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RESEARCH ARTICLE

Behavioural Intention and Readiness for AI Adoption among Lecturers in Northwest Nigerian Universities

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Abstract: This study investigated lecturers' behavioural intention and readiness to adopt artificial intelligence (AI) for academic engagement in federal universities across Northwest Nigeria. Anchored on the Diffusion of Innovation (DOI) theory and the Unified Theory of Acceptance and Use of Technology (UTAUT), a descriptive survey design was employed. Data were collected from 759 lecturers using the AI Technology Adoption Questionnaire (AITAQ) and analysed with descriptive statistics and Spearman's Rank Correlation. Findings revealed that lecturers demonstrated moderate levels of behavioural intention, readiness, and acceptance of AI, with an overall weighted mean of 3.43. Socioeconomic status had a weak, insignificant effect on AI adoption, whereas institutional support had a significant, though modest, positive effect, highlighting the importance of enabling environments over financial capacity. The study concludes that professional motivation, institutional structures, and perceived usefulness outweigh personal financial resources in determining AI adoption, with practical implications for policymakers to strengthen infrastructure, training, and leadership support for sustainable AI integration in higher education. These findings contribute to the growing body of knowledge on AI integration in education, providing practical information for educators and policymakers seeking to enhance academic engagement through AI innovations.

Keywords: AI technology, behavioural intention, readiness to adopt, technology acceptance, technology adoption, institutional support, socioeconomic status

1 Introduction

Technological advancements, along with the high-level requirements and expectations of stakeholders, have made it imperative for teachers and educational institutions to continually upgrade their strategies. This includes the full-scale application of technology in education to remain effective and competitive in the growing educational system. According to Thelma et al. (2024), stakeholders, including policymakers, parents, and industry leaders, expect educational institutions to produce graduates proficient in current and emerging technologies, enabling them to thrive and contribute to the digital economy. This requires educators to go beyond traditional methods and incorporate technology to meet these expectations, ensuring that students receive a relevant, high-quality education that prepares them for future challenges and opportunities. From e-libraries and mobile applications to virtual reality and gamification, the educational system has undergone a significant transformation with the advent of innovative tools and technologies (Khanduri & Teotia, 2023). Among these, Artificial Intelligence (AI) stands out because of its ability to address systemic challenges in education while preparing students for emerging opportunities in a digital world.

AI offers distinctive capabilities that set it apart from other digital tools frequently utilised in academic environments. While e-books and e-libraries improve access to information, VR enhances experiential learning, and AI provides adaptability, efficiency, and personalised engagement (Das & Malaviya, 2025). It allows lecturers to analyse student performance, customise learning pathways, and streamline administrative tasks. Furthermore, AI supports remote and blended learning models, bridging educational access gaps across various contexts (Edwards-Fapohunda & Adediji, 2024). These qualities position AI as a groundbreaking innovation capable of modernising teaching, promoting inclusive education, and equipping graduates with essential digital skills. As global demand for innovation continues to rise, AI adoption in universities becomes central to achieving institutional relevance and ensuring long-term competitiveness.

Despite these potential benefits, evidence indicates that deep-rooted resistance to innovation continues to shape how lecturers approach the use of new technologies in their instructional practices (Nwisagbo et al., 2025). Many educators remain hesitant to shift from traditional pedagogical methods, driven by long-held beliefs about teaching and learning. This reluctance is often fueled by doubts about the relevance or effectiveness of new tools, especially when these tools challenge familiar routines (Rogers, 2003). Instead of adopting new technologies early, some educators prefer to delay until innovations are widely accepted, while others choose to maintain the comfort of existing practices. These skepticism patterns slow down progress and prevent institutions from fully utilising technology in teaching, research, and administration.

This skepticism often stems from misconceptions about emerging technologies, limited exposure to their educational benefits, and concerns about long-term implications (Venkatesh et al., 2003). Many lecturers question whether AI genuinely simplifies academic responsibilities or improves learning outcomes, and some express concerns that automation may threaten job security. These uncertainties contribute to emotional and cognitive barriers that discourage lecturers from exploring AI tools. Without clear confidence in AI's benefits, lecturers are more likely to resist or delay adoption, undermining the overall efficiency of institutional strategies for technological integration. Such hesitation creates a widening gap between the potential for innovation and actual classroom practice.

This study, therefore, investigates these persistent challenges to uncover the root causes of lecturers' resistance to adopting AI in academic settings. Understanding these dynamics is critical to addressing misconceptions, reducing resistance, and supporting lecturers in navigating educational transformation. Without such an inquiry, misconceptions will persist, skepticism will deepen, and opportunities for improved teaching and research may be lost. The findings from this investigation will offer clarity on the barriers affecting AI adoption, providing a vital foundation for informed interventions, capacity building, and policy reforms that support effective educational innovation.

1.1 Research Questions

The following questions guided the conduct of this study:

(1) What is the behavioral intention of university lecturers to adopt AI technologies for academic engagement in Northwest Nigeria?

(2) What is the perceived readiness of university lecturers to adopt AI technologies for academic engagement in universities in Northwest Nigeria?

(3) What is the level of university lecturers' acceptance of AI technologies for academic engagement among universities in Northwest Nigeria?

1.2 Research Hypotheses

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

H_{01}: There is no significant relationship between socioeconomic status and lecturers' behavioral intention to adopt AI technologies.

H_{02}: There is no significant relationship between institutional support and lecturers' behavioral intention to adopt AI technologies.

H_{03}: There is no significant relationship between socioeconomic status and lecturers' acceptance of AI technologies.

H_{04}: There is no significant relationship between institutional support and lecturers' acceptance of AI technologies.

2 Literature Review

The integration of AI into higher education offers new opportunities to enhance teaching, research, and academic engagement while supporting inclusive, skill-based pedagogical practices. This literature review synthesises existing research to build a clear understanding of AI adoption, focusing on behavioural intention, readiness, technology acceptance, and the role of institutional and socioeconomic factors. It examines how these variables interact to shape lecturers' engagement with AI technologies in universities, particularly within resource-constrained environments in Northwest Nigeria. Drawing on established theoretical perspectives and empirical evidence, the review provides the foundation for analysing adoption dynamics. To ground the discussion, the review begins with the theoretical and hypothetical framework guiding this study.

2.1 Theoretical and Hypothetical Framework

This study draws on the Diffusion of Innovation (DOI) theory and the Unified Theory of Acceptance and Use of Technology (UTAUT), which provide complementary perspectives on how university lecturers adopt artificial intelligence (AI) technologies for academic engagement. DOI (Rogers, 2003) focuses on how innovations spread through social systems, shaped by attributes like relative advantage, compatibility, complexity, trialability, and observability. UTAUT (Venkatesh et al., 2003) complements this by identifying individual-level drivers, performance expectancy, effort expectancy, social influence, and facilitating conditions that influence behavioural intention and actual use.

The integration of DOI and UTAUT is justified by their complementary strengths. This combination is relevant in higher education, where mobile access, cloud-based platforms, and informal learning increasingly shape AI engagement. DOI captures broad patterns of innovation diffusion but lacks depth in explaining individual-level motivators and barriers (Granić, 2024). Conversely, UTAUT is robust in predicting personal adoption behaviours but often overlooks organisational and contextual factors that are vital in higher education (Naseri & Abdullah, 2024). Neither framework alone adequately captures the complex realities of AI adoption in Nigerian universities, where both institutional norms and individual readiness play critical roles. Recognising these limitations, this study developed a hypothetical framework that combines the macro-level focus of DOI with the micro-level precision of UTAUT, producing a more comprehensive model for analysing lecturers' behavioural intention and readiness to adopt AI.

In the model presented in this study (Figure 1), behavioural intention is treated as an antecedent to acceptance and readiness. Lecturers' perception of AI's relative advantage and ease of use influences intention, while institutional communication channels promote awareness and shared learning. Readiness to adopt AI is the dependent construct, shaped by lecturers' digital competence, perceived usefulness, and available support systems. Two moderating factors, institutional support and socioeconomic status, bridge the gap between intention and readiness. Institutional support (training, infrastructure, policy) creates the enabling conditions for adoption (Erdmann & Toro-Dupouy, 2025). Socioeconomic status affects access to mobile devices, data, and AI-driven platforms, influencing both intention and acceptance.

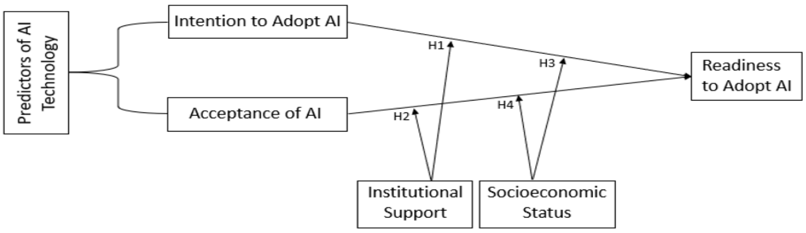

Figure 1 Researchers' Hypothetical Framework. Source: Field Study (2025)

The framework thus illustrates a progression from perception to intention, through acceptance and readiness, leading to adoption for academic engagement. It also reflects how AI integration increasingly occurs through mobile and cloud-based learning environments, where lecturers interact with adaptive platforms, data-driven feedback, and generative tools. This combined model (DOI + UTAUT) provides a structured explanation for how institutional and personal factors jointly determine AI adoption within Nigerian higher education.

2.2 AI Technology in Higher Education

AI has become a central driver of educational technology transformation in universities, integrating with mobile and digital learning tools to enhance accessibility and engagement. According to Ayeni et al. (2024), AI applications now personalise instruction, provide adaptive resources, and track student progress in real time through mobile-compatible learning management systems and digital platforms (Papadakis et al., 2023a, 2023b). Unlike traditional classroom methods, these technologies analyse student performance data and recommend suitable materials to meet individual learning needs anywhere, anytime. Du Plooy et al. (2024) agree that such personalised and mobile-enabled feedback strengthens learner engagement and academic achievement. AI-powered tutoring apps and chatbots available on smartphones now provide continuous support beyond the classroom, allowing lecturers to manage large enrolments while maintaining teaching quality.

Beyond teaching, AI is reshaping scholarly activities in higher education. Dalsaniya and Patel

(2022) observed that AI tools simplify data analysis, automate repetitive tasks, and improve the accuracy of research outcomes through integrated, cloud-based, mobile-accessible platforms. For instance, machine learning algorithms help researchers handle large datasets, enabling them to uncover patterns that might otherwise remain hidden. Similarly, text-mining applications assist in literature reviews by quickly scanning and summarising thousands of academic sources. Chashechnikova et al. (2024) believe that these innovations save researchers important time, allowing them to focus more on critical thinking and interpretation. Reducing the burden of routine work, AI empowers academics to produce more impactful research within shorter time frames.

AI also enhances university administration through educational technologies that improve efficiency and responsiveness (Lavidas et al., 2022a). Mupaikwa (2025) reported that AI systems are now embedded in digital management platforms for admissions, scheduling, and student records. Mobile chatbots, for example, allow students to access real-time information about registration, fees, or academic policies, reducing delays and administrative workload. Cao and Mai (2025) further noted that predictive analytics powered by AI help institutions anticipate enrolment patterns, monitor retention, and design targeted interventions for at-risk students. Collectively, these developments demonstrate how AI, when embedded within mobile and educational technologies, strengthens teaching, research, and administration in higher education.

2.3 Behavioural Intention to Adopt AI Technologies

Behavioural intention remains central to understanding why lecturers choose to adopt or resist AI tools in academic practice, particularly as AI increasingly integrates with mobile and educational technologies. According to Venkatesh et al. (2003), performance expectancy, effort expectancy, and social influence jointly influence an individual's willingness to engage with technology. In higher education, lecturers' intention to adopt AI often aligns with the perceived benefits of mobile-enabled AI tools that enhance flexibility in teaching and research. When lecturers believe that AI platforms and mobile applications can simplify content delivery, automate grading, or provide real-time feedback, their motivation to adopt increases. Hang (2024) also found that ease of use remains vital; educators are more inclined to use AI tools when mobile interfaces are intuitive and require minimal technical training.

Rogers (2003) identified relative advantage, compatibility, and complexity as determinants of innovation adoption, and these attributes also apply to mobile AI applications for learning management, collaboration, and research assistance. Sajja et al. (2025) observed that lecturers who viewed AI as compatible with their teaching style and mobile teaching habits showed stronger adoption intentions (Lavidas et al., 2022b). Similarly, Ateş and Gündüzalp (2025) reported that institutional and peer encouragement, through mobile-based communities of practice or professional learning networks, strengthens confidence in adopting AI. Shaikh et al. (2025) added that perceived relative advantage, including time-saving and interactive engagement through AI-powered mobile platforms, significantly predicts actual adoption. That is why it is vital to examine empirical evidence to gain a clearer understanding of how educators decide to adopt AI and the factors that support its integration into higher education.

The study of Zhang and Hou (2024) investigated college teachers' behavioural intention to adopt AI-assisted teaching systems in China, integrating TAM and Innovation Diffusion Theory. Their study, based on 529 teachers, used SEM to explore how perceived ease of use, usefulness, and sociocultural factors influenced intention. While their model is theoretically sound, it relies heavily on technology-centric constructs and underrepresents institutional variables that shape real adoption environments. The exclusive focus on Chinese universities also limits generalisability, as sociocultural and infrastructural realities differ widely across regions. This study builds upon this by adopting a broader theoretical framework that combines DOI and UTAUT to capture both institutional and individual factors. With a larger and more diverse sample from multiple universities across Northwest Nigeria, it provides richer, cross-institutional insights into behavioural intention and readiness in the developing countries.

Salifu et al. (2024) examined the behavioural intentions and actual use of ChatGPT among Ghanaian economics students using the extended UTAUT model with 306 participants. The study found that perceived trust, performance expectancy, motivation, and facilitating conditions significantly shaped intentions and use. Yet, its narrow focus on students and a single discipline weakens its relevance to academic staff who design and deliver instruction. The hybrid SEM-ANN approach yielded robust findings but was unable to capture the institutional and infrastructural enablers of adoption. This research extends beyond student usage by targeting lecturers, the key actors in AI integration, and includes constructs like institutional support and socioeconomic status to explain readiness. It also applies a correlational survey with a much larger, multi-university sample to enhance the external validity of its results.

Another study by Ayanwale et al. (2022) examined the readiness and intention of Nigerian teachers to teach AI technologies, using data from 368 in-service teachers. The study found that teachers' confidence in teaching AI predicts their intention to use it, while the relevance of AI strongly predicts readiness. Other factors, like anxiety and AI for social good, did not significantly influence readiness or intention. Although the study is useful, it has limitations, including its small sample of 368 in-service teachers in Nigeria, which may not be representative of the broader teacher population or other regions. Additionally, the study's location-specific findings related to Nigerian educational settings may not be directly applicable to different cultural or academic environments, thereby limiting the broader relevance of its conclusions. These constraints limit its wider applicability and highlight the need for more comprehensive frameworks that encompass both individual and institutional factors when examining educators' readiness to adopt AI in teaching (Lampropoulos & Papadakis, 2025). This leads to a broader examination of educators' readiness to integrate AI technology into instructional activities.

2.4 Readiness to Adopt AI for Academic Engagement

Readiness to adopt AI in higher education depends not only on lecturers' technology competence but also on how they engage with mobile and digital learning systems that increasingly integrate AI functions. According to Lyu et al. (2025), technology readiness reflects an individual's optimism, innovativeness, and confidence in using digital tools, qualities that strongly influence willingness to engage with AI-driven platforms, including mobile-based learning applications and intelligent tutoring systems. In resource-limited environments, however, this readiness is often constrained by weak infrastructure and limited access to connected devices that support AI-enhanced instruction. Anurogo et al. (2023) emphasised that digital competence, skills in locating, evaluating, and applying online and AI-enabled resources, is vital for successful adoption. Without adequate support or training, lecturers may view AI and mobile-based systems as too complex or incompatible with their daily teaching tasks.

Building on this perspective, readiness also reflects institutional realities and access to mobile learning resources. Even technologically skilled lecturers struggle when network reliability, mobile connectivity, or institutional support is lacking. Those who benefit from targeted professional development and exposure to AI-based mobile tools show stronger readiness and confidence in using them for teaching and research. Okada et al. (2025) found that readiness goes beyond basic digital skills; it includes the confidence to use AI application tools in teaching and research, even when resources are limited. In universities across Northwest Nigeria, persistent infrastructure gaps create uneven readiness among lecturers. Hence, evaluating readiness must consider both personal competence and the academic conditions that shape effective AI use for academic engagement. Reviewing empirical studies exploring how these factors influence readiness to adopt AI technologies is vital.

The study of Alnasib (2023) assessed the readiness of Jordanian science teachers to integrate AI, focusing on their perceptions, challenges, and training needs among 136 respondents. The study identified optimism about AI's potential but noted barriers like limited resources, privacy concerns, and a lack of professional development. While it offers valuable insights into readiness, its scope is limited by the small sample, single subject area, and exclusion of behavioural intention as a predictor of readiness. It also treats readiness descriptively rather than relationally. The study addresses these gaps by examining behavioural intention readiness and acceptance within a relational framework grounded in DOI and UTAUT. It provides a more generalisable and theoretically connected understanding of AI adoption readiness by surveying 759 lecturers across multiple federal universities.

Mnguni et al. (2024) explored the behavioural intentions of pre-service science teachers in South Africa and Thailand using the Theory of Planned Behaviour. Their comparative survey of 192 participants revealed positive attitudes but varying levels of control and normative beliefs across contexts. The study's cross-cultural scope is a strength, yet its small sample size and focus on pre-service teachers limit its explanatory depth for institutionalised adoption among professional lecturers. It also omits structural variables such as organisational support or technology infrastructure, which are vital in actual adoption. The study extends beyond intention alone by linking intention to readiness and incorporating intervening factors, such as institutional support and socioeconomic status. This makes it better suited for understanding systemic adoption among experienced lecturers in resource-constrained environments.

Another study by Ayanwale et al. (2022) investigated the factors influencing Nigerian teachers' readiness and intention to teach AI, using a survey of 368 in-service teachers from elementary to high school levels. The findings showed that confidence in teaching AI predicts intention, while the relevance of AI strongly predicts readiness. However, anxiety and social good did not significantly affect intention or readiness. Despite providing useful insights, the study has limitations that impact its broader applicability. Its limited sample and the location-specific nature limit the extent to which the results can be applied beyond the specific region. This highlights the need for broader research that captures both individual and institutional factors influencing educators' acceptance and use of AI in teaching.

2.5 Acceptance and Use of AI Technologies in Higher Education

Acceptance of AI technologies in higher education depends on how lecturers perceive their usefulness, accessibility, and integration within mobile and digital learning environments. According to Venkatesh et al. (2003), acceptance is driven by performance expectancy and effort expectancy. Lecturers adopt AI tools more readily when they improve teaching efficiency and are easy to use across multiple digital devices. Mutanga et al. (2024) found that adoption strengthens when AI platforms align with educational values and professional goals, especially in mobile-based learning, where flexibility and responsiveness matter. Conversely, when AI tools are perceived as complex or poorly suited to existing mobile teaching practices, lecturers show low acceptance. Grelle and Hofmann (2024) also highlighted that institutional support, policies, and continuous training increase acceptance, reinforcing the importance of system-wide structures that integrate AI with mobile learning applications and digital teaching platforms.

The acceptance process also depends on communication networks and shared learning experiences that promote diffusion. Rogers (2003) noted that innovations spread faster when peer communication supports understanding and confidence. Deraney (2022) observed that collaborative learning and mentoring encourage early adoption, especially when lecturers exchange experiences using AI-driven mobile platforms and applications. Similarly, Uzorka et al. (2025) reported that institutional workshops and seminars facilitate formal learning pathways that strengthen AI adoption and usage. In under-resourced universities, such communication channels and mobile access points are vital for building collective confidence in new technologies. Therefore, acceptance and actual use of AI reflect both individual motivation and the communication systems that sustain innovation in mobile and digital learning environments. Reviewing empirical studies exploring how these factors influence readiness to adopt AI technologies is vital.

The study of Sobaih et al. (2024) analysed Saudi students' acceptance and use of ChatGPT using the UTAUT model with 520 respondents. Their results confirmed the effects of performance expectancy, effort expectancy, and social influence but revealed non-significant links between facilitating conditions and behavioural intention. The research provides useful evidence from a well-controlled university setting, but neglects broader institutional realities such as infrastructure and policy support. Its reliance on student data also constrains its implications for faculty-level AI adoption. This study fills this gap by focusing on lecturers, whose decisions determine actual classroom and research use. By integrating DOI and UTAUT, it encompasses both micro-level (intention, readiness) and macro-level (institutional support) dynamics across several universities, thereby enhancing generalisability beyond a single institutional context.

Ragheb et al. (2022) examined Egyptian students' behavioural intention to accept chatbot technology in higher education using the UTAUT framework. Their study of 385 respondents found that performance expectancy, effort expectancy, and social influence significantly influence intention, while demographic factors had no moderating effect. The research is limited by its single-institution focus and exclusive reliance on students, neglecting readiness and contextual enablers such as institutional policy or infrastructure. It also centres on chatbot technology rather than broader AI applications. The current research advances this work by situating AI adoption within a wider educational technology context, analysing behavioural intention and readiness jointly, and accounting for both personal and institutional influences using a larger, multi-university lecturer sample from Northwest Nigeria.

Another study by Ofosu-Ampong (2024) explored lecturers' acceptance of AI in teaching through an online survey of 94 university lecturers. The study found that most lecturers (84%) were willing to accept AI for their students, while 16% were not. Key predictors of acceptance included teaching experience, institutional support, and attitude toward AI. However, the study had several limitations. It relied on convenience and snowball sampling, which may have introduced bias and reduced representativeness. The use of online questionnaires, shared mainly via WhatsApp and email, likely restricted participation to more digitally literate lecturers. Combined with the small sample size, these factors limit the extent to which the results can be applied to the broader academic community.

2.6 Institutional and Socioeconomic Determinants of AI Adoption in Higher Education

Institutional support plays a decisive role in how lecturers adopt AI, particularly when linked to mobile and digital learning systems. Khairullah et al. (2025) observed that leadership commitment and clear institutional policies establish strategic direction and promote confidence in adopting AI-enabled teaching tools. Shonubi (2024) noted that reliable internet connectivity, functional mobile devices, and access to cloud-based AI platforms significantly enhance lecturers' readiness. Similarly, Aithal and Aithal (2023) found that targeted training and continuous professional development strengthen lecturers' ability to integrate AI mobile learning applications. Institutional culture further drives this process; universities that promote innovation and recognise technology-based teaching encourage wider experimentation with AI tools for academic engagement. In this sense, institutional support is not limited to infrastructure but includes leadership, mobile access, and skill development systems that collectively sustain AI adoption.

Socioeconomic realities also shape how lecturers use AI technologies in higher education. Njeri and Taym (2024) reported that disparities in income and resource access determine whether educators can afford mobile devices, data plans, and reliable connectivity, key enablers of AI adoption for academic engagement. Flavián et al. (2022) added that demographic factors, such as age and exposure to technology, influence both confidence and willingness to adopt AI tools. In developing contexts, the digital divide deepens this gap, as lecturers at underfunded institutions face limitations that limit their participation in AI-supported teaching. This shows that adoption is not merely a matter of personal motivation but also depends on institutional capacity and socioeconomic access to mobile and digital resources that enable AI adoption.

3 Methodology

This study adopted a descriptive survey research design, which is suitable for examining lecturers' behavioural intention and readiness to adopt AI for academic engagement. The design enables the collection of data from a large population at a single point in time, allowing for the description of existing conditions and patterns without manipulating variables. It aligns with the study's framework, which draws on the Diffusion of Innovation (DOI) theory and the Unified Theory of Acceptance and Use of Technology (UTAUT), as both theories focus on how individuals and institutions respond to new technologies. The study captures lecturers' perceptions, experiences, and readiness levels using this design and provides reliable evidence to understand adoption pathways within the university context.

The population of this study comprises lecturers from federal universities in North West Nigeria, including Kano, Kaduna, Katsina, Kebbi, Jigawa, Sokoto, and Zamfara. These universities host lecturers from diverse disciplines, making them key stakeholders in the adoption of AI. From a population of 6,837 lecturers, a sample size of 610 was recommended, but the researchers increased it to 759 to improve statistical power. This decision aligns with Andrade's (2020) perspective, which argues that a sufficiently large sample size is vital for effectively detecting even the smallest meaningful effects or relationships between variables.

A multi-stage sampling approach was employed to ensure proportional and representative coverage. In the first stage, proportionate sampling was used to allocate respondents based on each university's staff strength: For instance, University A, with 1623 lecturers, contribute 180 respondents; University B, with 1506 lecturers, contribute 167 respondents; University C, with 1264 lecturers, contribute 141 respondents; University D, with 716 lecturers, contribute 80 respondents; University E, with 706 lecturers, contribute 78 respondents; University F, with 614 lecturers, contribute 68 respondents; and University G, with 408 lecturers, contribute 45 respondents. This allocation preserved each university's relative weight within the total population. In the second stage, simple random sampling identified individual participants, ensuring that every lecturer had an equal chance of selection and that institutional representation remained balanced. Data were collected through both physical questionnaires and Microsoft Forms, ensuring broader participation and accessibility. This method provided a fair representation of lecturers across the region, supporting reliable and generalisable findings on AI readiness.

The primary instrument for data collection in this study is the AI Technology Adoption

Questionnaire (AITAQ), which measures factors influencing lecturers' readiness to adopt AI in Northwest Nigerian universities. The questionnaire is based on the UTAUT and DOI frameworks, examining both macro- and micro-level dynamics, thus offering a comprehensive assessment of AI adoption readiness. This ensures that it captures key adoption variables, such as behavioural intention, readiness, and acceptance of AI. It is divided into four sections (A-D), comprising a total of 26 items that cover both intervening variables and adoption-related constructs: 2 for the intervening variable, 8 for behavioural intention, 8 for readiness, and 8 for acceptance. A four-point modified Likert scale was used, ranging from awareness levels to agreement and likelihood ratings, depending on the section. This structured design ensures comprehensive data collection, providing a clear picture of how different factors influence lecturers' adoption of AI technologies.

The AITAQ instrument was designed to comprehensively capture factors influencing lecturers' readiness to adopt AI technologies for academic engagement. Its validity was established through expert evaluation covering face, content, construct, and criterion-related validity. Educational technology specialists confirmed the clarity and relevance of items, ensuring they measure what they intend to. Measurement experts verified that the instrument adequately represents constructs such as behavioural intention, readiness, and acceptance. AI and educational technology experts confirmed alignment with the study's theoretical framework, while evaluators established criterion-related validity by benchmarking with validated tools. Collectively, these assessments confirm the AITAQ's robustness and theoretical alignment for measuring AI adoption among university lecturers.

To establish reliability, a pilot study was conducted with 62 lecturers from a university outside the main study area. The split-half method, supported by the Spearman-Brown prophecy formula, was used to test internal consistency because a retest was impractical. The reliability coefficients were excellent across the constructs with Behavioural Intention (0.96), AI Acceptance (0.95), and Readiness (0.94), yielding an overall reliability index of 0.95. According to Octafia et al. (2020), a reliability coefficient closer to 1.0 signifies stronger consistency and dependability of an instrument, while a coefficient near 0 indicates weaker reliability. These results demonstrate that the AITAQ instrument is internally consistent, stable, and reliable for assessing university lecturers' AI adoption readiness.

This study adhered to strict ethical standards to ensure research integrity and participant protection. Informed consent was obtained, with participants fully briefed on the study's purpose, procedures, risks, and benefits. Confidentiality and anonymity were maintained through unique identifiers and secure data storage. Participants retained the right to withdraw at any time without consequence. Ethical approval was obtained from the relevant institutional review boards prior to data collection. All data were collected and reported transparently, with no manipulation or fabrication. Access to personal information was restricted to the research team, and published findings used aggregated data to prevent identification. These measures reflect a commitment to ethical research and respect for participants' rights. The data in this study were analysed using quantitative methods to answer the research questions and test the hypotheses. Descriptive statistics such as means, standard deviations, and weighted averages were used to measure behavioural intention, readiness, and acceptance of AI technologies among lecturers. Scores below the average indicated weaker levels, while those above showed stronger levels of intention, readiness, or acceptance. Spearman's Rank Correlation was employed to test hypotheses and examine relationships among variables, including socioeconomic status, institutional support, behavioural intention, and acceptance of AI. It was chosen over regression and SEM because the data were ordinal and violated the normality and linearity assumptions, despite the large sample. This non-parametric technique provided a reliable measure of association for ranked, non-normally distributed data, ensuring valid interpretation without overfitting. Relationships were considered significant; a p-value less than 0.05 indicated a significant relationship, while a value above 0.05 showed no significant relationship, supporting analytical accuracy and methodological appropriateness for the study's objectives.

4 Results

4.1 Analysis of Institutional Support and Socioeconomic Status on AI Adoption

This section presents the analysis and interpretation of the intervening variables, Institutional Support and Socioeconomic Status, to understand their possible influence on AI adoption among university lecturers in Northwest Nigeria. These variables provide information about related factors that may influence readiness, intention, and the capacity to integrate AI technologies into academic activities. The analysis explores how institutional provisions such as policies, training, and infrastructure, alongside individual financial stability, intersect with lecturers' adoption behaviours, thus enriching the study's broader findings on technology integration in higher education. The descriptive analysis is presented in Table 1 and 2.

Table 1 Institutional Support Status on AI Technology Adoption

Valid	Frequency	Percent	Valid Percent	Cumulative Percent
No Support	184	24.2	24.2	24.2
Minimal Support	461	60.7	60.7	85.0
Some Support	99	13.0	13.0	98.0
Moderate Support	15	2.0	2.0	100.0
Total	759	100.0	100.0	

Source: Field Survey, 2025.

Table 2 Socioeconomic Status on AI Technology Adoption

Valid	Frequency	Percent	Valid Percent	Cumulative Percent
Basic Income	302	39.8	39.8	39.8
Moderate Income	236	31.1	31.1	70.9
Comfortable Income	69	9.1	9.1	80.0
Financially Secure	152	20.0	20.0	100.0
Total	759	100.0	100.0	

Source: Field Survey, 2025.

The analysis shows that most lecturers perceive institutional support for AI adoption as weak. As shown in Table 1, a large proportion, 60.7% (n = 461), reported receiving only minimal support, while 24.2% (n = 184) said they had no support at all. Together, this represents 84.9% of respondents, highlighting a significant gap in institutional efforts. Only 13.0% (n = 99) reported some support, and 2.0% (n = 15) acknowledged moderate support, while none experienced strong support. These findings suggest that universities in the study area lack the structured policies, infrastructure, training, and incentives necessary to promote AI adoption, reflecting a low overall level of institutional readiness to integrate AI into academic activities.

The analysis of socioeconomic status presented in Table 2 reveals that a significant proportion of university lecturers operate on modest financial means. Nearly 40% of respondents reported having a basic income, indicating that financial limitations may pose a barrier to accessing or adopting AI tools. Another 31.1% described their income as moderate, suggesting relative financial stability but still limited discretionary resources. In contrast, only 9.1% considered their income comfortable, while 20% reported being financially secure. This pattern suggests that while a minority of lecturers may have the economic flexibility to invest in AI-related tools or training, the majority may be constrained by limited resources. Financial capacity, therefore, plays a vital role as an intervening factor influencing readiness and access to AI technology in academic settings.

4.2 Analyses and Interpretation of Results Based on Research Questions

This section presents the interpretation of results based on the three research questions that guided this study. All the research questions were analysed using descriptive statistics, specifically the mean and standard deviation, to capture patterns in lecturers' responses regarding their intention, readiness, and acceptance toward AI technologies. The interpretations aim to provide a clear understanding of lecturers' perspectives and readiness for AI integration in academic activities across universities in Northwest Nigeria.

4.2.1 Research Question One

What is the behavioural intention of university lecturers to adopt AI technologies for academic engagement in Northwest Nigeria?

This section presents the table containing all the items used to measure the study's first research objective, focusing on university lecturers' behavioural intention to adopt AI technologies for academic engagement in Northwest Nigeria. The responses were analysed using descriptive statistics, particularly the mean and standard deviation. The summary of findings is presented in Table 3.

Table 3 Descriptive Analysis of Behavioural Intention to Adopt AI Technologies (n = 759)

S/No	Statements	N	Mean	SD	Remark
1	I am willing to explore how AI technologies can improve my instructional delivery.	759	3.4032	0.65644	High
2	I feel motivated to learn more about AI tools relevant to my academic responsibilities.	759	3.3874	0.64986	Low
3	I intend to use AI technologies if provided with adequate support and training.	759	3.5652	0.65432	High
4	I believe that integrating AI into my work will enhance my professional effectiveness.	759	3.5165	0.66929	High
5	I am open to adjusting my teaching methods to incorporate AI innovations.	759	3.4216	0.68443	Low
6	I am confident that utilising AI tools will have a positive impact on student learning outcomes.	759	3.2727	0.74130	Low
7	I am prepared to invest time in learning how to use AI effectively in teaching and research.	759	3.4177	0.58183	Low
8	I am mentally prepared to incorporate the use of AI into my academic activities.	759	3.4506	0.54832	High
	Weighted Average		3.43		

Source: Field Survey, 2025.

The analysis of university lecturers' behavioural intention to adopt AI technologies, as presented in Table 3, reveals a generally positive disposition toward AI integration in academic settings. With a weighted mean score of 3.43, the responses suggest a strong willingness to engage with AI, particularly when adequate support and training are available (M = 3.57). Lecturers also expressed confidence that AI can enhance their professional effectiveness (M = 3.52) and showed openness to adjusting teaching methods (M = 3.42). However, slightly lower mean scores on motivation to learn about AI (M = 3.39) and readiness to invest time (M = 3.42) indicate a need for continuing institutional encouragement. Overall, the findings reflect a constructive behavioural intention, shaped by perceived benefits and the availability of necessary resources and support systems.

4.2.2 Research Question Two

What is the perceived readiness of university lecturers to adopt AI technologies for academic engagement in universities in Northwest Nigeria?

This section presents the findings addressing the second research objective, which investigates the perceived readiness of university lecturers to adopt AI technologies for academic engagement in universities across Northwest Nigeria. The responses were analysed using descriptive statistics, specifically mean scores and standard deviations, to assess lecturers' readiness. The results of this analysis are clearly outlined and summarised in Table 4.

Table 4 Descriptive Analysis of Perceived Readiness to Adopt AI Technologies (n = 759)

S/No	Statements	N	Mean	SD	Remark
1	I am confident in my ability to transition into AI-supported teaching and research.	759	3.0013	0.65681	Low
2	I have developed enough understanding to adopt AI technologies without needing extensive support.	759	3.1304	0.57209	Low
3	I consider myself ready to participate in institutional AI-related initiatives or pilot projects.	759	3.1752	0.52597	Low
4	I can take the initiative to adopt AI tools even without being mandated to do so.	759	3.1318	0.57294	Low
5	I am psychologically prepared to explore and integrate AI in teaching, learning, or research.	759	3.1186	0.63675	Low
6	I feel ready to make informed decisions about which AI tools to adopt in my academic work.	759	3.3729	0.57370	High
7	I have set personal goals related to adopting or experimenting with AI tools in my work.	759	3.3136	0.58721	High
8	I am prepared to support or mentor colleagues on AI use when the opportunity arises.	759	3.3215	0.56218	High
	Weighted Average		3.20		

Source: Field Survey, 2025.

The analysis of lecturers' perceived readiness to adopt AI technologies for academic engagement in Northwest Nigeria reveals a generally moderate level of readiness. As presented in Table 4, most respondents reported low levels of readiness across several key areas, including confidence in transitioning to AI-supported academic work and psychological readiness for integrating AI. Mean scores for five of the eight items fell below the threshold of 3.30, suggesting persistent uncertainties and a lack of full preparedness among many lecturers. However, higher mean scores were observed for items relating to informed decision-making (M = 3.37), goal-setting (M = 3.31), and willingness to support colleagues (M = 3.32), indicating that while general readiness may be modest, there is a growing group of lecturers beginning to embrace AI adoption more actively. These findings point to a transitional readiness phase rather than full institutional maturity.

4.2.3 Research Question Three

What is the level of university lecturers' acceptance of AI technologies for academic engagement among universities in Northwest Nigeria? This section presents the analysis of data used to address the third research objective, which explores university lecturers' level of acceptance of AI technologies for academic engagement in Northwest Nigeria. The data were analysed using descriptive statistics, specifically mean and standard deviation, to capture the lecturers' views. The results are summarised and presented in Table 5.

Table 5 Descriptive Analysis of Acceptance of AI Technologies (n = 759)

S/No	Statements	N	Mean	SD	Remark
1	I currently use AI tools in teaching, research, and other academic-related activities.	759	3.2859	0.75577	High
2	I am open to adopting newly introduced AI tools in my department or institution.	759	3.2675	0.57740	High
3	I participate in training or learning activities to support my acceptance of AI use.	759	3.1014	0.69600	Low
4	I have recommended the use of AI tools to colleagues for academic purposes.	759	3.1225	0.70953	Low
5	I recognise AI as a vital component of future academic and instructional innovation.	759	3.2187	0.62879	High
6	My past experiences with technology have positively influenced my acceptance of AI tools.	759	3.2596	0.56953	High
7	Colleagues who positively use AI influence my acceptance of these technologies.	759	3.1041	0.63410	Low
8	Ethical and security concerns do not deter me from accepting the use of AI in education.	759	3.0870	0.67392	Low
	Weighted Average			3.18	

Source: Field Survey, 2025.

The analysis of lecturers' acceptance of AI technologies, as presented in Table 5, reveals a generally favourable disposition among university lecturers in Northwest Nigeria. With a weighted mean of 3.18, the findings indicate a moderate to high level of acceptance. Respondents showed strong agreement with statements related to current use (M = 3.29), openness to newly introduced tools (M = 3.27), recognition of AI's future importance (M = 3.22), and the positive influence of past technological experiences (M = 3.26). However, lower mean scores were recorded for items concerning participation in training activities (M = 3.10), peer influence (M = 3.10), and ethical or security concerns (M = 3.09). This suggests that while many lecturers are already using or willing to adopt AI tools, ongoing support mechanisms, such as peer learning, structured training, and addressing ethical concerns, are needed to strengthen institutional acceptance.

4.3 Analyses and Interpretation of Results Based on Research Hypotheses

This section presents the statistical analyses and interpretations of the research hypotheses formulated for this study. Each hypothesis was tested at the 0.05 level of significance to examine relationships between the identified variables. The analyses and interpretations are presented in line with the study's objectives.

4.3.1 Hypothesis One

H_{01}: There is no significant relationship between socioeconomic status and lecturers' behavioural intention to adopt AI technologies.

This section presents the analysis of data used to test Hypothesis One, which examines the relationship between socioeconomic status and university lecturers' behavioural intention to adopt AI technologies for academic engagement. The analysis, presented in Table 6, employed Spearman's Rank Correlation to determine the strength and significance of the association between the two variables.

Table 6 Spearman's Rank Correlation Result of Financial Status and Behavioural Intention to Adopt AI Technologies

Correlations				BehaviouralIntetion_Score
Spearman's rho	How would you describe your current financial situation based on your monthly income and expenses	Correlation Coefficient	1.000	0.006
		Sig. (2-tailed)	.	0.872
		N	759	759
	BehaviouralIntetion_Score	Correlation Coefficient	0.006	1.000
		Sig. (2-tailed)	0.872	.
		N	759	759

Source: Field Survey, 2025.

The Spearman's Rank Correlation analysis in Table 6 shows a very weak positive correlation (r = 0.006) between socioeconomic status and lecturers' behavioural intention to adopt AI technologies. However, the relationship is not statistically significant, as indicated by a p-value of .872, which is far above the 0.05 threshold. This suggests that lecturers' financial situations, as reflected in their monthly income and expenses, do not meaningfully influence their intention to adopt AI technologies. Therefore, the null hypothesis, which states that there is no significant relationship between socioeconomic status and behavioural intention, is retained. In practice, lecturers' financial backgrounds may not be a key determinant of their intent to integrate AI into academic activities.

4.3.2 Hypothesis Two

H$_{02}$: There is no significant relationship between institutional support and lecturers' behavioural intention to adopt AI technologies.

This section presents the analysis of data used to test Hypothesis Two, which examines the relationship between institutional support and university lecturers' behavioural intention to adopt AI technologies for academic engagement. The analysis, presented in Table 7, employed Spearman's Rank Correlation to determine the strength and significance of the association between the two variables.

Table 7 Spearman's Rank Correlation Result of Institutional Support and Behavioural Intention to Adopt AI technologies

Correlations				BehaviouralIntetion_Score
Spearman's rho	How would you rate the level of support your institution provides for the adoption of technologies in teaching and research	Correlation Coefficient	1.000	0.090*
		Sig. (2-tailed)	.	0.013
		N	759	759
	BehaviouralIntetion_Score	Correlation Coefficient	0.090*	1.000
		Sig. (2-tailed)	0.013	.
		N	759	759

Note: * Correlation is significant at the 0.05 level (2-tailed). Source: Field Survey, 2025.

Spearman's rank correlation analysis reveals a statistically significant but weak positive relationship ($\rho = 0.090$, $p = 0.013$) between institutional support and university lecturers' behavioural intention to adopt AI technologies. Since the p-value is less than the 0.05 significance threshold, the null hypothesis is rejected, indicating that as perceived institutional support increases through policies, infrastructure, training, incentives, and leadership, lecturers show a slight increase in their willingness to adopt AI tools for teaching and research. Although the strength of the association is modest, the finding underscores the relevance of supportive institutional environments in shaping positive behavioural intentions toward AI integration in academic settings.

4.3.3 Hypothesis Three

H$_{03}$: There is no significant relationship between socioeconomic status and lecturers' acceptance of AI technologies.

This section presents the analysis of data used to test Hypothesis Three, which examines the relationship between socioeconomic status and university lecturers' acceptance of AI technologies for academic engagement. The analysis, as shown in Table 8, employed Spearman's Rank Correlation to assess the direction, strength, and significance of the relationship between the two variables.

Table 8 Spearman's Rank Correlation Result of Financial Status and lecturers' acceptance of AI technologies

Correlations				Acceptance_Score
Spearman's rho	How would you describe your current financial situation based on your monthly income and expenses	Correlation Coefficient	1.000	0.033
		Sig. (2-tailed)	.	0.365
		N	759	759
	Acceptance_Score	Correlation Coefficient	0.033	1.000
		Sig. (2-tailed)	0.365	.
		N	759	759

Source: Field Survey, 2025.

The Spearman's rank correlation analysis in Table 8 reveals a very weak positive relationship ($\rho = 0.033$, p = 0.365) between socioeconomic status and university lecturers' acceptance of AI technologies for academic engagement. Although the correlation coefficient suggests a slight upward trend, the association is not statistically significant at the 0.05 level of significance. This means that variations in lecturers' financial standing do not meaningfully influence their acceptance of AI technologies in this context. Given the high p-value, the null hypothesis is retained, indicating that there is no significant relationship between the two variables. The result suggests that financial circumstances, whether perceived as stable or constrained, do not appear to influence lecturers' willingness to accept and integrate AI into their academic activities. Other non-economic factors may therefore play a more prominent role in shaping acceptance.

4.3.4 Hypothesis Four

H_{04}: There is no significant relationship between institutional support and lecturers' acceptance of AI technologies.

This section presents the analysis of data used to test Hypothesis Four, which explores the relationship between institutional support and university lecturers' acceptance of AI technologies for academic engagement. The analysis, presented in Table 9, employed Spearman's rank correlation to assess the strength and significance of the association between perceived institutional support and lecturers' levels of acceptance of AI technologies.

Table 9 Spearman's Rank Correlation Result of Institutional Support and Acceptance of AI Technologies

Correlations				Acceptance_Score
Spearman's rho	How would you rate the level of support your institution provides for the adoption of AI technologies in teaching and research	Correlation Coefficient	1.000	0.092*
		Sig. (2-tailed)	.	0.011
		N	759	759
	Acceptance_Score	Correlation Coefficient	0.092*	1.000
		Sig. (2-tailed)	0.011	.
		N	759	759

Note: * Correlation is significant at the 0.05 level (2-tailed). Source: Field Survey, 2025.

The Spearman's rank correlation analysis in Table 9 reveals a statistically significant but weak positive relationship ($\rho = 0.092$, $p = 0.011$) between institutional support and university lecturers' acceptance of AI technologies for academic engagement. Although the correlation coefficient indicates a weak association, the significance value is below the 0.05 threshold, suggesting that institutional support, such as policies, infrastructure, training, and leadership encouragement, has a meaningful influence on lecturers' willingness to adopt AI technologies. This implies that universities offering structured, visible support mechanisms are slightly more likely to have lecturers receptive to integrating AI into their teaching and learning activities. Therefore, the null hypothesis, which states that there is no significant relationship between institutional support and lecturers' acceptance of AI technologies, is rejected.

5 Discussion of Findings

The results presented revealed significant patterns in lecturers' behavioural intention, readiness, and acceptance of AI technologies for academic engagement across universities in Northwest Nigeria. The discussion that follows interprets these findings within the broader theoretical context of the DOI and the UTAUT, while situating them in recent international, African, and Nigerian scholarship. It also connects the findings to emerging forms of mobile and ubiquitous learning, where AI tools are increasingly integrated into flexible, device-mediated learning for academic activities.

The study found that lecturers' behavioural intention was strongly shaped by perceived usefulness, compatibility, and social influence, consistent with Zhang and Hou (2024), who reported that Chinese college teachers' intention to use AI-assisted teaching systems was driven by perceived ease of use and sociocultural support. Yet, their model was technology-centric and overlooked institutional dynamics. This study extends that perspective by demonstrating that institutional support, though weakly correlated ($\rho = 0.090$, $p < 0.05$), remains a statistically significant determinant of behavioural intention. It also situates this finding within the realities of African higher education, where infrastructural deficits and mobile-based access largely define digital engagement. In Ghana, Salifu et al. (2024) similarly found that motivation and facilitating conditions influenced students' use of ChatGPT, but their work underplayed the institutional dimension of digital readiness. This study bridges that gap by showing that institutional support, through access to AI-enabled mobile applications, continuous training, and supportive policies, amplifies lecturers' intention to adopt AI tools. Within the Nigerian context, this aligns with Ayanwale et al. (2022), who found that teachers' confidence and perceived relevance predict AI adoption intention. The novelty here lies in the broader, multi-university dataset (N = 759), which captures regional adoption dynamics and demonstrates that behavioural intention operates not in isolation but as part of a systemic interaction linking individual belief structures with institutional capacity in mobile learning environments. The findings revealed a moderate level of readiness, with many lecturers expressing limited confidence and psychological readiness for AI adoption. Although a subset of respondents indicated readiness to make informed decisions and support colleagues, most reported low preparedness across key indicators. This transitional stage mirrors the diffusion process described in DOI, where early adopters pave the way but institutional maturity remains limited. This pattern aligns with Alnasib (2023), who found that Jordanian teachers were optimistic about AI yet constrained by inadequate resources and training. Unlike Alnasib's small-scale analysis, this study shows a broader readiness pattern across multiple Nigerian universities, revealing that readiness grows where lecturers have mobile connectivity, access to AI platforms, and targeted professional development. Similarly, Mnguni et al. (2024) reported that pre-service teachers' readiness varied with contextual support in South Africa and Thailand, but their cross-national sample was too limited to generalise. In contrast, this study integrates both contextual (DOI) and personal (UTAUT) determinants, offering a richer view of how readiness evolves in a resource-constrained environment. Locally, the results expand Ayanwale et al. (2022), showing that lecturers' readiness depends less on anxiety or social good motives and more on institutional structures that sustain continuous learning. This reflects a shift toward mobile-mediated readiness, in which lecturers' engagement with AI increasingly occurs via smartphones, mobile learning management systems, and cloud-based apps rather than fixed infrastructure.

Lecturers' acceptance of AI technologies was moderate to high; it depends mainly on institutional communication and peer diffusion processes, consistent with Sobaih et al. (2024), who found that performance expectancy and social influence shaped students' acceptance of ChatGPT. Yet, the current findings go beyond individual perception by demonstrating how acceptance is reinforced through professional networks and mobile-based collaboration channels. For example, many lecturers in this study reported learning about AI applications through WhatsApp groups, Telegram research clusters, and mobile LMS platforms, forms of mobile-mediated diffusion largely absent in earlier models. This reaffirms DOI's argument that communication networks accelerate the uptake of innovation. Compared with Ragheb et al. (2022), whose study on Egyptian students omitted contextual moderators, the present findings incorporate institutional readiness and policy frameworks as critical enablers of acceptance. In Nigeria, these results parallel Ofosu-Ampong (2024), who showed that lecturers' acceptance depends on institutional support and prior exposure, but this study provides stronger empirical evidence due to its broader scope and inclusion of mobile-based engagement variables.

The correlation analyses revealed that institutional support significantly, but weakly, predicts both behavioural intention and acceptance, whereas socioeconomic status showed no meaningful relationship with either variable. This aligns with UTAUT's theoretical position that facilitating conditions are external enablers of technology adoption (Venkatesh et al., 2003), and with DOI's emphasis on the social and institutional diffusion process (Rogers, 2003). In other words, lecturers' willingness to engage with AI is less about individual wealth and more about institutional climate, policies, incentives, and technological access. This study offers a novel explanatory framework for understanding AI adoption in higher education systems in developing countries by integrating DOI and UTAUT. The DOI lens clarifies how innovations spread across institutional contexts, while UTAUT explains why individuals choose to engage with technology. Together, they illuminate how personal motivation interacts with institutional structures to shape behavioural intention, readiness, and acceptance. The large-scale dataset (N = 759) strengthens the empirical base for these theoretical integrations and provides rare regional insight into lecturers' adaptive behaviours in resource-limited environments.

This study advances the global conversation on technology adoption in higher education by integrating the DOI and UTAUT frameworks into a unified explanatory model that captures both individual and institutional dimensions of AI uptake. It empirically validates a combined set of these frameworks that explains AI adoption as a multilevel process linking personal intention, institutional readiness, and systemic support. Its large multi-university Nigerian dataset, spanning 759 lecturers, offers one of the most comprehensive quantitative accounts of AI adoption in African higher education, extending comparative insights to the Global South. It situates AI adoption within mobile and emerging learning contexts, showing that mobile access, data-driven platforms, and ubiquitous learning tools increasingly mediate adoption. For policymakers, this implies that promoting mobile infrastructure, subsidising data access, and integrating AI capacity-building into professional development will significantly enhance readiness and sustainability. Institutional leaders should therefore view AI adoption not as a technological challenge but as an organisational transformation requiring coordinated policy, infrastructure, and capacity alignment.

6 Conclusion

This study examined lecturers' readiness to adopt artificial intelligence (AI) technologies in universities across Northwest Nigeria, focusing on behavioural intention, readiness, acceptance, and the role of intervening factors, including socioeconomic status and institutional support. The findings reveal that lecturers generally expressed a positive behavioural intention to adopt AI, with many recognising its potential value for teaching, learning, and research. However, their level of readiness was moderate, marked by limited confidence, uneven preparedness, and cautious engagement. This suggests that while lecturers are mentally open to adopting AI, they require more substantial support to move from intention to consistent practice. However, socioeconomic status showed no significant relationship with either behavioural intention or acceptance, suggesting that financial standing is not a decisive factor in AI adoption. Institutional support, in contrast, demonstrated a significant though weak relationship with both behavioural intention and acceptance. These finding highlights that while lecturers are generally receptive to AI integration, meaningful adoption will depend less on individual socioeconomic capacity and more on institutional structures that provide enabling conditions. Universities that strengthen such support mechanisms are more likely to achieve sustained AI adoption in teaching and research. The results also reinforce the relevance of the UTAUT framework, which identifies behavioural intention as a core predictor of adoption and stresses the role of facilitating conditions. Lecturers' moderate readiness suggests that intention alone is insufficient without institutional support and capacity-building. Similarly, the findings resonate with the DOI theory, which emphasises perceived advantages and supportive environments as key to diffusion.

7 Recommendations

Based on the findings of this research, the following recommendations are proposed to enhance lecturers' engagement with AI in public universities in North West Nigeria:

(1) Strengthen Institutional Support Mechanisms: The study highlights institutional support as a significant factor shaping lecturers' behavioural intention and acceptance of AI. Universities should introduce clear policies, provide infrastructure, and invest in desired AI training programmes for staff. A key challenge lies in limited funding and competing institutional priorities, which may hinder sustained investment. To overcome this, universities can adopt a phased implementation strategy, prioritising low-cost, high-impact interventions such as training workshops and policy frameworks before scaling up to larger infrastructural investments.

(2) Enhance Lecturer Readiness through Continuous Capacity Building: Findings reveal that, while the intention is positive, readiness is moderate due to limited confidence and uneven willingness. Regular, situation-specific capacity-building programmes personalised to different disciplines are recommended. The challenge is lecturers' resistance to additional workload and possible low motivation to attend training. To address this, institutions should integrate AI training into existing professional development structures and provide incentives such as certification, promotion points, or research grants. Linking training to practical teaching and research benefits will further encourage participation.

(3) Promote a Supportive AI Adoption Culture: Although lecturers showed moderate acceptance of AI, peer influence and collaborative practices were weak. Building a culture of shared learning, where early adopters mentor colleagues and pilot projects showcase practical benefits, is crucial. However, institutional fragmentation and limited cross-departmental collaboration may slow down the diffusion. To counter this, universities should establish AI learning communities and departmental champions who model use cases. Providing recognition or rewards for AI innovators can also strengthen motivation and reduce reluctance.

(4) Address Ethical, Security, and Policy Concerns: Universities should establish clear ethical guidelines, robust data protection policies, and effective accountability frameworks for the responsible use of AI in teaching and research. The challenge lies in limited local expertise and weak regulatory systems that may delay policy formulation. A feasible solution is to adapt global best practices while gradually building internal knowledge through collaborations with professional associations and international research networks.

(5) Bridge the Gap Between Intention and Practice: Positive behavioural intention does not automatically translate into full adoption. Institutions must provide practical opportunities, such as pilot projects, funded research, or teaching innovations, that allow lecturers to move from intention to real application. A challenge here is ensuring sustainability beyond initial projects, as enthusiasm often diminishes without follow-up. To mitigate this, universities should embed AI use in core teaching and research processes rather than treating it as an add-on. Monitoring mechanisms and regular evaluations should also be introduced to track adoption, address challenges, and sustain momentum.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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