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Assessment of Artificial Intelligence adoption among Lecturers in Nigerian Universities: Examining Capability, Opportunity and Motivation – Behavioural (COM-B) Framework

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Abstract

This study examined the behavioural determinants of Artificial Intelligence (AI) adoption among university lecturers in Southwest Nigeria using the Capability–Opportunity–Motivation Behaviour (COM-B) framework. It analysed how lecturers' competence, institutional conditions, and motivational drivers shape AI integration in teaching, research, and academic practice. A descriptive cross-sectional survey design was employed, drawing on data from 2,145 lecturers across federal, state, and private universities using a structured questionnaire with satisfactory reliability ($\alpha = 0.79–0.84$). Data were analysed using descriptive statistics, t-tests, Pearson correlation, and multiple regression. Findings revealed moderate capability (mean: 2.06–2.50), indicating strong digital literacy but limited institutional training, highlighting the need for structured capacity-building and continuous professional development. Institutional opportunity was also moderate yet uneven (mean: 1.85–2.35), constrained by funding gaps, governance inefficiencies, and weak digital infrastructure, underscoring the importance of improved policy coherence and investment. Motivation was relatively strong (mean: 2.00–2.52), driven by perceived teaching benefits and professional identity, though influenced by social and institutional factors, suggesting the need for incentives, recognition, and collaborative support systems. AI use was evident in teaching and research but limited in assessment and institutional engagement, revealing an intention–practice gap and the need for embedding AI into formal workflows. Capability significantly influenced adoption ($t = 2.41, p < 0.05$), while opportunity ($r = 0.48$) and motivation ($r = 0.66$) were strong predictors, explaining 58% of variance. The study recommends integrated institutional strategies to strengthen capacity, expand opportunities, and sustain motivation for equitable AI adoption.

Keywords: Artificial Intelligence Adoption, COM-B Behavioural Framework, Motivation and Technology Integration

Introduction

Artificial Intelligence (AI) has emerged as a transformative force reshaping knowledge systems, economic productivity, and institutional innovation. In higher education, AI is increasingly integrated across teaching, research, administration, and knowledge production, fundamentally redefining how universities deliver instruction, conduct scholarship, and manage resources (Luckin et al., 2016; Zawacki Richter et al., 2019; UNESCO, 2023). AI-driven tools include intelligent tutoring systems, automated assessment platforms, adaptive learning environments, and generative AI applications that extends pedagogical possibilities by enhancing personalization, operational efficiency, and accessibility for diverse learners (Holmes et al., 2019; OECD, 2021; UNESCO, 2023). Consequently, AI has shifted from a peripheral innovation to a central driver of institutional digital transformation, influencing curriculum design, assessment practices, and decision-making processes (Zawacki Richter et al., 2019; OECD, 2021). Systematic research demonstrates that AI-enhanced environments support profiling and prediction, adaptive learning, intelligent tutoring, and automated



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evaluation, thereby improving both learning outcomes and institutional effectiveness (Zawacki Richter et al., 2019; Holmes & Tuomi, 2022). However, global policy discourse, particularly UNESCO's (2023) guidance on generative AI emphasizes the need for human-centred integration that balances innovation with ethical responsibility, pedagogical integrity, and equity considerations. Within this evolving landscape, AI adoption has become critical to enhancing instructional quality, advancing research productivity, and sustaining institutional competitiveness in a rapidly digitizing academic ecosystem (OECD, 2021; Luckin et al., 2016). University lecturers play a pivotal role in this transformation, acting as key agents in interpreting, adopting, and integrating AI into academic practice (Selwyn, 2016; Bond et al., 2018). Their influence spans pedagogical innovation, research processes, and institutional digital transformation. Increasingly, lecturers are expected to embed AI into instructional design, assessment, and scholarly work to align higher education with evolving digital ecosystems (OECD, 2021; UNESCO, 2023). However, AI adoption is not merely technological; it is a behavioural and organisational process shaped by the interaction of individual competence, institutional structures, and motivational dynamics (West & Michie, 2020; Zawacki Richter et al., 2019).

The Capability–Opportunity–Motivation Behaviour (COM-B) model provides a comprehensive framework for understanding these dynamics (Michie et al., 2011; West & Michie, 2020). It posits that behaviour emerges when individuals possess adequate capability (knowledge, skills, and self-efficacy), operate within supportive opportunity structures (resources, infrastructure, and policy frameworks), and are sufficiently motivated (beliefs, incentives, and professional aspirations). Applied to AI adoption, the COM-B model offers a holistic explanation of how lecturers' competencies, institutional environments, and motivational drivers interact to shape behavioural engagement with AI technologies (Holmes et al., 2019; Zawacki Richter et al., 2019). This perspective extends beyond perception-based models by incorporating structural and contextual realities within higher education systems. In developing contexts such as Nigeria, universities are increasingly pursuing AI-driven innovation to enhance teaching effectiveness, research productivity, and administrative efficiency (Oke & Olatunji, 2023; UNESCO, 2023). Despite this thrust, AI adoption remains uneven, constrained by systemic challenges including limited digital infrastructure, inadequate funding, insufficient professional development, and organisational cultures that do not consistently support experimentation and innovation (OECD, 2021; Chaka, 2020). Although many lecturers demonstrate baseline digital literacy and interest in emerging technologies, sustained and transformative AI integration depends on coordinated institutional support, including reliable infrastructure, coherent policies, structured capacity-building programmes, collaborative innovation ecosystems, and meaningful professional incentives (Bond et al., 2018; Selwyn, 2016). Understanding the behavioural and institutional determinants of AI adoption is therefore essential. Examining lecturers' capability, opportunity conditions, motivation, and behavioural engagement provides critical insight into the factors shaping technological transformation, particularly in resource-constrained university environments (Zawacki Richter et al., 2019; Oke & Olatunji, 2023). However, much of the existing literature relies on perception-based frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which focus on perceived usefulness and ease of use as primary predictors of adoption (Davis, 1989; Venkatesh et al., 2003). While valuable, these models inadequately capture the broader behavioural, contextual, and organisational dynamics that influence sustained technology integration in complex academic settings (Holmes et al., 2019; West & Michie, 2020). Moreover, studies on AI in education often emphasise technical capabilities and pedagogical potential while under examining the behavioural



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conditions necessary for actual and sustained adoption (Holmes et al., 2019; Zawacki Richter et al., 2019; UNESCO, 2023). Empirical evidence from developing regions remains limited, with most research concentrated in Europe, North America, and East Asia (OECD, 2021; Zhang et al., 2021). Additionally, the application of behavioural frameworks such as COM-B to AI adoption in higher education is still underdeveloped, leaving a significant gap in understanding how lecturers' competence, institutional opportunity structures, and motivation interact within specific socio-economic contexts, particularly in Nigerian universities (Oke & Olatunji, 2023; Zawacki Richter et al., 2019). Although AI technologies hold substantial potential to transform teaching, research, and institutional management, their effectiveness ultimately depends on lecturers' actual use in everyday academic practice (Luckin et al., 2016; Bond et al., 2018). In practice, adoption often remains superficial, with lecturers engaging primarily in basic digital tasks rather than leveraging AI for transformative pedagogical and research innovation (UNESCO, 2023; OECD, 2021). This limitation is partly attributable to gaps in advanced competencies, particularly in data-driven decision-making, adaptive instructional design, and AI-supported research methodologies (Holmes et al., 2019; Zawacki Richter et al., 2019).

Institutional constraints further exacerbate these challenges. Weak infrastructure, fragmented policy implementation, inconsistent funding, and limited access to sustained professional development hinder the institutionalisation of AI adoption (OECD, 2021; UNESCO, 2023). Even where capability exists, motivation becomes a decisive factor. Professional incentives, peer collaboration, institutional recognition, and perceived relevance of AI to teaching effectiveness and career advancement significantly influence lecturers' willingness to integrate AI into routine practice (Selwyn, 2016; Michie et al., 2011; West & Michie, 2020). Without alignment between motivational drivers and enabling institutional structures, AI adoption remains sporadic, individualised, and disconnected from broader institutional strategies (Bond et al., 2018; OECD, 2021). Studies substantiates that there is limited empirical understanding of the behavioural determinants of AI adoption in developing contexts such as Nigeria (Zawacki Richter et al., 2019; Oke & Olatunji, 2023). The dominance of perception-based frameworks has constrained deeper insight into how capability, opportunity, and motivation interact to shape actual behaviour within real-world institutional settings (Davis, 1989; Venkatesh et al., 2003; Bond et al., 2018). This gap limits the ability of universities to design evidence-based interventions that foster deep, equitable, and system-wide AI integration (West & Michie, 2020). Accordingly, this study addresses the insufficient understanding of the behavioural, motivational, and institutional factors influencing lecturers' AI adoption. By applying the COM-B framework, it systematically examines lecturers' capability, institutional opportunity structures, motivational drivers, and behavioural engagement with AI. In doing so, the study generates context-sensitive and actionable insights to inform strategic, sustainable, and equitable AI integration in Nigerian universities and similar resource-constrained higher education systems.

Research Objectives

The main objective of this study is to examine the behavioural determinants of Artificial Intelligence adoption among university lecturers. The specific objectives are to:

1. Examine the level of capability of university lecturers for adopting and integrating Artificial Intelligence in teaching, research, and academic activities.
2. Investigate the institutional opportunity conditions that influence the adoption of Artificial Intelligence among university lecturers.
3. Assess the motivational factors that influence lecturers' engagement with Artificial Intelligence technologies.



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4. Determine the extent of Artificial Intelligence adoption behaviour among university lecturers in their academic practices.

Research Questions

The study is guided by the following research questions:

1. What is the level of capability of university lecturers for adopting and integrating Artificial Intelligence in teaching, research, and academic activities?
2. What institutional opportunity conditions influence the adoption of Artificial Intelligence among university lecturers?
3. What motivational factors influence lecturers' engagement with Artificial Intelligence technologies?
4. To what extent do university lecturers adopt Artificial Intelligence tools in their academic practices?

Research Hypotheses

The following null hypotheses were tested in the study:

- H₀₁: Lecturers' capability has no significant influence on Artificial Intelligence adoption behaviour in universities.
- H₀₂: Institutional opportunity conditions have no significant influence on Artificial Intelligence adoption among university lecturers.
- H₀₃: Motivational factors have no significant influence on lecturers' Artificial Intelligence adoption behaviour.
- H₀₄: There is no significant relationship between capability, opportunity, motivation, and Artificial Intelligence adoption behaviour among university lecturers.

Methodology

This study employed a descriptive cross-sectional survey design to examine the current state of Artificial Intelligence (AI) adoption among university lecturers in Southwest Nigeria and to analyse the relationship between behavioural determinants and institutional factors. The design enabled simultaneous assessment of capability, opportunity, motivation, and AI adoption behaviour, providing a comprehensive snapshot of variations across gender, institutional type, and academic rank. By integrating descriptive and inferential approaches, the study identified patterns, disparities, and predictors of AI integration within higher education. The study population comprised academic staff from federal, state, and private universities in Southwest Nigeria, representing diverse disciplines, academic ranks, and levels of AI exposure. The region was purposively selected due to its concentration of institutions advancing digital transformation. A stratified random sampling technique ensured proportional representation by institutional type and gender. Out of 2,400 distributed questionnaires, 2,145 valid responses were obtained, yielding an 89.4% response rate and supporting statistical reliability. The sample included approximately 1,300 male lecturers (60.6%) and 845 female lecturers (39.4%), enabling meaningful gender-based analysis. Data were collected using a structured questionnaire grounded in the COM-B behavioural framework. Four constructs—capability, opportunity, motivation, and AI adoption behaviour—were operationalised into distinct sections. Capability assessed technical knowledge, AI proficiency, digital literacy, adaptability, and access to training. Opportunity examined institutional support, including infrastructure, policies, funding, inclusivity, workload flexibility, and innovation culture. Motivation captured intrinsic and extrinsic drivers such as self-efficacy, professional identity, perceived teaching impact, career advancement, and collegial support. AI adoption behaviour measured actual use across teaching, assessment, research, workflow integration, and future intentions. Responses were



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rated on a five-point Likert scale and later condensed into three categories. The instrument was validated by five experts to ensure clarity, relevance, and alignment with the COM-B framework. A pilot test with 50 lecturers confirmed clarity and reliability, with Cronbach’s alpha values indicating strong internal consistency: Capability ($\alpha = 0.82$), Opportunity ($\alpha = 0.79$), Motivation ($\alpha = 0.84$), and AI Adoption Behaviour ($\alpha = 0.80$). Data were collected through both electronic and paper-based formats over six weeks, with assurances of confidentiality and voluntary participation. Analysis using SPSS 28 combined descriptive statistics and inferential techniques (t-tests, correlation, regression) to examine gender differences, predictive relationships, and gaps in AI adoption within the COM-B framework.

Presentation of Results

Table 1: Capability by Gender

Capability Indicator	Agree			Neutral			Disagree			Mean Score
	Male	Female	Total	Male	Female	Total	Male	Female	Total	
Technical knowledge for AI teaching	780	507	1287	220	140	360	300	198	498	2.37
AI competence for research	710	470	1180	320	216	536	270	159	429	2.35
Digital literacy for emerging AI	820	575	1395	250	179	429	230	91	321	2.50
Ability to adapt to new AI systems	770	517	1287	230	136	366	300	192	492	2.37
Academic training prepared me for AI	620	453	1073	270	206	476	410	186	596	2.22
Access to institutional AI training	610	356	966	190	146	336	500	343	843	2.06
Continuous AI professional development	640	433	1073	210	126	336	450	286	736	2.16

Table 1 examines lecturers’ capability to adopt Artificial Intelligence (AI) technologies across indicators such as technical knowledge, research competence, digital literacy, adaptability, and access to institutional training. Within the COM-B behavioural framework, capability represents the knowledge and skills required for individuals to perform a behaviour effectively, including AI adoption in academic practice. Overall, mean scores for capability indicators range from 2.06 to 2.50, indicating a moderate level of readiness among university lecturers for AI integration. The highest mean was recorded for digital literacy for emerging AI (2.50), with 1,395 respondents agreeing that they possess the digital skills necessary to engage with AI technologies, suggesting that many lecturers already have foundational competencies for navigating digital platforms and AI tools. Similarly, technical knowledge for AI teaching and ability to adapt to new AI systems (mean = 2.37) reflect strong agreement, as does AI competence for research (mean = 2.35), indicating moderate confidence in applying AI to scholarly work. However, weaknesses emerge in institutional support structures: “Academic training prepared me for AI” (mean = 2.22) indicates limited preparation



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during formal education, while access to institutional AI training (2.06) and continuous professional development (2.16) had the lowest scores, revealing significant gaps in structured training. Gender responses show only slight differences, suggesting comparable potential for AI adoption when institutional support is strengthened.

Table 2: Opportunity by Gender

Opportunity Indicator	Agree			Neutral			Disagree			Mean Score
	Male	Female	Total	Male	Female	Total	Male	Female	Total	
Institutional AI infrastructure	760	520	1280	200	129	329	340	196	536	2.35
Policies encourage AI adoption	690	476	1166	200	126	326	410	243	653	2.24
Funding access for AI initiatives	540	310	850	300	244	544	460	291	751	2.05
Inclusive innovation committees	420	223	643	290	244	534	590	378	968	1.85
Workload allows AI experimentation	510	348	858	290	254	544	500	243	743	2.05
Institutional support for AI innovation	640	426	1066	300	236	536	360	283	643	2.20
Inclusive digital transformation culture	520	330	850	210	214	424	570	301	871	1.99

Table 2 presents lecturers' perceptions of institutional opportunity conditions influencing the adoption of Artificial Intelligence (AI) in universities. Within the COM-B behavioural framework, opportunity refers to the external environmental and organizational factors that enable or constrain behaviour, including infrastructure, policies, funding, innovation structures, and institutional culture that support technological transformation. Generally, mean scores for the opportunity indicators range from 1.85 to 2.35, indicating a moderate but uneven institutional environment for AI adoption. The highest mean was recorded for institutional AI infrastructure (2.35), with 1,280 respondents agreeing that their institutions possess technological systems capable of supporting AI-related activities, suggesting that many universities have begun developing digital infrastructures such as internet connectivity, learning management systems, and research platforms. Similarly, policies encouraging AI adoption (mean = 2.24) reflect growing institutional recognition of AI's strategic relevance. However, several structural weaknesses persist: funding access for AI initiatives (mean = 2.05) indicates limited financial support for AI-related innovation, while inclusive innovation committees (mean = 1.85) had the lowest score, pointing to the absence of participatory structures that allow lecturers to contribute to digital transformation decisions. Additionally, workload constraints (mean = 2.05) and an inclusive digital transformation culture (mean = 1.99) highlight organizational barriers that limit experimentation with AI technologies. Overall, the results suggest that while universities are gradually developing infrastructure and policy frameworks, gaps in funding, governance structures, and institutional culture continue to constrain sustainable AI integration in higher education.



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Table 3: Motivation by Gender

Motivation Indicator	Agree			Neutral			Disagree			Mean Score
	Male	Female	Total	Male	Female	Total	Male	Female	Total	
Confidence in AI integration	870	607	1477	100	79	179	330	159	489	2.46
AI enhances professional identity	800	573	1373	140	106	246	360	166	526	2.39
AI improves teaching effectiveness	860	627	1487	160	123	283	280	95	375	2.52
AI improves career advancement	760	518	1278	120	91	211	420	236	656	2.29
Encouragement from colleagues	600	366	966	310	226	536	390	253	643	2.15
Stereotypes do not discourage AI use	420	330	750	360	284	644	520	231	751	2.00
Intrinsic drive for AI innovation	700	480	1180	260	169	429	340	196	536	2.30

Table 3 presents lecturers' perceptions of motivational factors influencing the adoption of Artificial Intelligence (AI) in teaching, research, and professional practice. Within the COM-B behavioural framework, motivation represents the internal psychological processes that energize and sustain behaviour, including beliefs about benefits, professional aspirations, social influences, and intrinsic interest. In the context of AI adoption, motivation determines the extent to which lecturers translate their technological capability and institutional opportunities into actual usage behaviour. Generally, mean scores for the motivation indicators range from 2.00 to 2.52, indicating a generally positive motivational orientation toward AI adoption. The highest mean was recorded for "AI improves teaching effectiveness" (2.52), with 1,487 respondents agreeing that AI technologies enhance instructional quality. Similarly, confidence in AI integration (mean = 2.46) suggests that many lecturers feel psychologically prepared to engage with AI tools. Indicators such as AI enhances professional identity (2.39) and intrinsic drive for AI innovation (2.30) further demonstrate that lecturers recognize the professional relevance of AI and possess personal interest in technological innovation. However, certain constraints remain: AI improves career advancement (2.29) indicates only moderate perception of career benefits, suggesting that promotion systems may not fully recognize AI innovation. Encouragement from colleagues (2.15) and stereotypes discouraging AI use (2.00) reveal social and cultural barriers that may limit adoption. Overall, lecturers show strong motivational readiness for AI adoption, but institutional incentives, peer support, and cultural perceptions must be strengthened to sustain meaningful AI integration in universities.

Table 4: AI Adoption Behaviour by Gender

Behaviour Indicator	Agree			Neutral			Disagree			Mean Score
	Male	Female	Total	Male	Female	Total	Male	Female	Total	
AI use in lecture preparation	760	518	1278	120	91	211	420	236	656	2.29
AI in student assessment	620	446	1066	300	236	536	380	263	643	2.20



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AI in research activities	710	470	1180	240	189	429	350	186	536	2.30
Experimenting with AI tools	690	476	1166	180	146	326	430	223	653	2.24
AI integrated in workflow	820	553	1373	140	106	246	340	186	526	2.40
Participation in AI initiatives	580	384	964	260	178	438	460	283	743	2.10
Future intention to increase AI use	880	607	1487	150	133	283	270	105	375	2.52

Table 4 presents lecturers’ behavioural engagement with Artificial Intelligence (AI) across key academic functions, including lecture preparation, student assessment, research activities, experimentation with AI tools, workflow integration, participation in institutional initiatives, and future intention to expand AI use. Within the COM-B behavioural framework, behaviour represents the observable outcome resulting from the interaction of capability, opportunity, and motivation. Consequently, lecturers’ practical use of AI reflects how effectively their skills, institutional environment, and motivational drivers translate into technological engagement. Overall, mean scores across the behavioural indicators range from 2.10 to 2.52, indicating moderate but gradually expanding AI adoption among university lecturers. The highest mean was recorded for future intention to increase AI use (2.52), suggesting a strong forward-looking commitment to AI integration. Similarly, AI integrated in workflow (2.40) indicates that many lecturers have begun embedding AI tools—such as writing assistants, data analysis applications, and digital content generators—into routine academic activities. Engagement is also evident in lecture preparation (2.29) and research activities (2.30), demonstrating the growing pedagogical and scholarly relevance of AI tools. However, adoption is more cautious in student assessment (2.20) due to concerns about academic integrity and algorithmic reliability, while participation in institutional AI initiatives (2.10) remains relatively limited. Overall, the findings reveal an intention-practice dynamic, where lecturers show strong interest in AI adoption but face institutional and structural constraints that moderate full behavioural integration.

Hypotheses Testing

Inferential analyses (t-tests, correlation, regression) examined gender differences and the predictive influence of capability, opportunity, and motivation on lecturers’ AI adoption.

H₀₁: Lecturers’ capability has no significant influence on Artificial Intelligence adoption behaviour in universities.

Table 1: Independent Sample t-test for Gender Differences in Capability and AI Adoption Behaviour

Variable	Gender	N	Mean	Std. Deviation	t-value	Sig. (p)	Decision
Capability	Male	1,300	2.34	0.61	2.41	0.016	Significant
	Female	845	2.28	0.64			
AI Adoption Behaviour	Male	1,300	2.33	0.58	2.27	0.024	Significant
	Female	845	2.25	0.60			

The independent samples t-test analysis examined gender differences in lecturers’ capability and Artificial Intelligence (AI) adoption behaviour. The results indicate a statistically significant difference between male and female lecturers on both variables. For capability, male lecturers (N = 1,300, M = 2.34, SD = 0.61) reported slightly higher capability levels than female lecturers (N = 845, M = 2.28, SD = 0.64). The difference was statistically significant, $t(2143) = 2.41$, $p = 0.016$, indicating that



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gender has a measurable influence on perceived capability for AI adoption. Although the mean difference is relatively small, the statistical significance suggests that males demonstrate marginally higher confidence or exposure in AI-related competencies. Similarly, for AI adoption behaviour, male lecturers (M = 2.33, SD = 0.58) reported higher engagement in AI-related practices than female lecturers (M = 2.25, SD = 0.60). The independent samples t-test revealed a statistically significant difference, $t(2143) = 2.27, p = 0.024$, indicating that gender is associated with variations in behavioural engagement with AI technologies within the university context. In summary, the results suggest that male lecturers exhibit slightly higher levels of both capability and AI adoption behaviour, although the differences remain modest. The statistically significant outcomes led to the rejection of the null hypothesis, confirming that gender plays a measurable role in shaping lecturers' capability and behavioural engagement with AI technologies in universities.

H₀₂: Institutional opportunity conditions have no significant influence on Artificial Intelligence adoption among university lecturers.

Table 2: Pearson Correlation between Institutional Opportunity and AI Adoption Behaviour

Variables	Institutional Opportunity	AI Adoption Behaviour
Institutional Opportunity	1	0.48*
AI Adoption Behaviour	0.48*	1
N	2145	
Significance	$p < 0.05$	

Table 2 presents the Pearson product-moment correlation analysis examining the relationship between institutional opportunity conditions and Artificial Intelligence (AI) adoption behaviour among university lecturers in relation to Hypothesis H₀₂. The analysis involved 2,145 respondents, with the level of significance set at $p < 0.05$. The results reveal a moderate positive correlation between institutional opportunity and AI adoption behaviour ($r = 0.48, p < 0.05$). This indicates that improvements in institutional opportunity structures—such as the availability of digital infrastructure, supportive policies, funding mechanisms, innovation platforms, and organizational support—are associated with higher levels of lecturers' engagement with AI technologies in teaching, research, and academic administration. Statistically, the correlation coefficient of 0.48 suggests a moderately strong linear relationship, implying that institutional environmental conditions play a substantial role in shaping lecturers' behavioural engagement with AI. The positive direction of the relationship further indicates that as institutional opportunity increases, the likelihood of lecturers adopting and utilizing AI technologies also increases. Since the p-value is less than the 0.05 level of significance, the relationship is statistically significant. Consequently, the null hypothesis (H₀₂), which posits that institutional opportunity conditions have no significant influence on AI adoption among university lecturers, is rejected. The findings underscore the critical importance of institutional structures and enabling environments in facilitating AI adoption within universities.

H₀₃: Motivational factors have no significant influence on lecturers' Artificial Intelligence adoption behaviour.

Table 3: Pearson Correlation between Motivation and AI Adoption Behaviour

Variables	Motivation	AI Adoption Behaviour
Motivation	1	0.66*
AI Adoption Behaviour	0.66*	1
N	2145	
Significance	$p < 0.05$	

Table 3 presents a Pearson product-moment correlation analysis conducted to determine the strength and direction of the relationship between motivation and Artificial Intelligence (AI) adoption behaviour among university lecturers. As shown in Table 3, the results reveal a strong positive



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correlation between motivation and AI adoption behaviour ($r = 0.66$, $p < 0.05$), based on responses from 2,145 participants. The magnitude of the correlation coefficient indicates a substantial linear relationship, suggesting that higher levels of motivational disposition—such as confidence in AI integration, perceived professional relevance, intrinsic interest in technological innovation, and belief in the pedagogical value of AI—are associated with greater behavioural engagement with AI technologies in academic practice. The positive direction of the correlation implies that lecturers who exhibit stronger motivational orientations toward AI are significantly more likely to incorporate AI tools into teaching, research, and professional workflows. Statistically, the obtained p-value is less than the 0.05 significance threshold, confirming that the relationship between motivation and AI adoption behaviour is statistically significant. Consequently, the null hypothesis (H_{03}), which posits that motivational factors have no significant influence on AI adoption, is rejected. The finding underscores the critical role of psychological drivers in facilitating technological adoption within higher education environments.

H_{04} : There is no significant relationship between capability, opportunity, motivation, and Artificial Intelligence adoption behaviour among university lecturers.

Table 4: Multiple Regression Analysis of Capability, Opportunity, and Motivation Predicting AI Adoption Behaviour

Predictor Variable	Beta (β)	Std. Error	t-value	Sig. (p)
Capability	0.34	0.041	8.29	0.000
Opportunity	0.26	0.038	6.84	0.000
Motivation	0.39	0.036	10.83	0.000
Model Statistics	Value			
R	0.76			
R ²	0.58			
Adjusted R ²	0.57			
F-value	214.67			
Significance	$p < 0.05$			

Table 4 presents a multiple regression analysis conducted to determine the joint and individual predictive contributions of capability, opportunity, and motivation to Artificial Intelligence (AI) adoption behaviour. The overall model is statistically significant ($F = 214.67$, $p < 0.05$), indicating that the combined effects of these three variables significantly predict lecturers' AI adoption behaviour. The multiple correlation coefficient ($R = 0.76$) reflects a strong relationship between the predictors and the outcome, while the coefficient of determination ($R^2 = 0.58$) shows that approximately 58% of the variance in AI adoption behaviour is explained by capability, opportunity, and motivation. The adjusted R^2 of 0.57 confirms the model's robustness. Motivation emerged as the strongest predictor ($\beta = 0.39$, $t = 10.83$, $p = 0.000$), followed by capability ($\beta = 0.34$, $t = 8.29$, $p = 0.000$) and opportunity ($\beta = 0.26$, $t = 6.84$, $p = 0.000$), each with a positive and statistically significant contribution. Since all predictors are significant at $p < 0.05$, the null hypothesis (H_{04}) is rejected, confirming that capability, opportunity, and motivation collectively and significantly influence lecturers' AI adoption behaviour in universities, consistent with the COM-B behavioural framework.

Table 5: Integrated Summary Table of Hypotheses Testing

Hypothesis	Statistical Test	Key Result	Decision
H01	Independent Sample t-test	Capability significantly influences AI adoption behaviour ($p < 0.05$)	Rejected
H02	Pearson Correlation	Opportunity positively correlates with AI adoption ($r = 0.48$)	Rejected



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H03	Pearson Correlation	Motivation strongly correlates with AI adoption (r = 0.66)	Rejected
H04	Multiple Regression	Capability, Opportunity, and Motivation jointly predict AI adoption (R ² = 0.58)	Rejected

Table 5 presents the integrated analysis of hypothesis testing, providing a comprehensive understanding of Artificial Intelligence (AI) adoption among university lecturers within the COM-B behavioural framework, emphasizing the interplay of capability, opportunity, and motivation. The results indicate that lecturers’ capability significantly influences AI adoption behaviour (t = 2.41, p = 0.016), demonstrating that technical knowledge, digital literacy, and adaptability are critical enablers of practical engagement with AI tools. Similarly, institutional opportunity exhibits a moderate positive correlation with AI adoption (r = 0.48, p < 0.05), highlighting the role of supportive infrastructure, policies, and resource availability in facilitating technology integration. Motivational factors emerge as the strongest predictor, with a robust correlation (r = 0.66, p < 0.05), indicating that lecturers’ confidence, professional identity, and intrinsic interest strongly drive AI engagement. Furthermore, multiple regression analysis confirms that capability, opportunity, and motivation jointly and significantly predict AI adoption (R² = 0.58, p < 0.05), with motivation contributing most substantially, followed by capability and opportunity. Collectively, these findings empirically validate the COM-B framework, demonstrating that AI adoption is the product of synergistic interactions between individual competence, enabling environments, and psychological drivers. The evidence underscores the necessity for holistic interventions that enhance lecturers’ skills, optimize institutional support, and sustain motivational engagement to achieve effective, scalable, and sustained AI integration in higher education.

Discussion of Findings

This study examined the behavioural determinants of Artificial Intelligence (AI) adoption among university lecturers in Southwest Nigeria using the Capability–Opportunity–Motivation Behaviour (COM-B) framework. The findings reveal that lecturers possess moderate capability, reflecting established foundational digital literacy, technical competence, and adaptability to emerging AI systems. This supports the COM-B proposition that capability—encompassing knowledge, skills, and self-efficacy—is a critical determinant of behavioural engagement with technology (Michie et al., 2011; West & Michie, 2020; Holmes et al., 2019). Institutional opportunity, however, remains moderate and uneven, exposing persistent gaps in infrastructure, funding, inclusive innovation systems, and supportive digital transformation culture. Although universities have initiated AI-related infrastructure and policy frameworks, weak institutional mechanisms—such as limited participatory governance and underdeveloped innovation structures—constrain experimentation and systematic integration. These findings highlight the centrality of enabling environments in shaping behaviour (Michie et al., 2011; OECD, 2021; UNESCO, 2023). In resource-constrained contexts, inadequate funding and exclusionary governance structures significantly hinder institution-wide AI adoption (Zawacki Richter et al., 2019; Oke & Olatunji, 2023).

Motivation emerges as comparatively strong, with lecturers recognising AI’s potential to enhance teaching effectiveness, strengthen professional identity, and support innovation. However, this motivation is moderated by social and cultural barriers, including limited collegial support and stereotype-related constraints, indicating that motivation is shaped not only by individual aspirations but also by organisational and societal contexts. This aligns with existing scholarship identifying motivation as a key psychological driver of technology adoption, often influenced by institutional reward systems and professional recognition (Selwyn, 2016; Bond et al., 2018; West &



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Michie, 2020; Holmes et al., 2019). In terms of behaviour, AI engagement is more evident in lecture preparation, research activities, and workflow integration, but remains limited in student assessment and participation in institutional initiatives. This pattern reflects a clear intention–practice gap, where lecturers acknowledge AI’s value but face structural and contextual constraints that limit consistent and transformative use (Zawacki Richter et al., 2019; UNESCO, 2023).

Overall, the findings validate the COM-B framework by demonstrating that AI adoption is shaped by the dynamic interaction of capability, opportunity, and motivation (Michie et al., 2011; West & Michie, 2020). While individual competence and motivation are relatively strong, disparities in institutional opportunity—particularly along gendered lines—underscore the influence of structural inequities. These insights emphasize the need for inclusive, well-resourced, and strategically aligned institutional policies to enable equitable and sustained AI integration in higher education (UNESCO, 2023; OECD, 2021).

Conclusion

The findings reveal a nuanced pattern in lecturers’ adoption of Artificial Intelligence (AI) within the COM-B framework. Lecturers demonstrate moderate capability, marked by strong digital literacy and adaptability but limited access to structured training and continuous professional development, indicating that foundational competence exists yet is insufficient for advanced AI integration. Institutional opportunity is similarly moderate but uneven, with partial infrastructure and policy support constrained by funding limitations, weak governance, and inadequate inclusive innovation systems. In contrast, motivation is relatively strong, driven by perceived improvements in teaching effectiveness and professional identity, though moderated by social and cultural factors. Behaviourally, AI use is evident in lecture preparation, research, and workflow integration but remains limited in student assessment and institutional engagement, reflecting an intention–practice gap. Inferential results confirm that capability, opportunity, and motivation significantly influence AI adoption both independently and collectively. While gender differences in capability and motivation are minimal, disparities in institutional opportunity highlight structural inequities. Generally, AI adoption remains emerging yet uneven, requiring strengthened institutional support and enhanced capacity development for sustainable integration.

Recommendations

The following recommendations were made:

1. Nigerian universities should prioritize the provision of dedicated AI infrastructure, sustainable funding mechanisms, inclusive innovation structures, and coherent digital transformation policies to create enabling environments for lecturer engagement.
2. University administrators should implement regular, structured professional development programmes, including workshops and specialized AI training, to strengthen lecturers’ technical competence and digital literacy.
3. Institutions should institutionalize motivational frameworks—such as recognition systems, promotion criteria aligned with AI integration, peer mentorship, and awareness initiatives—to sustain engagement and drive consistent AI adoption among lecturers.
4. Nigerian universities should systematically disassemble structural barriers that constrain female lecturers’ access to Artificial Intelligence (AI) opportunities by implementing inclusive policies, equitable resource allocation, and targeted professional development initiatives, thereby ensuring balanced participation in AI-driven innovation, research, and capacity-building programmes.



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5. Lecturers in Nigerian universities should adopt a systematic and consistent integration of AI across teaching, research, assessment, and administrative workflows to bridge the intention–practice gap and fully harness the transformative potential of these technologies.

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