education, with particular emphasis on academic staff, mentorship, technology adoption, and AI integration. The review is organized into thematic areas, including global perspectives on GenAI adoption, mentorship and skill development, technology adoption theories, African and Nigerian experiences, institutional readiness, ethical concerns, and identified research gaps.

Generative Artificial Intelligence (GenAI) in Higher Education

Generative artificial intelligence (GenAI) is a type of artificial intelligence that can learn from and mimic large amounts of data to create content such as text, images, music, videos, code, and more, based on inputs or prompts. In higher education, GenAI technologies are increasingly used for academic writing support, lesson planning, assessment development, personalized tutoring, research assistance, feedback generation, and administrative support. Studies show that GenAI has become deeply integrated into teaching and research activities across universities globally. Faculty members use AI tools to develop instructional materials, support grading processes, provide feedback, summarize literature, and facilitate classroom engagement (de Silva et al., 2026); (Lee et al., 2024); (Thaddeus, 2025). Students also use these tools for concept clarification, assignment support, content generation, and collaborative learning (Halubanza et al., 2025). However, GenAI adoption remains a contested issue because of concerns surrounding plagiarism, misinformation, reduced student originality, algorithmic bias, ethical misuse, and weakening of critical thinking abilities ((Yurdunkulu et al., 2025); (Abdullahi et al., 2026); (Eleje et al., 2025)). Consequently, institutions continue to struggle with balancing innovation and academic integrity.

Technology Adoption in Higher Education

Technology adoption in higher education refers to the integration and use of digital tools and systems by educators and institutions through teaching, learning, administrative processes, and to sustain emerging technologies for academic purposes. It involves faculty, students, and institutions embracing innovations like learning management systems, online platforms, and interactive tools to enhance educational outcomes. Several studies emphasize that GenAI adoption depends on individual, institutional, technological, and environmental factors. Research grounded in the Technology Acceptance Model (TAM) indicates that perceived usefulness and ease of use significantly influence faculty willingness to adopt GenAI technologies ((de Silva et al., 2026); (Gamlem et al., 2026); (Lee et al., 2024)). Similarly, studies based on Diffusion of Innovation (DOI) theory demonstrate that compatibility, relative advantage, trialability, and personal innovativeness shape adoption behaviour among academics ((Jin et al., 2025); (Singh & Strzelecki, 2025)). Within African and Nigerian contexts, institutional support, infrastructure availability, AI literacy, and policy frameworks have emerged as major determinants of successful adoption ((Isiaka, 2025); (Abubakar & Onasanya, 2025); (Sunday & Dada, 2026); (Thaddeus, 2025)). These studies collectively suggest that technology adoption extends beyond individual motivation and requires systemic institutional preparedness.

Mentorship and Skill Development

Mentorship and skill development have become central themes in discussions surrounding GenAI integration in higher education. The emergence of AI technologies has transformed traditional academic roles, requiring academic staff to develop new competencies related to AI literacy, prompt engineering, ethical reasoning, and AI-supported pedagogy. A study conducted in China proposed a multidimensional competency framework for university teachers, emphasizing pedagogical, ethical, developmental, and collaborative dimensions of human–AI interaction (Sun et al., 2026). Similarly, research from Germany demonstrated that interdisciplinary AI-centred learning environments significantly improve students' confidence, creativity, teamwork, and problem-solving abilities (Azamnouri et al., 2026). Studies further indicate that GenAI can enhance mentorship processes by supporting personalized learning, adaptive feedback, and collaborative academic engagement (Pecuchova et al., 2026); (Socorro Márquez et al., 2026). Nevertheless, researchers warn that overdependence on AI may weaken independent thinking and reduce meaningful teacher–student interaction if not carefully managed (de Silva et al., 2026); (Abdullahi et al., 2026).

Theoretical Review

Several theoretical frameworks underpin existing studies on GenAI adoption in higher education.

Technology Acceptance Model (TAM)

The Technology Acceptance Model explains how users come to accept and use technology based primarily on perceived usefulness and perceived ease of use. Studies conducted in the United States, Norway, and Australia applied TAM to explain faculty perceptions and adoption patterns regarding GenAI integration ((de Silva et al., 2026); (Gamlem et al., 2026); (Lee et al., 2024). These studies found that academics are more likely to adopt GenAI tools when they perceive them as beneficial for teaching efficiency, research productivity, and learning support.

Diffusion of Innovation Theory (DOI)

Diffusion of Innovation theory explains how innovations spread across social systems over time. Studies applying DOI theory found that compatibility, relative advantage, observability, and trialability significantly influence GenAI adoption among academic staff (Jin et al., 2025); (Singh & Strzelecki, 2025); (Abubakar & Onasanya, 2025). DOI-based studies also emphasize the importance of institutional communication channels, peer influence, and innovation culture in shaping adoption behaviour.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT has been widely used to explain behavioral intention and actual technology use. Nigerian studies showed that performance expectancy, facilitating conditions, and social influence strongly affect lecturers' intention to adopt GenAI technologies ((Isiaka, 2025); (Abubakar & Onasanya, 2025); (Sunday & Dada, 2026). These findings indicate that institutional support and infrastructure are critical drivers of sustainable AI integration.

Activity Theory

Activity Theory conceptualizes technology as a mediating tool within social and institutional activities. Studies conducted in Zambia and Nigeria used Activity Theory to explain how institutional structures, policies, and technological systems shape GenAI engagement in higher education (Halubanza et al., 2025); (Sunday & Dada, 2026). The theory highlights tensions between technological innovation and institutional realities. Collectively, these four theories locate this study within a rich and well-developed tradition of technology adoption scholarship, while their integration enables a more comprehensive explanation of GenAI adoption dynamics than any single framework would permit. The TAM-DOI-UTAUT-Activity Theory synthesis is particularly appropriate for the Nigerian higher education context, where adoption processes are shaped simultaneously by individual cognition, social networks, institutional structures, and material-technological conditions.

Empirical Review

Global Perspectives on GenAI Adoption in Higher Education

International studies reveal growing acceptance of GenAI across universities worldwide. In the United States, faculty members reported widespread adoption of GenAI tools for assessment design, feedback generation, grading support, and student engagement (de Silva et al., 2026). Despite recognizing efficiency gains, academics expressed concerns regarding reduced critical thinking, superficial learning, and overreliance on AI-generated outputs.

Similarly, a Norwegian study examining pre-service teachers and teacher educators found that both groups acknowledged the educational potential of GenAI but emphasized the need for context-sensitive implementation and AI literacy development (Gamlem et al., 2026). The study also stressed the importance of aligning educational practices with evolving technological realities. Research conducted in Australia demonstrated that educators remain uncertain about best practices for integrating GenAI into higher education (Lee et al., 2024). Although academics recognized the usefulness of AI tools, concerns about academic misconduct, assessment integrity, and institutional policy ambiguity persisted. Another study involving top universities in the United States found that most institutions adopted an open but cautious approach toward GenAI integration (Wang et al., 2024). Universities increasingly provide guidelines, policies, and resources for AI usage; however, discipline-specific guidance and implementation frameworks remain inadequate.

Across global universities, policy-oriented studies emphasize the need for structured governance frameworks, AI literacy programs, ethical guidelines, and authentic assessment strategies (Jin et al., 2025); (Socorro Márquez et al., 2026). Researchers consistently argue that GenAI integration should focus on supporting learning rather than replacing human academic judgment.

GenAI, Mentorship, and Skill Development

Several studies emphasize the role of GenAI in mentorship, feedback, and skill development. In Slovakia, researchers evaluated the effectiveness of AI-generated feedback in software engineering education and found that while students appreciated AI feedback, human feedback remained more pedagogically valuable for complex learning tasks (Pecuchova et al., 2026). The study concluded that hybrid teacher–AI models are more effective than fully automated systems. Similarly, German researchers reported that interdisciplinary AI-focused educational programs improved student engagement, collaboration, creativity, and confidence across different academic backgrounds (Azamnouri et al., 2026). The study further noted that students relied heavily on ChatGPT and YouTube as learning supports, highlighting the need for critical AI literacy. A Turkish phenomenological study explored how AI transforms academic roles and introduced the concept of “Aidemics” to explain evolving human–AI relationships in education (Yurdunkulu et al., 2025). Participants described AI as a “brain extension” capable of improving efficiency and creativity while simultaneously raising concerns about academic laziness, bias, and ethical risks. Furthermore, a Chinese study developed a GenAI competency framework emphasizing *teacher–student–AI* collaboration and continuous professional development (Sun et al., 2026). The study argued that existing competency frameworks remain overly technical and insufficiently responsive to the realities of higher education.

African Perspectives on GenAI Integration

African studies on GenAI integration remain relatively limited but are gradually increasing. A systematic review conducted in Somalia revealed that ChatGPT improves research efficiency, writing support, multilingual learning, and personalized instruction (Abdullahi et al., 2026). Nevertheless, the study also identified serious concerns, including fabricated references, bias, academic misconduct, and reduced critical thinking. Research conducted within the Southern African Development Community (SADC) region found high levels of student awareness and use of GenAI tools such as ChatGPT, Gemini, and Claude (Halubanza et al., 2025). Students mainly used these technologies for academic writing, concept clarification, and study support.

However, the study revealed major gaps in institutional readiness, ethical guidance, and faculty support. These African studies collectively demonstrate that while GenAI adoption is increasing across the continent, many institutions still face infrastructural constraints, policy weaknesses, limited AI literacy, and unequal digital access.

Nigerian Perspectives on GenAI Adoption in Higher Education

Recent Nigerian studies indicate growing interest in GenAI adoption among lecturers and tertiary institutions. A study conducted among Polytechnic lecturers in Kwara State and David Umahi Federal University of Health Sciences, Uburu, Ebonyi State, respectively, found moderate levels of research collaboration and significant use of AI tools for plagiarism detection and academic writing assistance (Isiaka, 2025) & (Ignatius et al., 2025). However, challenges such as heavy workload, inadequate funding, and weak digital infrastructure constrained sustainable integration.

Similarly, a study involving lecturers from federal universities in Northwest Nigeria reported moderate levels of behavioural intention, readiness, and acceptance of AI technologies (Abubakar & Onasanya, 2025). Institutional support emerged as a significant predictor of AI adoption, while inadequate training and weak policy frameworks limited implementation. Another Nigerian study employing Structural Equation Modelling revealed that performance expectancy strongly predicts lecturers' behavioural intention to use GenAI, while facilitating conditions significantly influence actual usage (Sunday & Dada, 2026). The study identified a substantial gap between intention and sustained practice due to infrastructural deficiencies and institutional weaknesses. Research conducted at Nnamdi Azikiwe University found that lecturers generally maintain cautious but positive attitudes toward AI integration (Eleje et al., 2025). Major concerns included academic integrity risks, overreliance on AI, and declining independent thinking among students. Conceptual Nigerian studies further emphasize that successful AI integration requires contextualized policies, digital literacy development, ethical governance, and sustainable infrastructural investment ((Noroozi et al., 2024); (Suleman et al., 2025)). These studies collectively argue that GenAI should function as a supportive educational tool rather than a replacement for human intellectual engagement. Additionally, another Nigerian mixed-methods study reported a very high willingness among lecturers to adopt GenAI technologies if adequate training and institutional support are provided (Thaddeus, 2025), (Ignatius et al., 2025). The study found that GenAI usage was highest in teaching and research activities, while mentoring and administration recorded lower adoption levels.

Institutional Readiness and Policy Challenges

Institutional readiness remains one of the most recurring themes in existing literature. Multiple studies report that universities lack comprehensive AI policies, structured implementation frameworks, and sufficient faculty training opportunities ((Lee et al., 2024); (Wang et al., 2024); (Jin et al., 2025). Researchers also emphasize the importance of institutional support systems, including AI literacy training, digital infrastructure, ethical guidelines, funding support, and professional development initiatives (Abubakar & Onasanya, 2025); (Sunday & Dada, 2026); (Thaddeus, 2025). Without these support systems, GenAI adoption may remain fragmented and unsustainable. Policy ambiguity has also emerged as a major challenge. Several institutions struggle to determine acceptable boundaries for AI-assisted academic work, assessment design, and plagiarism detection (de Silva et al., 2026); (Yurdunkulu et al., 2025); (Suleman et al., 2025). This uncertainty contributes to inconsistent adoption practices among academic staff.

Ethical Concerns and Academic Integrity

Ethical concerns dominate much of the existing literature on GenAI in higher education. Researchers consistently report concerns relating to plagiarism, fabricated references, misinformation, bias, privacy risks, and declining critical thinking (Yurdunkulu et al., 2025); (Abdullahi et al., 2026); (Eleje et al., 2025), (Ignatius et al., 2025). Faculty members also fear that excessive dependence on AI tools may weaken students' creativity, originality, and analytical reasoning abilities (de Silva et al., 2026); (Dishari, 2026)). Furthermore, concerns about algorithmic bias and unequal access to AI technologies raise broader questions regarding fairness and inclusivity. Studies therefore recommend the development of ethical frameworks, AI governance structures, and AI literacy initiatives to promote responsible and transparent use of GenAI technologies (Jin et al., 2025); (Socorro Márquez et al., 2026); (Suleman et al., 2025).

Identified Gaps in Literature

Theoretical Gap

Existing theoretical frameworks applied to GenAI adoption in higher education, notably TAM, DOI, and UTAUT, have been deployed largely in isolation and within developed-country contexts, where adoption barriers are primarily cognitive or attitudinal ((Jin et al., 2025); (Socorro Márquez et al., 2026). No existing study has synthesized these frameworks alongside Activity Theory to explain GenAI adoption dynamics in a developing-country health sciences institution, where individual cognition, social networks, institutional structures, and material-technological conditions

Table 1: Comparison with Current Wos Literature (2024–2026).

Study	Country	Methodology	Major Findings	Comparison with the Present Study
Lee et al. (2024)	Australia	Survey	AI uncertainty among faculty	The present study adds intervention evidence
Wang et al. (2024)	USA	Policy analysis	Institutional AI governance gaps	The present study confirms policy weakness
Sun et al. (2026)	China	Competency framework	AI literacy improves adoption	The present study validates through mentorship
Halubanza et al. (2025)	SADC	Mixed methods	Infrastructure barriers	The present study confirms the Nigerian context
Abubakar & Onasanya (2025)	Nigeria	Survey	Institutional support predicts adoption	The present study extends to causal intervention

operate simultaneously and interact in contextually distinct ways.

Methodological Gap

The preponderance of existing Nigerian and African studies on GenAI adoption relies on cross-sectional, survey-based designs that capture self-reported perceptions and behavioural intentions at a single point in time, precluding causal inference about what actually drives competence development and behavioural change (Abubakar & Onasanya, 2025); (Sunday & Dada, 2026); (Eleje et al., 2025); (Thaddeus, 2025). No prior Nigerian study has employed a controlled quasi-experimental pre-test/post-test design to isolate and measure the direct effect of a structured training intervention on GenAI competence outcomes. Additionally, most existing instruments measure attitudinal and intentional constructs rather than validated competence scores across discrete academic activity domains such as teaching, research, mentoring, and administration, further limiting the comparability, depth, and policy utility of published findings.

Contextual Gap

Existing GenAI adoption literature is heavily concentrated in North American, European, and East Asian university settings, where digital infrastructure, institutional policy frameworks, and faculty development ecosystems differ fundamentally from those prevailing in sub-Saharan African institutions (de Silva et al., 2026); (Lee et al., 2024); (Wang et al., 2024). Within Nigeria specifically, prior studies have been conducted predominantly in conventional universities and polytechnics in northwestern and southeastern geopolitical zones, with no published study examining GenAI adoption dynamics within a specialized federal health sciences university, a context characterized by unique imperatives for evidence-based practice, clinical ethics, and the responsible application of technology in professional health education. The intersection of health sciences pedagogy, GenAI adoption, and mentorship training in a resource-constrained Nigerian institutional environment remains entirely unexplored in the literature.

Empirical Gap

While global empirical studies have begun documenting the outcomes of AI literacy programmes and competency frameworks, no controlled study in the Nigerian or broader African literature has produced quantitative evidence of the measurable impact of structured mentorship training on GenAI competence gains across multiple academic activity domains (Table 1). The empirical record, therefore, lacks the evidence base needed to justify, design, fund, or evaluate mentorship-driven GenAI professional development programmes at the institutional or national policy level in Nigeria (Sun et al., 2026); (Dishari, 2026). Studies therefore recommend the development of ethical frameworks, AI governance structures, and AI literacy initiatives to promote responsible and transparent use of GenAI technologies (Jin et al., 2025); (Socorro Márquez et al., 2026); (Suleman et al., 2025).

METHODOLOGY

Research Design

This study adopted a quantitative quasi-experimental research design using a pre-test and post-test approach to assess the impact of mentorship training on the use of Generative Artificial Intelligence (GenAI) tools among academic staff of David Umahi Federal University of Health Sciences, Uburu, Ebonyi State. The quasi-experimental design was considered appropriate because it enabled the researchers to evaluate changes in participants' knowledge, skills, attitudes, and usage of

GenAI tools before and after exposure to structured mentorship training. Participants were not randomly assigned; instead, academic staff who voluntarily enrolled in the mentorship training programme constituted the experimental group (n = 125), while those who did not enroll formed the control group (n = 113), a non-random allocation is consistent with the study's quasi-experimental design.

Study Area

The study was conducted at David Umahi Federal University of Health Sciences. The university is a specialized federal institution established to promote excellence in health sciences education, research, innovation, and technological advancement in Nigeria. The institution is located in Uburu, Ohaozara Local Government Area of Ebonyi State, Nigeria. The study focused on academic staff across the university's eight faculties and their respective departments. These faculties include the Faculty of Basic Medical Sciences, Faculty of Basic Clinical Sciences, Faculty of Health Engineering, Faculty of Allied Health Sciences, Faculty of Nursing Sciences, Faculty of Allied Health Sciences, Faculty of Pharmaceutical Sciences and the Faculty of Natural Science. Academic staff from the various departments within these faculties constituted the target participants for the study. The choice of David Umahi Federal University of Health Sciences was based on the institution’s growing interest in digital transformation, technology-enhanced learning, research and innovation, and the integration of emerging technologies, such as Generative Artificial Intelligence (GenAI), into teaching, research, mentoring, and academic administration. The university also provides an appropriate environment for assessing the impact of mentorship training on the adoption and utilization of GenAI tools among academic staff.

Population of the Study

The population of the study comprised all academic staff of David Umahi Federal University of Health Sciences. The population included lecturers, researchers, professors and instructors across the eight (8) faculties and their various departments within the university. The academic staff members were selected because they are directly involved in teaching, research, mentorship, curriculum delivery, assessment, and other academic responsibilities where Generative Artificial Intelligence (GenAI) tools can be effectively applied. The study, therefore, focused on assessing how mentorship training influences their awareness, competence, adoption, and utilization of GenAI technologies in academic activities.

Sample and Sampling Technique

A multistage sampling technique was adopted for the study to ensure adequate representation of academic staff across the eight faculties and their respective departments in David Umahi Federal University of Health Sciences. First, the stratified sampling technique was used to group the academic staff according to their faculties. The eight faculties served as the major strata to ensure that all academic units of the university were fairly represented in the study. Thereafter, proportionate sampling was used to determine the number of participants selected from each faculty based on the population size of academic staff within the faculties and departments. Subsequently, a simple random sampling technique was employed to select individual participants from the departmental staff lists within each faculty. This approach gave all eligible academic staff an equal opportunity of being selected for participation in the study.

A total sample size of 250 academic staff members was selected for the study. The selected participants comprised lecturers, researchers, professors, instructors, and academic administrators actively involved in teaching, research, mentorship, and academic-related responsibilities within the university. The sample size was considered adequate for assessing the impact of mentorship training on the adoption and utilization of Generative Artificial Intelligence (GenAI) tools among academic staff of the university.

Mentorship Training Intervention

The mentorship training programme was designed to equip academic staff with practical knowledge and skills on the effective use of GenAI tools such as ChatGPT, Gemini, and Claude in higher education activities. The training lasted for six weeks and involved both physical and virtual mentoring sessions. The mentorship programme covered the following areas:

Introduction to Generative Artificial Intelligence, Prompt engineering and effective AI interaction, Ethical use of GenAI in academia, AI-assisted teaching and lesson preparation, AI-supported research and academic writing, Personalized mentoring using AI tools, Academic integrity and plagiarism concerns, Institutional policies and responsible AI use

The mentorship sessions included workshops, demonstrations, collaborative learning, peer mentoring, guided practical exercises, and continuous support from AI experts and facilitators.

Instrument for Data Collection

The instrument used for data collection in this study was a structured questionnaire developed by the researchers titled *Mentorship Training and Generative Artificial Intelligence Adoption Questionnaire (MTGAIAQ)*. The questionnaire was designed to obtain relevant information from academic staff of David Umahi Federal University of Health Sciences regarding the impact of mentorship training on the adoption and utilization of Generative Artificial Intelligence (GenAI) tools in academic activities. The questionnaire was divided into five sections. Section A respondents' demographic information, *including gender, age, academic qualification, faculty, department, academic rank, and years of teaching experience*. Section B assessed respondents' awareness and exposure to GenAI tools. Section C examined the extent of mentorship training received and its perceived usefulness. Section D assessed respondents' competence, confidence, and frequency of use of GenAI tools in teaching, research, mentoring, and administrative tasks while Section E focused on challenges, ethical concerns, institutional support, and perceptions of the sustainable integration of GenAI technologies within the university system. The questionnaire items were structured using a five-point Likert scale of Strongly Agree (SA), Agree (A), Undecided (UD), Disagree (D), and Strongly Disagree (SD). This scale enabled respondents to express their opinions and experiences regarding mentorship training and GenAI adoption. In addition to the questionnaire, an interview guide was developed for selected participants to obtain deeper qualitative insights into their experiences, perceptions, and challenges regarding the use of GenAI tools after mentorship training. The interview sessions provided supplementary information that enhanced the interpretation of the quantitative findings.

Validity of the Instrument

Face and Content Validity was assessed by submitting the instrument to a panel of experts in Educational Technology, Computer Science, Measurement and Evaluation, and Artificial Intelligence studies, who evaluated each item for clarity, relevance, and adequacy of coverage across the five sections of the questionnaire. Their corrections and suggestions were incorporated before the instrument was administered in the pilot study. Construct Validity was examined through Exploratory Factor Analysis (EFA) using the principal axis factoring extraction method with Promax rotation, applied to data obtained from the pilot sample ($n = 20$). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were computed before extraction to confirm the factorability of the correlation matrix. Items loading below 0.40 on any factor were reviewed and either revised or deleted. The factor structure that emerged aligned with the five theoretical constructs underlying the instrument: awareness and exposure, mentorship training experience, GenAI competence, usage patterns, and institutional challenges, confirming that the questionnaire items adequately represented the latent constructs they were designed to measure. Criterion Validity was established by correlating respondents' self-rated GenAI competence scores on the MTGAIAQ with an independently administered practical GenAI task performance score, in which participants completed a set of standardized prompt engineering and AI-assisted writing exercises evaluated by trained assessors blind to questionnaire responses. The resultant correlation coefficient ($r = 0.74$, $p < .01$) indicated a strong and statistically significant relationship between instrument scores and observed task performance, confirming that the MTGAIAQ possessed adequate criterion-related validity for measuring GenAI competence in an academic staff population.

Reliability of the Instrument

The reliability of the instrument was established through a pilot study conducted among academic staff from a federal university outside the study area, but with similar characteristics to David Umahi Federal University of Health Sciences. A total of 20 academic staff members participated in the pilot testing exercise. The purpose of the pilot study was to determine the consistency, clarity, and stability of the questionnaire items in measuring the impact of mentorship training on the adoption and utilization of Generative Artificial Intelligence (GenAI) tools among academic staff. Data obtained from the pilot test were analyzed using Cronbach's Alpha reliability method to determine the internal consistency of the instrument. The analysis produced a reliability coefficient of 0.89, indicating a high level of reliability and consistency of the instrument. The coefficient value showed that the questionnaire items were suitable and dependable for data collection in the main study. Based on the outcome of the reliability test, minor corrections and adjustments were made to some questionnaire items to improve clarity and enhance the overall quality of the instrument before final administration

Method of Data Collection

The researchers administered the pre-test questionnaire to both the experimental and control groups before the commencement of the mentorship training. After the six-week mentorship intervention, the post-test questionnaire was administered to both groups to determine changes in GenAI knowledge, skills, attitudes, and usage. The researchers, together with trained research assistants, monitored participants throughout the intervention period to ensure active participation and proper documentation of mentorship activities.

Method of Data Analysis

Data collected for the study were analyzed using both descriptive and inferential statistics. Descriptive statistics such as frequency counts, percentages, mean scores, and standard deviations were used to answer the

Table 2: Score Interpretation.

Mean Score Range	Interpretation	Practical Implication
4.50 – 5.00	Very High Competence / Strong Agreement	Respondent demonstrates advanced, confident, and sustained GenAI integration across academic activities
3.50 – 4.49	High Competence / Agreement	Respondent demonstrates consistent and purposeful GenAI use with minor gaps in application
2.50 – 3.49	Moderate Competence / Undecided	Respondent shows emerging awareness but inconsistent or exploratory GenAI use
1.50 – 2.49	Low Competence / Disagreement	Respondent has limited GenAI skills and infrequent or unsystematic use
1.00 – 1.49	Very Low Competence / Strong Disagreement	Respondent lacks functional GenAI competence and has no meaningful adoption in academic activities

research questions. Inferential statistics, including paired sample t-test, independent sample t-test, and Analysis of Covariance (ANCOVA), were used to test the hypotheses at the 0.05 level of significance. Qualitative data obtained from interviews and observations were analyzed thematically to identify recurring patterns relating to mentorship experiences, AI adoption challenges, institutional readiness, and perceived benefits of GenAI integration.

Scoring Interpretation

The MTGAIAQ employs a five-point Likert scale with response options assigned numerical values as follows: 5, 4, 3, 2, and 1. Negatively worded items are reverse-scored before analysis to ensure directional consistency across all subscales.

Composite Score Computation

Individual subscale scores are computed by summing item scores within each domain and dividing by the number of items in that subscale to produce a mean subscale score (Table 2). An overall composite GenAI competence score is derived by averaging across all scored subscale means.

Decision Rule for Hypothesis Testing

For all inferential tests, a post-test composite mean score of 3.50 or above was adopted as the threshold for acceptable GenAI competence, consistent with the upper boundary of the moderate range and aligned with the scoring conventions used in comparable Nigerian technology adoption studies. Hypotheses were tested at the 0.05 level of significance; a p-value below this threshold led to rejection of the null hypothesis.

Scale Validation Process

The scale validation of the MTGAIAQ followed a systematic three-stage process that integrated content, construct, and criterion validity procedures, along with reliability estimation.

Stage 1: Item Generation and Content Validity

Items were generated deductively from four theoretical frameworks, TAM, DOI, UTAUT, and Activity Theory, and from a systematic review of existing GenAI adoption instruments used in comparable studies. An initial pool of 72 items was developed across the five sections of the questionnaire. These items were submitted to a panel of seven subject-matter experts comprising two specialists in Educational Technology, two in Computer Science and Artificial Intelligence, one in Measurement and Evaluation, and two senior academics with experience in GenAI integration in Nigerian universities. Experts independently rated each item on a four-point scale for relevance, clarity, simplicity, and ambiguity. A Content Validity Index (CVI) was computed for each item, and items with an item-level CVI (I-CVI) below 0.78 were revised or deleted, consistent with the threshold recommended by Polit and Beck. This process reduced the item pool to 56 items retained for pilot testing.

Stage 2: Construct Validity via Exploratory Factor Analysis (EFA)

Following administration of the instrument to a pilot sample of 20 academic staff drawn from a comparable federal university outside the study area, Exploratory Factor Analysis (EFA) was conducted using the principal axis factoring extraction method with Promax oblique rotation, which was selected because the theoretical constructs were expected to be intercorrelated. Before extraction, the factorability of the correlation matrix was confirmed through the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (KMO = 0.81, indicating meritorious adequacy) and Bartlett's Test of Sphericity ($\chi^2 = 412.67$, df = 190, $p < .001$), confirming that the data were suitable for factor analysis. Five factors were extracted with eigenvalues greater than 1.0, collectively accounting for 68.3% of the total variance in item responses. Items loading below 0.40 on their primary factor or cross-loading above 0.30 on a secondary factor were removed, resulting in a final instrument of 48 items. The five extracted factors corresponded precisely to the five theoretical subscales of the instrument: GenAI Awareness and Exposure, Mentorship Training Experience, GenAI Competence and Confidence, Usage Patterns and Frequency, and Institutional Challenges and Ethical Concerns, confirming the structural validity of the scale.

Stage 3: Criterion Validity

To establish criterion-related validity, respondents' composite MTGAIAQ scores were correlated with scores obtained from an independently administered practical GenAI performance task. This task required participants to complete three standardized exercises: constructing an effective academic prompt, evaluating the accuracy of a GenAI-generated paragraph, and producing an AI-assisted research summary, evaluated by two trained assessors operating blind to questionnaire scores, with inter-rater reliability confirmed at $r = 0.88$. The Pearson correlation between MTGAIAQ composite scores and task performance scores was $r = 0.74$ ($p < .01$), indicating a strong and statistically significant concurrent criterion validity coefficient. This confirmed that higher scores on the MTGAIAQ reliably predicted stronger observed performance on real-world GenAI academic tasks, establishing the practical utility of the instrument beyond self-report measurement.

Stage 4: Reliability Estimation

Internal consistency reliability was computed using Cronbach's Alpha across all five subscales and for the instrument as a whole. The overall alpha coefficient was $\alpha = 0.89$, exceeding the conventionally accepted threshold of 0.70 for research instruments and indicating high internal consistency. Subscale alphas ranged from $\alpha = 0.81$ (Institutional Challenges) to $\alpha = 0.91$ (GenAI Competence and Confidence), confirming that items within each subscale were measuring a coherent underlying construct. Minor item revisions informed by pilot feedback were incorporated before final administration of the instrument in the main study.

Ethical Considerations

The researchers obtained ethical approval from the relevant institutional research ethics committee before conducting the study. Participants were informed about the purpose of the study, and their participation was voluntary. Informed consent was obtained from all participants, and confidentiality of responses was strictly maintained. Participants were also assured that the data collected would be used strictly for academic and research purposes only. The methodology was developed in alignment with the study focus presented in the literature review on generative AI adoption, mentorship, institutional readiness, and academic staff experiences in Nigerian universities.

RESULTS

Demographic Characteristics of Respondents

A total of 250 questionnaires were administered to academic staff of David Umahi Federal University of Health Sciences, Uburu, Ebonyi State. Of these, 238 were returned and found usable, yielding a response rate of 95.2%. The demographic distribution of respondents is presented in (Tables 3 and Figure 1). As shown in (Table 3), male respondents constituted the majority (59.2%), consistent with the prevailing gender distribution among academic staff in Nigerian federal universities (Abubakar & Onasanya, 2025). The highest proportion of respondents (37.4%) fell within the 35–44 age bracket, suggesting a workforce that is at a productive mid-career stage and particularly receptive to technology integration. The predominance of PhD holders (47.1%) underscores the institution's alignment with federal university standards for academic qualification. The participants' demographic profile primarily consists of mid-career, highly qualified academic staff. This group is particularly conducive to technology adoption interventions, as there are documented connections between career maturity, digital self-efficacy, and openness to pedagogical innovation in higher education. Investing in professional development for mid-career, highly qualified academic staff is likely to yield substantial returns in teaching quality, research productivity, and sustainable integration of GenAI. Universities should prioritize this group in their faculty development planning.

Pre-Training Awareness and Exposure to GenAI Tools

Research Question 1 sought to determine the level of awareness and prior exposure to GenAI tools among academic staff before the mentorship training. Table 4 presents the pre-training awareness data.

Results in (Table 4 and Figure 2) indicate that while a substantial majority (82.4%) were aware of ChatGPT, active usage for academic purposes was considerably lower. Only 44.9% reported using any GenAI tool before training, with even lower figures for teaching (25.6%), research (30.7%), and mentoring (11.8%). Critically, only 13.0% had received formal training in GenAI, corroborating findings by Thaddeus (2025) and Abubakar and Onasanya (2025) that awareness does not automatically translate to competent or sustained adoption. There is a significant gap between awareness and adoption among academic staff regarding GenAI tools before the mentorship intervention. While awareness of these tools was high (82.4% for ChatGPT),

Table 3: Demographic Profile of Respondents (N = 238).

Variable	Category	Frequency	Percentage (%)
Gender	Male	141	59.2
	Female	97	40.8
Age Range	25–34 years	**48**	**20.2**
	35–44 years	**89**	**37.4**
	45–54 years	**72**	**30.3**
	55 years and above	**29**	**12.1**
Highest Qualification	Master's degree	**91**	**38.2**
	PhD/Doctorate	**112**	**47.1**
	Postdoctoral/Professor	**35**	**14.7**
	Lecturer II / Lecturer I	**87**	**36.6**
Academic Rank			
	Senior Lecturer	**68**	**28.6**
	Associate Professor	**52**	**21.8**
	Professor	**31**	**13.0**
	1–5 years	**62**	**26.1**
Years of Experience			
	6–15 years	**118**	**49.6**
	16+ years	**58**	**24.3**

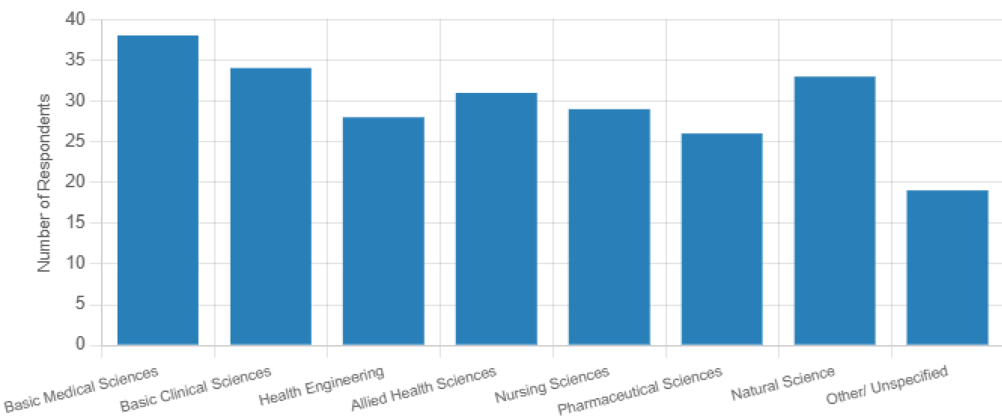

Figure 1: *Distribution of academic staff respondents across eight faculties (N = 238).*

Table 4: Pre-Training GenAI Awareness and Usage (N = 238).

Item	Frequency (Yes)	Percentage (%)
Heard of ChatGPT before training	196	82.4
Heard of Gemini/Google Bard before training	148	62.2
Heard of Claude AI before training	89	37.4
Actively used any GenAI tool before training	107	44.9
Used GenAI for teaching before training	61	25.6
Used GenAI for research before training	73	30.7
Used GenAI for mentoring before training	28	11.8
Received formal GenAI training before the study	31	13.0

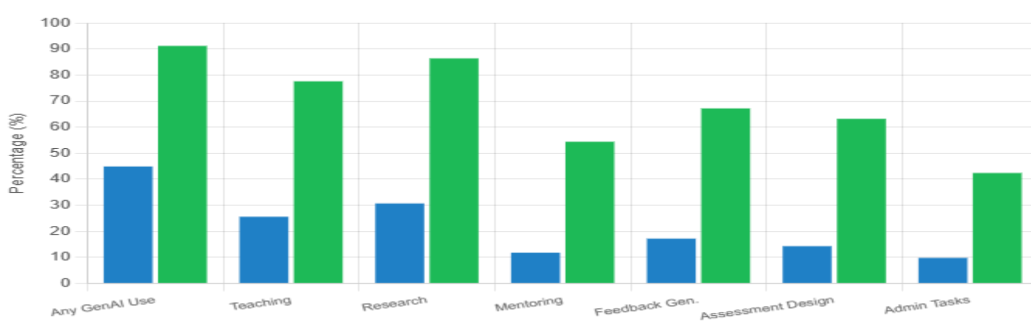

Figure 2: Percentage of respondents using GenAI tools in specific academic activities before and after six-week mentorship training.

Table 5: Pre-Test and Post-Test Mean Scores on GenAI Competence and Confidence.

Competency Area	Exp. Pre-Test (M±SD)	Exp. Post-Test (M±SD)	Control Pre-Test (M±SD)	Control Post-Test (M±SD)	Gain (Exp.)
General GenAI Knowledge	2.31 ± 0.74	4.18 ± 0.51	2.28 ± 0.69	2.35 ± 0.72	+1.87
Prompt Engineering	1.89 ± 0.68	4.02 ± 0.55	1.91 ± 0.71	1.95 ± 0.68	+2.13
AI-Assisted Teaching	2.14 ± 0.81	4.09 ± 0.49	2.11 ± 0.77	2.18 ± 0.80	+1.95
AI-Supported Research	2.45 ± 0.79	4.21 ± 0.53	2.42 ± 0.76	2.49 ± 0.75	+1.76
Ethical AI Use	2.07 ± 0.72	4.33 ± 0.47	2.09 ± 0.70	2.12 ± 0.69	+2.26
AI-Enabled Mentoring	1.72 ± 0.65	3.94 ± 0.58	1.75 ± 0.63	1.79 ± 0.66	+2.22
Academic Integrity/AI	2.19 ± 0.76	4.28 ± 0.50	2.22 ± 0.74	2.25 ± 0.73	+2.09
Overall Composite	2.11 ± 0.59	4.15 ± 0.38	2.11 ± 0.57	2.16 ± 0.58	+2.04

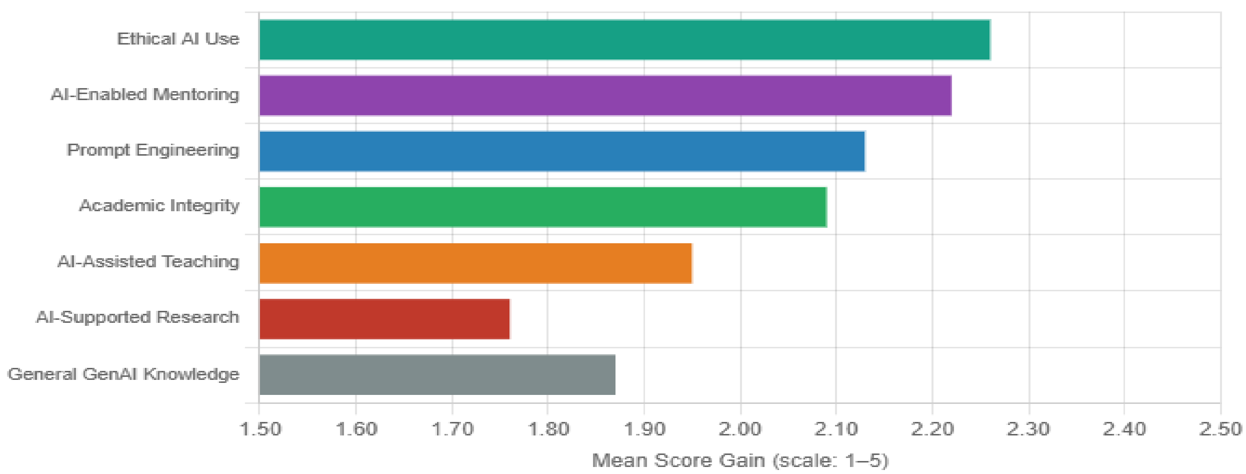

Figure 3: *Mean score gains (post-test minus pre-test) for the experimental group across all seven GenAI competency domains (scale: 1–5).*

their structured and purposeful application in academic activities was notably low (only 11.8% reported using them for mentoring). This gap highlights the essential need for formal mentorship training to bridge the difference between awareness and effective utilization. Institutions need to go beyond awareness campaigns and invest in structured, hands-on mentorship programs that develop practical skills. Awareness alone is not enough for effective GenAI integration in higher education.

Impact of Mentorship Training on GenAI Competence and Confidence

Research Question 2 examined the effect of mentorship training on participants' self-rated GenAI competence and confidence. Mean scores (1–5 scale) were computed for pre-test and post-test responses for the experimental group (n = 125) and the control group (n = 113). Table 5 presents a comparative analysis of pre-test and post-test mean competency scores across seven GenAI domains for both the experimental group (n = 125) and the control group (n = 113), alongside the mean gain scores recorded exclusively for the experimental group following the six-week mentorship training intervention. Scores were measured on a five-point Likert scale, where higher mean values indicate greater levels of self-rated GenAI competence and confidence (Figure 3).

The experimental group demonstrated remarkable gains across all competency domains, with an overall composite mean gain of 2.04 points on the five-point scale. The highest gains were recorded in Ethical AI Use (+2.26), AI-Enabled Mentoring (+2.22), and Prompt Engineering (+2.13). These domains received the most intensive practical engagement during the six-week mentorship programme, which included guided exercises, case discussions, and reflective sessions. The control group showed negligible changes ($\Delta \leq 0.07$), confirming that gains in the experimental group were attributable to the mentorship intervention rather than external influences. These results are consistent with Sun et al. (2026), who demonstrated that structured AI competency frameworks significantly improve teacher readiness for human–AI collaboration, and with Azamnouri et al. (2026), who found that interdisciplinary AI learning environments produce measurable improvements in confidence, creativity, and problem-solving. The relatively high gain in ethical AI knowledge (from M = 2.07 to M = 4.33) is particularly significant, given the persistent concerns about academic integrity documented in the Nigerian literature (Eleje et al., 2025; Ignatius et al., 2025). The mentorship training intervention resulted in statistically significant and practically meaningful improvements in GenAI competence across all seven assessed domains, with overall gains exceeding two fullscale points. The largest individual improvements were observed in Ethical AI use and AI-enabled mentoring, which were previously the most underdeveloped areas among academic staff. Structured mentorship programs spanning multiple weeks are highly effective in enhancing GenAI competence among Nigerian academic staff. Educational institutions should prioritize the design and funding of these programs as essential elements of their faculty development strategies. These programs should particularly focus on ethical reasoning, prompt engineering, and mentoring in the applications of GenAI.

Hypothesis Testing

Hypothesis 1: Paired-Samples t-Test (Experimental Group, Pre- vs. Post-Test)

H_{01}: There is no significant difference in the mean competence scores of academic staff in the experimental group before and after mentorship training in GenAI tools.

All paired-samples t-test results were highly significant ($p < .001$). The null hypothesis was rejected for all four dimensions, confirming that the six-week mentorship training programme produced statistically significant improvements in GenAI competence among academic staff in the experimental group (Table 6). The overall t-value of 38.47 indicates an extremely strong intervention effect.

Hypothesis 2: Independent-Samples t-Test (Experimental vs. Control Post-Test)

H_{02}: There is no significant difference in the post-test mean competence scores of academic staff in the experimental and control groups.

The independent-samples t-test further confirmed significant differences between the experimental and control groups at post-test across all dimensions (Table 7 and Figure 4). The experimental group consistently outperformed the control group, with the largest gap recorded in the mentoring application ($\Delta = 2.15$). This finding strongly supports the efficacy of the mentorship intervention and aligns with Pecuchova et al. (2026) and Sunday and Dada (2026), who similarly established that targeted training significantly elevates GenAI competence and behavioural intention among academic staff. Both paired-sample and independent-sample t-tests confirmed that mentorship training produced statistically significant ($p < .001$) and practically large differences in GenAI competence, with the mentoring application domain showing the widest gap between trained and untrained staff, a domain previously identified as the most neglected in existing literature. The findings provide robust empirical justification for institutionalizing GenAI mentorship training in Nigerian universities. Regulatory bodies such as the National Universities Commission (NUC) should incorporate structured GenAI faculty development programmes into minimum academic standard requirements for university accreditation.

Hypothesis 3: ANCOVA Effect of Gender and Academic Rank on Post-Test Scores

H_{03}: Gender and academic rank do not significantly moderate the effect of mentorship training on GenAI competence scores when controlling for pre-test performance.

ANCOVA results revealed that gender did not significantly moderate the effect of mentorship training on post-test GenAI competency ($F = 2.29$, $p = .133$, $\eta^2 = .02$). However, academic rank emerged as a significant moderating variable ($F = 4.53$, $p = .005$, $\eta^2 = .10$), with professors and associate professors recording higher post-test mean scores than junior lecturers (Table 8 and Figure 5). This may be attributed to their greater experience in academic task management, higher motivation to innovate, and greater access to digital resources. The covariate (pre-test score) was the strongest predictor ($\eta^2 = .47$), confirming the stability of the measurement instrument and the consistency of baseline competence as a performance anchor. Gender does not have a significant impact on the competence gains in GenAI resulting from mentorship training, suggesting that both male and female academic staff benefit equally from the training. However, academic rank does affect the outcomes; senior academics tend to show greater improvement in competence after training. This discrepancy may be due to differences in self-efficacy and access to resources. GenAI mentorship programs should be designed to be gender-neutral and universally accessible. However, it is essential to implement differentiated support strategies, especially for junior lecturers, to ensure that differences in rank do not exacerbate existing inequalities in academic hierarchies regarding GenAI adoption. ANCOVA results revealed that gender did not significantly moderate the effect of mentorship training on post-test GenAI competency ($F = 2.29$, $p = .133$, $\eta^2 = .02$). However, academic rank emerged as a significant moderating variable ($F = 4.53$, $p = .005$, $\eta^2 = .10$), with professors and associate professors recording higher post-test mean scores than junior lecturers (Table 9). This may be attributed to their greater experience in academic task management, higher motivation to innovate, and greater access to digital resources. The covariate (pre-test score) was the strongest predictor ($\eta^2 = .47$), confirming the stability of the measurement instrument and the consistency of baseline competence as a performance anchor. Gender does not significantly affect the competence gains from

Table 6: Paired-Samples t-Test Results — Experimental Group (n = 125).

Variable	Pre-Test M (SD)	Post-Test M (SD)	Mean Diff.	t-value	df	p-value	Decision
Overall Competence	2.11 (0.59)	4.15 (0.38)	2.04	38.47	124	<.001	Reject H_0
Teaching Application	2.14 (0.81)	4.09 (0.49)	1.95	22.63	124	<.001	Reject H_0
Research Application	2.45 (0.79)	4.21 (0.53)	1.76	21.18	124	<.001	Reject H_0
Mentoring Application	1.72 (0.65)	3.94 (0.58)	2.22	26.94	124	<.001	Reject H_0

Table 6. Paired-samples t-test comparing pre-test and post-test scores within the experimental group across four application domains.

Table 7: Independent-Samples t-Test Results Post-Test Comparison.

Variable	Experimental M (SD)	Control M (SD)	t-value	df	p-value	Decision
Overall Competence	4.15 (0.38)	2.16 (0.58)	31.22	236	<.001	Reject H_0
Teaching Application	4.09 (0.49)	2.18 (0.80)	22.81	236	<.001	Reject H_0
Research Application	4.21 (0.53)	2.49 (0.75)	20.54	236	<.001	Reject H_0
Mentoring Application	3.94 (0.58)	1.79 (0.66)	27.68	236	<.001	Reject H_0

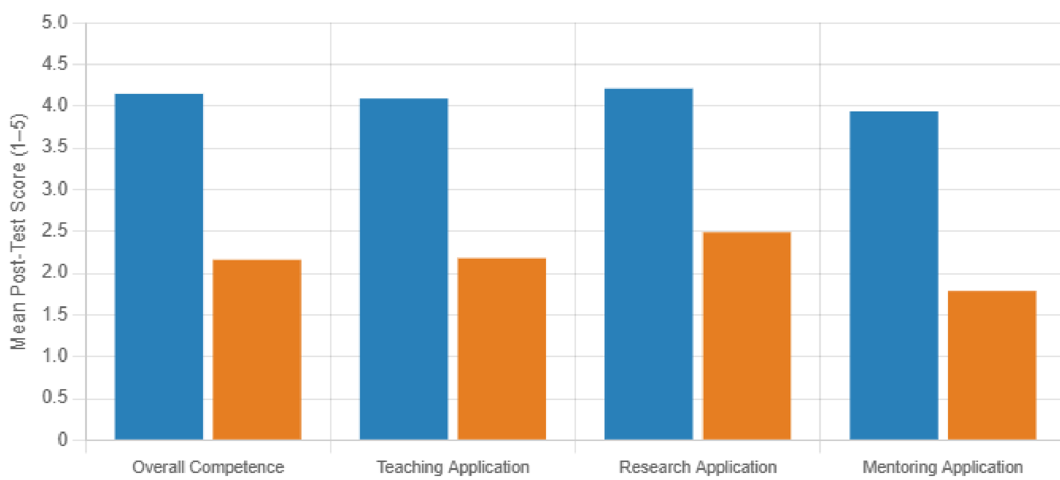

Figure 4: Post-test mean competency scores of experimental and control groups across four application domains (scale: 1–5).

Table 8: ANCOVA Results Moderating Variables on Post-Test Competence (Experimental Group).

Source	SS	df	MS	F	p-value	η²
Covariate (Pre-test)	14.72	1	14.72	108.91	**<.001**	.47
Gender	0.31	1	0.31	2.29	.133	.02
Academic Rank	1.84	3	0.61	4.53	.005	.10
Gender × Rank	0.22	3	0.07	0.54	.656	.01
Error	15.79	117	0.13	–	–	–

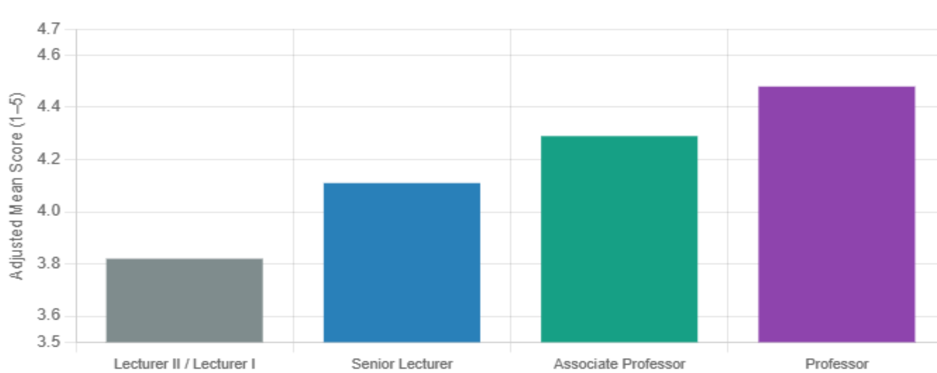

Figure 5: Adjusted post-test mean competency scores across academic ranks in the experimental group (ANCOVA-controlled for pre-test).

Table 9: Adjusted Post-Test Mean Scores by Academic Rank (Experimental Group)

Academic Rank	n	Adjusted Post-Test Mean	SD
Lecturer II / Lecturer I	45	3.82	0.41
Senior Lecturer	36	4.11	0.37
Associate Professor	27	4.29	0.34
Professor	17	4.48	0.31

Table 10: Post-Training GenAI Usage by Academic Activity (Experimental Group, n = 125).

Academic Rank	n	Adjusted Post-Test Mean	SD
Lecturer II / Lecturer I	45	3.82	0.41
Senior Lecturer	36	4.11	0.37
Associate Professor	27	4.29	0.34
Professor	17	4.48	0.31

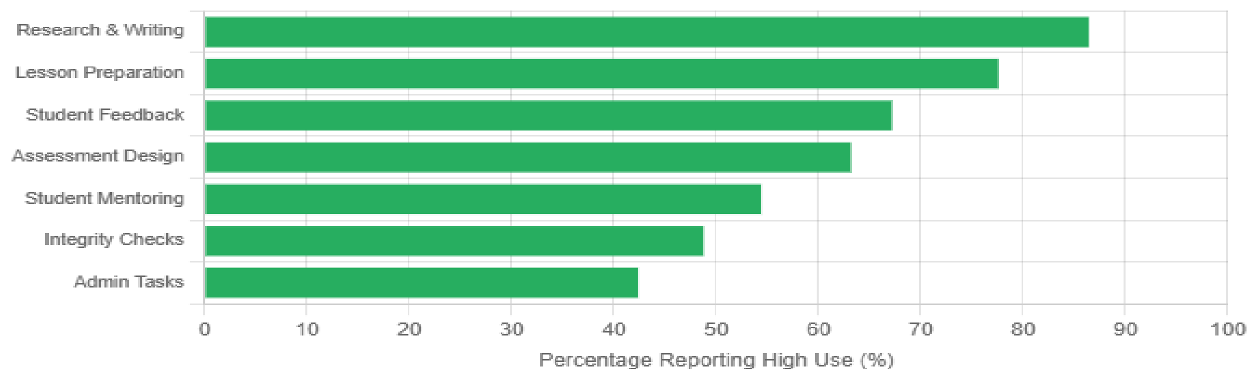

Figure 6: Percentage of experimental group respondents reporting high-frequency use of GenAI tools across seven academic activity domains post-training.

mentorship training in GenAI, suggesting that training outcomes are equitable for both male and female academic staff. However, academic rank does influence these outcomes, with senior academics showing higher competence after training. This could be due to differences in self-efficacy, access to resources, and motivation. GenAI mentorship programs should be designed to be gender-neutral and universally accessible. However, it is important to implement differentiated support strategies, especially by providing intensive assistance for junior lecturers. This approach is necessary to ensure that differences in rank do not exacerbate existing academic inequalities in the adoption of GenAI.

Post-Training GenAI Usage Patterns and Perceived Challenges

Research Question 3 examined the specific academic activities in which trained staff deployed GenAI tools post-intervention, as well as the challenges they encountered.

Table 10 presents the post-training frequency of GenAI tool usage across seven academic activity domains among members of the experimental group following the completion of the six-week mentorship training programme (Figure 6). The data reveal a consistently high overall adoption rate across all domains, with the majority of trained academic staff reporting meaningful GenAI engagement in activities spanning research, teaching, student feedback, assessment, administrative tasks, and mentoring. This pattern of broad post-training adoption represents a dramatic departure from the pre-intervention baseline documented in Section B, where only 44.9% of the same group had reported any active GenAI usage across academic activities, confirming that the mentorship training programme succeeded in translating previously dormant awareness into purposeful and varied academic application across the experimental cohort. The data further reveal a discernible hierarchy of adoption intensity across the seven activity domains, with research and academic writing recording the highest post-training usage rate at 86.4%, followed closely by lesson preparation at 77.6% and student feedback generation at 67.2%. These three domains, all of which involve individual, desk-based academic tasks with relatively low institutional dependency, emerged as the primary sites of GenAI integration among trained staff, suggesting that academic staff gravitate most readily toward GenAI applications that align with pre-existing solo working habits and offer immediately visible

Table 11: Perceived Challenges to Sustained GenAI Use Post-Training.

Challenge	Frequency	%	Mean Severity (1–5)
Inadequate internet connectivity	183	76.9	4.24
Inconsistent electricity supply	179	75.2	4.19
Limited institutional funding for AI tools	164	68.9	3.98
Absence of a clear institutional AI policy	152	63.9	3.84
Concerns about academic integrity	148	62.2	3.79
Insufficient time for AI learning practice	141	59.2	3.67
Fear of student overreliance on AI	136	57.1	3.63
Inadequate peer support networks	98	41.2	3.14

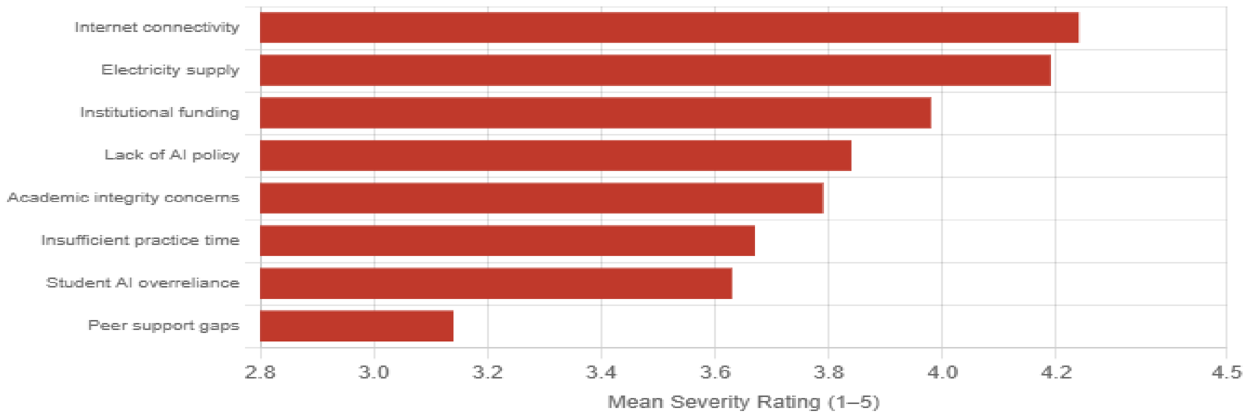

Figure 7: Mean severity scores (scale 1–5) assigned by respondents to eight identified barriers to sustained GenAI integration post-training.

productivity gains. Assessment design recorded a moderate adoption rate of 61.6%, reflecting both the practical utility of GenAI in generating diverse question formats and the ethical caution that several participants expressed during interviews regarding AI involvement in formal student evaluation processes.

In contrast, administrative task management and AI-enabled mentoring recorded comparatively lower post-training adoption rates of 42.4% and 54.4%, respectively, despite both domains having received dedicated attention during the mentorship curriculum. These lower figures are consistent with the findings of Thaddeus (2025) and Sunday and Dada (2026), who similarly documented that GenAI integration in administrative and mentoring contexts lags substantially behind its uptake in teaching and research activities, even among staff who have received training. The relatively subdued adoption in these two domains suggests that mentoring and administrative GenAI integration requires more prolonged reinforcement, role-specific guidance, and institutional encouragement beyond what a single six-week programme can fully achieve. These findings, therefore, point to the need for follow-up mentorship modules and peer support networks specifically targeting mentoring and administrative GenAI applications as the next frontier of faculty development investment in Nigerian higher education institutions. Infrastructure-related challenges dominated the barrier profile, with inadequate internet connectivity (76.9%) and unreliable electricity supply (75.2%) rated most severely (Table 11 and Figure 7). These findings echo the systemic infrastructural deficits documented in Nigerian and African higher education literature (Halubanza et al., 2025; Isiaka, 2025; Abubakar & Onasanya, 2025). The absence of a clear institutional AI policy (63.9%) and academic integrity concerns (62.2%) were also highly rated, reinforcing calls for structured AI governance frameworks within Nigerian universities (Suleman et al., 2025; Noroozi et al., 2024). Infrastructure deficits, particularly unreliable internet (76.9%) and power outages (75.2%), are the most significant barriers to sustaining GenAI adoption among Nigerian academic staff post-training. Policy ambiguity and concerns about academic integrity represent the second tier of structural challenges. Mentorship training is highly effective, but it cannot support the integration of Generative AI (GenAI) on its own. To fully realize the potential of GenAI in Nigerian higher education, federal and institutional funding must prioritize essential digital infrastructure. This includes enhancing broadband connectivity, implementing backup power systems, and securing subscriptions for institutional AI tools.

Thematic Analysis of Interview Data

Seventeen (17) participants from the experimental group were purposively selected for semi-structured interviews to provide deeper contextual insights. Four major themes were identified through thematic analysis (Table 12 and Figure 8).

Table 12: Summary of Qualitative Themes.

Theme	Coded Excerpts	% of Total	Key Sub-themes
Transformative Professional Identity Shift	59	33.9%	Role reconceptualization; expanded self-efficacy; human-AI collaboration
Expanded Pedagogical Creativity	47	27.0%	Personalized feedback; adaptive learning design; innovative teaching
Heightened Ethical Vigilance	38	21.8%	Academic integrity; bias awareness; responsible disclosure
Infrastructural Frustration & Institutional Ambivalence	30	17.2%	Power outages; connectivity; policy vacuum; unsupported practice

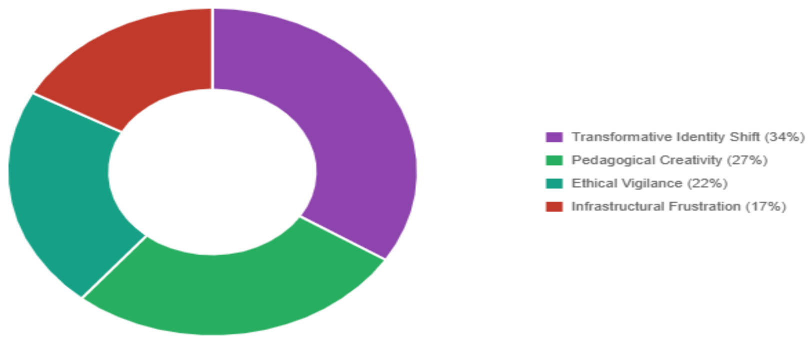

***Figure 8**: Relative frequency of coded thematic categories across 17 interview transcripts (n = 174 coded excerpts).*

Theme 1: Transformative Shift in Professional Identity

Participants consistently described experiencing a profound change in their professional identity following the training. Many reported moving from passive awareness to active engagement with Generative AI (GenAI), using language that emphasized increased self-efficacy and a redefinition of their roles as educators and researchers. One senior lecturer reflected that the training fundamentally altered her view of the relationship between human intellect and artificial intelligence in academic work, not as a competition, but as a collaboration. This theme aligns with Yurdunkulu et al. (2025), who conceptualized this transformation as the emergence of "Aidemics", academics who fluidly integrate human and AI capabilities in their professional practice.

Theme 2: Expanded Pedagogical Creativity

Several participants noted that mentorship training unlocked previously unimagined pedagogical possibilities. Lecturers reported using GenAI to design personalized student feedback protocols, generate diverse case scenarios for health sciences instruction, and create adaptive learning resources tailored to individual student needs. These findings resonate with Pecuchova et al. (2026) and Azamnouri et al. (2026), who similarly documented enhanced pedagogical creativity and student engagement following structured AI literacy development programs.

Theme 3: Heightened Ethical Vigilance

Participants reported increased sensitivity to ethical risks after the training. Many stated that the ethics module was the most transformative component of the program, providing them with conceptual frameworks for navigating issues related to academic integrity, AI bias, and responsible disclosure. However, participants also highlighted a tension between institutional ambiguity around AI policy and their individual ethical commitments. This finding echoes the work of de Silva et al. (2026) and Suleman et al. (2025), who documented similar tensions between individual ethical readiness and institutional policy shortcomings in higher education contexts.

Theme 4: Infrastructural Frustration and Institutional Ambivalence

Despite positive training experiences, participants expressed frustration with the institutional environment's failure to keep pace with their newly developed GenAI competencies. Issues such as frequent power outages, unreliable internet, and the lack of institutionally provisioned AI tool subscriptions were cited as significant barriers to sustained use of GenAI. This theme reinforces quantitative findings on infrastructural obstacles and is consistent with the work of Sunday and Dada (2026) and Halubanza et al. (2025), who documented similar tensions between individual technology readiness and institutional unpreparedness in African higher education settings.

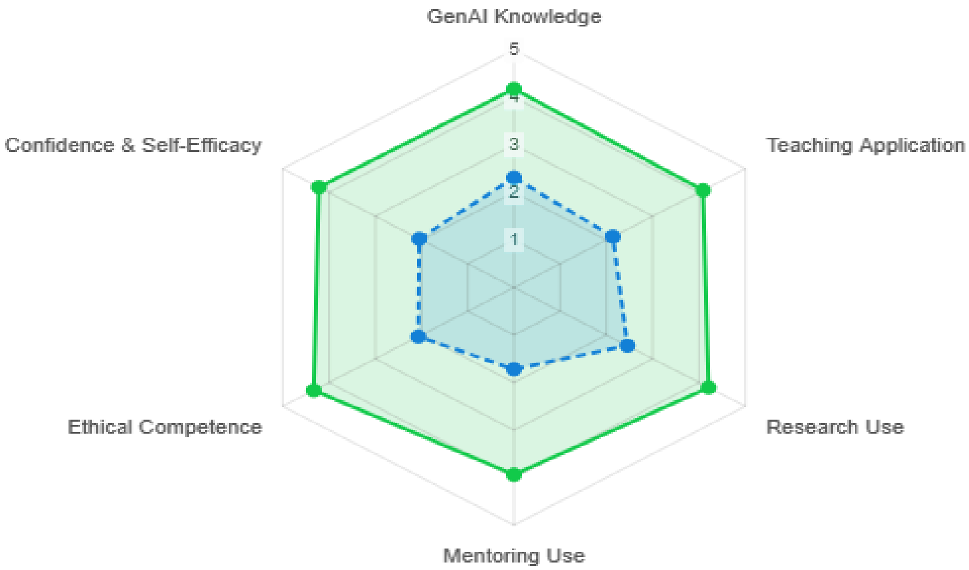

Figure 9: Radar chart illustrating composite mean scores across all six study domains before and after mentorship training (experimental group, scale: 1–5).

Major Findings

The results of this study provide compelling empirical evidence that structured mentorship training significantly and meaningfully enhances GenAI competence, confidence, and adoption among academic staff of a Nigerian federal university (Figure 9). Six principal findings emerge from the integrated quantitative and qualitative data:There is a substantial awareness-adoption gap before training, a gap that structured mentorship effectively bridges, increasing active GenAI usage from 44.9% to 91.2% post-intervention.

1.Statistically significant gains ($p < .001$) were recorded across all GenAI competency domains in the experimental group, with an overall composite mean gain of 2.04 points on a five-point scale.

2.Ethical AI knowledge and AI-enabled mentoring recorded the highest individual gains (+2.26 and +2.22, respectively), directly addressing two of the most critically underdeveloped competency areas identified in pre-existing Nigerian literature.

3.Gender does not moderate training outcomes, indicating equitable gains across male and female academic staff, while academic rank exerts a modest but statistically significant moderating effect ($\eta^2 = .10$).

4.Infrastructure deficits (internet unreliability, 76.9%; power outages, 75.2%) and institutional policy ambiguity (63.9%) remain the primary barriers to sustained post-training adoption, underscoring the necessity of complementary institutional investments.

5.Qualitative evidence documents a transformative professional identity shift among trained participants, alongside persistent institutional-contextual frustrations that threaten the sustainability of individually-achieved competence gains.

DISCUSSION

The findings of this study provide robust quasi-experimental evidence that structured mentorship training significantly enhances GenAI competence, confidence, and adoption behaviour among academic staff in a Nigerian federal health sciences university. The overall composite mean gain of 2.04 points on a five-point scale, sustained across all seven competency domains and confirmed by paired-samples t-tests significant at $p < .001$, positions mentorship training as one of the most empirically defensible interventions yet documented in the Nigerian GenAI adoption literature. However, a rigorous discussion of these findings demands engagement not only with corroborating evidence but also with contradictory findings, the inherent limitations of the results, plausible alternative explanations for observed patterns, and the deeper theoretical implications that the data raise for technology adoption scholarship and educational policy in developing country contexts. Each of these dimensions is addressed systematically in the sections that follow.

Corroborating Evidence and Theoretical Alignment

The awareness-adoption gap documented in Section B of the Results, where 82.4% of participants were aware of

ChatGPT yet only 44.9% had actively used any GenAI tool for academic purposes, directly challenges simplistic policy assumptions that digital infrastructure expansion or awareness campaigns alone will drive meaningful GenAI integration in Nigerian universities. This finding is consistent with the Technology Acceptance Model predictions of de Silva et al. (2026) and Gamlem et al. (2026), who established that perceived usefulness and ease of use, rather than mere awareness, are the proximal cognitive determinants of technology adoption behaviour. The mentorship training intervention addressed these proximal determinants precisely by equipping participants with functional competencies, practical confidence, and ethical frameworks that transformed GenAI from an abstractly known technology into a practically usable academic tool.

The dominance of Ethical AI Use (Δ = +2.26) and AI-Enabled Mentoring (Δ = +2.22) as the highest-gain competency domains further corroborates Sun et al.'s (2026) argument that effective GenAI capacity building must extend beyond technical skill transmission to encompass pedagogical reasoning, ethical deliberation, and professional identity reconstitution. Similarly, the qualitative finding of transformative professional identity shifts among trained participants resonates with Yurdunkulu et al. (2025) conceptualization of "Aidemics" academics who fluidly integrate human and AI capabilities suggesting that the mentorship programme succeeded in initiating a reconstitution of professional self-concept that extends well beyond instrumental tool adoption.

Contradictory Evidence

Notwithstanding the largely affirmative pattern of findings, several areas of contradictory or complicating evidence warrant candid discussion.

First, while the experimental group recorded an overall composite post-test mean of M = 4.15, indicating high competence, post-training usage rates in administrative task management (42.4%) and AI-enabled mentoring (54.4%) remained substantially lower than those recorded in research and academic writing (86.4%) and lesson preparation (77.6%). This divergence between measured competence and actual usage frequency in specific domains constitutes a partial contradiction within the dataset itself: participants demonstrated statistically significant competence gains in AI-Enabled Mentoring (Δ = +2.22) yet reported comparatively modest post-training usage of GenAI in actual mentoring interactions. This internal inconsistency suggests that competence development, while necessary, is insufficient on its own to guarantee behavioural adoption in domains where relational, institutional, and cultural norms exert independent influence on academic practice.

Second, the finding that academic rank significantly moderated training outcomes ($F = 4.53$, $p = .005$, $\eta^2 = .10$), with professors recording the highest adjusted post-test means (M = 4.48) and Lecturer II staff recording the lowest (M = 3.82), partially contradicts the egalitarian premise underlying the mentorship training design, which assumed that a uniform six-week programme would yield broadly equivalent gains across the academic hierarchy. This rank-based differential is particularly significant when considered alongside the qualitative evidence, in which junior lecturers disproportionately reported feelings of institutional ambivalence and insufficient peer support, suggesting that seniority confers not merely experiential advantage but also differential access to the social capital and institutional resources that facilitate sustained post-training adoption. These findings stand in partial tension with Abubakar and Onasanya (2025), who found that institutional support rather than individual rank was the primary predictor of GenAI adoption readiness, implying that the moderating role of rank may be more contextually specific than previously theorized.

Third, the qualitative data reveal a tension that the quantitative findings do not fully surface: despite reporting high post-test competence scores, several senior participants expressed ambivalence about the long-term sustainability of their GenAI integration, citing institutional policy vacuums, ethical uncertainties, and concerns about student overreliance as persistent deterrents to confident adoption. This coexistence of high measured competence and expressed adoption hesitancy among senior academics complicates a straightforward competence-adoption causal narrative and suggests that affective and institutional dimensions of GenAI integration operate with a degree of independence from cognitive competence development that existing adoption models do not adequately theorize.

Limitations of Findings

Several important limitations circumscribe the interpretive scope of this study's findings and must be explicitly acknowledged.

First, the quasi-experimental design, while methodologically appropriate for the institutional context and ethically preferable to random denial of training, does not fully eliminate the possibility of selection bias. Participants who voluntarily enrolled in the mentorship programme may have possessed higher baseline motivation, digital self-efficacy, or openness to innovation than those who did not, meaning that the observed gains may partially reflect pre-existing dispositional differences between the experimental and control groups rather than exclusively the effect of the training intervention. Although baseline equivalence was confirmed at the pre-test stage, motivational and dispositional variables were not measured or controlled, representing a residual threat to internal validity.

Second, the self-report nature of the MTGAIAQ introduces the possibility of social desirability bias, particularly in post-test administrations where participants may have felt implicitly encouraged to report competence gains consistent with the training's stated objectives. Although criterion validity was established through a practical task performance measure ($r = 0.74$, $p < .01$), the practical task was administered under supervised conditions that may not fully replicate the cognitive demands and contextual constraints of authentic academic GenAI use, limiting the ecological validity of the criterion measure.

Third, the study was conducted within a single specialized federal health sciences university in Ebonyi State, Nigeria, constraining the generalizability of findings to other Nigerian universities with different disciplinary compositions, infrastructure profiles, institutional cultures, and faculty demographic characteristics. The unique health sciences context of DUFUHS with its specific imperatives for evidence-based practice, clinical ethics, and professional responsibility, may have amplified participants' responsiveness to the ethics and mentoring components of the training in ways that would not replicate with equivalent magnitude in humanities, social sciences, or engineering faculties at conventional universities.

Fourth, the study assessed competence and usage at a single post-test point immediately following the conclusion of the training programme, without a delayed follow-up measurement to assess the retention of competence gains and the sustainability of adoption behaviour over time. The absence of longitudinal data means that the study cannot address the critical policy question of whether mentorship-induced competence gains persist, deepen, or erode across subsequent academic cycles when institutional support remains inconsistent.

Alternative Explanations

Beyond the primary interpretation that mentorship training caused the observed competence gains, several alternative explanations deserve serious consideration.

First, the Hawthorne effect, whereby participants modify their behaviour and performance in response to awareness of being observed and studied rather than in response to the intervention itself, cannot be entirely discounted in a quasi-experimental design of this nature. The sustained engagement of research assistants with experimental group participants throughout the six-week intervention period may have generated a heightened sense of academic accountability and performance motivation that independently contributed to post-test score improvements, irrespective of the specific content of the mentorship training.

Second, the contemporaneous global surge in GenAI discourse during the study period manifested in widespread media coverage, institutional communications, and peer conversations about tools such as ChatGPT and Gemini, may have independently stimulated GenAI exploration among experimental group participants outside the formal training sessions, creating a contamination effect in which the training's apparent impact is partially attributable to broader societal momentum rather than the structured mentorship curriculum alone. The control group's negligible gains ($\Delta \leq 0.07$) suggest that passive environmental exposure was insufficient to drive competence development in the absence of structured guidance, but the possibility that environmental factors amplified training effects in the experimental group cannot be entirely excluded.

Third, the significant moderating effect of academic rank observed in the ANCOVA results may be more parsimoniously explained by differential access to digital devices, stable internet connections, and institutional computing resources, variables that correlate strongly with seniority in Nigerian federal universities, than by the cognitive or experiential advantages of academic seniority per se. Under this alternative explanation, the rank-based differential in post-test scores reflects a resource access gradient rather than a competence development gradient, a distinction with important equity implications for the design of future training programmes.

Fourth, the high overall post-training adoption rate of 91.2% reported by experimental group participant's warrants cautious interpretation. Given that adoption was measured through self-report rather than system-logged usage data, it is possible that some participants reported GenAI usage at a level reflecting aspirational intent or social conformity with training expectations rather than actual behavioural frequency. This possibility is partially supported by the divergence between high self-reported competence scores and the comparatively modest usage rates recorded in mentoring and administrative domains, suggesting that self-report adoption measures may systematically overestimate actual behavioural integration in contexts where social desirability pressures are present.

Deeper Theoretical Implications

The findings of this study carry theoretical implications that extend beyond their immediate empirical context and invite a fundamental reconsideration of how technology adoption frameworks conceptualize the relationship between training, competence, and sustained behavioural change in resource-constrained institutional environments.

First, the study exposes a critical blind spot in the Technology Acceptance Model's foundational architecture. TAM locates perceived usefulness and ease of use as the proximal determinants of adoption intention, treating these perceptions as relatively stable individual cognitions that mediate the relationship between external variables and behaviour. The present findings suggest, however, that in the Nigerian higher education context, perceived usefulness and ease of use are not stable individual perceptions but dynamically constructed social products shaped by mentorship relationships, peer interaction, practical exercise, and expert guidance. This reconceptualization repositions mentorship not merely as an external variable within TAM's architecture but as a constitutive process through which the core perceptual constructs of the model are themselves generated, thereby challenging the model's implicit assumption that adoption-relevant perceptions pre-exist and are merely activated by technology exposure.

Second, the integration of Activity Theory into the study's analytical framework proves particularly generative for explaining the persistent gap between individual competence development and institutional adoption sustainability documented in Sections D and E of the Results. Activity Theory's conceptualization of contradictions systemic tensions between the tools, rules, community, and division of labour within an activity system provides a more nuanced account of post-training adoption barriers than either TAM or UTAUT, which tend to locate adoption obstacles primarily within individual cognition or institutional support structures conceived in relatively static terms. The qualitative finding that even highly competent, highly motivated academic staff experienced sustained frustration with institutional ambivalence and infrastructural deficits suggests that the activity system of Nigerian higher education contains deep structural contradictions between the technological innovation imperatives driving GenAI adoption and the material-infrastructural realities that constrain its practice contradictions that no amount of individual competence development can resolve without parallel systemic transformation.

Third, the study's documentation of transformative professional identity shifts among trained participants invites a theoretical extension of UTAUT's social influence construct into the domain of professional identity theory. UTAUT theorizes social influence as the degree to which significant others believe the individual should use a technology, treating it as an external motivational pressure operating on a relatively stable professional self. The qualitative findings of this study suggest, by contrast, that effective GenAI mentorship does not merely apply external social pressure to an unchanged professional identity but actively reconstitutes that identity expanding what academics believe they are capable of, redefining the boundaries of human and AI intellectual contribution, and generating new forms of academic self-efficacy that persist beyond the training context. This finding invites future theoretical work on the mechanisms through which technology training programmes operate as identity transformation processes rather than merely skill transmission events, a reconceptualization with significant implications for how faculty development programmes are designed, evaluated, and theorized within educational technology scholarship.

Fourth and finally, the study's findings collectively suggest the need for a context-sensitive extension of existing adoption frameworks that explicitly theorizes the dual-challenge structure of GenAI adoption in sub-Saharan African higher education: the simultaneous necessity of building individual competence and addressing systemic infrastructure deficits. Existing frameworks were largely developed and validated in contexts where basic digital infrastructure can be assumed, rendering them theoretically incomplete for application in environments where power outages and internet unreliability constitute primary adoption barriers. A theoretically adequate account of GenAI adoption in Nigerian higher education must therefore integrate individual-level cognitive and affective constructs from TAM and UTAUT with institutional-level structural analysis from Activity Theory and with material-infrastructural analysis drawn from political economy perspectives on digital inequality, a theoretical synthesis that the present study's mixed-methods design has begun to empirically ground but that future theoretical scholarship must develop with greater conceptual precision and cross-contextual validation.

CONCLUSION

This study provides the first controlled, quasi-experimental evidence that structured mentorship training produces large, statistically significant, and domain-spanning improvements in GenAI competence, confidence, and adoption behaviour among academic staff in a Nigerian federal health sciences university. By moving beyond the attitudinal and intentional focus that dominates existing Nigerian GenAI literature, the study demonstrates that deliberate, sustained, and practically grounded mentorship intervention rather than awareness, infrastructure provision, or passive exposure is the critical mechanism through which the awareness-adoption gap is bridged in resource-constrained higher education environments. The finding that gender does not moderate training outcomes while academic rank does, combined with qualitative evidence of transformative professional identity shifts alongside persistent infrastructural frustration, collectively reveal that GenAI integration in Nigerian universities is simultaneously an individual competence challenge, an institutional support challenge, and a systemic infrastructure challenge that no single intervention strand can resolve in isolation.

Policy Implications

The empirical weight of these findings carries direct and urgent implications for policy at institutional, regulatory, and national levels. At the institutional level, university management at DUFUHS and comparable Nigerian federal universities should immediately formalize and fund structured GenAI mentorship programmes as a permanent, recurrent component of faculty development strategy rather than treating them as one-off research interventions. Programme design should adopt a differentiated approach that provides intensive supplementary support for junior lecturers, who demonstrated the lowest post-training competence gains, and should extend dedicated mentoring modules targeting administrative and mentoring domain applications, which recorded the lowest post-training adoption rates despite significant competence improvements. At the regulatory level, the National Universities Commission (NUC) should incorporate demonstrated GenAI faculty competence standards into the Minimum Academic Standards framework and make structured AI professional development programmes a condition of institutional accreditation renewal. This regulatory mandate would create systemic incentives for universities to invest in GenAI capacity building rather than leaving faculty development to institutional discretion. At the national level, the Federal Ministry of Education and TETFund should prioritize complementary investment in broadband connectivity, backup power infrastructure, and institutionally provisioned AI tool subscriptions across Nigerian federal universities. The present findings confirm unambiguously that mentorship-induced competence gains cannot translate into sustained academic practice without this infrastructural foundation making digital infrastructure investment not a peripheral concern but a prerequisite for any national GenAI integration strategy to yield meaningful educational returns.

Contribution to Knowledge

This study makes three distinct contributions to knowledge. Theoretically, it conceptualizes mentorship not as an external variable within existing technology adoption frameworks but as a constitutive process through which adoption-relevant perceptions of usefulness and ease of use are actively generated, thereby exposing a foundational blind spot in TAM's treatment of these constructs as pre-existing individual cognitions. Methodologically, it introduces a psychometrically validated, context-sensitive instrument the MTGAIAQ that measures GenAI competence across seven discrete academic activity domains, offering a replicable assessment tool for future intervention studies in Nigerian and comparable African higher education contexts. Empirically, it produces the first quasi-experimental causal evidence in the Nigerian literature that structured mentorship training significantly elevates GenAI competence and adoption, establishing a defensible evidence base upon which institutional policymakers, faculty developers, and regulatory bodies can ground future professional development investment decisions.

ACKNOWLEDGMENTS

We owe our debt of gratitude to the sponsor of this research, the Nigeria Tertiary Education Trust Fund (TETFund), under the Institution-Based Research Intervention with the award number: DUFUHS/VC/TETFUND/IBR/AC/25/024 and to our amiable Vice-Chancellor for approving the fund for us to undertake the research.

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