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Integrating Artificial Intelligence in Higher Education in Zambia: A Mixed-Methods Study on Future Prospects and Challenges

Shuchun Fan

Masters degree, Shungfengqiao Primary School, Beibei District, Chongqing, China, https://orcid.org/0009-0005-4824-9643

Gift Muyunda*

PhD Candidate, Faculty of Education, Southwest University, Chongqing, China, https://orcid.org/0000-0002-4468-9984

***Corresponding author:** *muyundagifted@icloud.com.*

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Abstract: Artificial intelligence (AI) has rapidly emerged as a transformative force in higher education, promising to enhance teaching, learning, and institutional efficiency. While the global adoption of AI tools, such as adaptive learning systems, chatbots, and predictive analytics, has accelerated, evidence from Sub-Saharan Africa, and Zambia in particular, remains scarce. This study employed a sequential explanatory mixed-methods design to investigate educators' perceptions, adoption factors, and contextual challenges surrounding the integration of AI in Zambian higher education. Quantitative data were collected from 230 faculty members across five universities through structured surveys, followed by semi-structured interviews with 24 educators to provide explanations and further insights into the statistical findings. Quantitative results indicated positive perceptions of AI's potential benefits (M = 4.12, SD = 0.81), with institutional support and digital literacy emerging as significant predictors of adoption ($p < .05$). However, qualitative insights revealed persistent barriers, including infrastructural deficits, ethical concerns, and policy gaps. The integration of datasets through joint displays highlighted both opportunities for personalised and equitable learning, as well as risks of deepening existing inequalities if adoption is not systematically managed. The study contributes to the growing discourse on AI in developing contexts by providing context-sensitive evidence from Zambia. It offers actionable recommendations for policymakers, universities, and stakeholders to foster the integration of inclusive and ethical AI.

Keywords: artificial intelligence, Zambian higher education, mixed-methods research, personalised learning, educational technologies, future education

Introduction

The rapid evolution of educational technologies has positioned artificial intelligence (AI) as a transformative force in higher education globally. Recent scholarship demonstrates that AI applications can enhance personalised learning, streamline assessment processes, and provide adaptive instructional support that strengthens student engagement (Reiss, 2021; Gardner, O'Leary, & Yuan, 2021; Singh, 2024). Beyond efficiency gains, AI is increasingly deployed in predictive analytics, intelligent tutoring systems, and generative tools that enable universities to respond more effectively to the diverse needs of learners, including those with disabilities (Pierrès, Darvishy, & Christen, 2024; Almassaad, Alajlan, & Alebaikan, 2024). However, scholars caution that integration requires careful attention to ethics, equity, and responsible pedagogy to avoid exacerbating existing inequalities (Tubella et al., 2023; Zembylas, 2023).

In sub-Saharan Africa, AI adoption faces persistent challenges, including fragile digital infrastructure, limited funding, and significant rural–urban disparities in access to technology. Studies indicate that while AI could expand educational access, implementation remains uneven due to insufficient faculty training, fragmented policy frameworks, and inadequate institutional support (Airaj, 2024; Chisango et al., 2021). For instance, UNESCO (2022) reports that less than 30% of African universities have integrated AI-related curricula, limiting student preparedness for future economies. In Zambia, these challenges are particularly acute, as higher education institutions face rising enrollment pressures amid resource constraints.

The novelty of this study lies in its focus on Zambia, a context underrepresented in the global discourse on AI in education. By adopting a mixed-methods approach, it not only quantifies educators' perceptions and institutional readiness but also situates findings within the broader African context. The study contributes practically by offering evidence-based recommendations for the ethical, inclusive, and sustainable adoption of AI, while advancing scientific understanding of how emerging technologies interact with resource-constrained educational systems.

Research Problem

The integration of artificial intelligence (AI) in higher education has become a pressing area of inquiry, as universities worldwide adopt digital innovations to enhance instructional quality and efficiency. In Zambia, however, adoption remains constrained by persistent infrastructural and policy challenges. National statistics indicate that Zambia has approximately 120,000 students enrolled in public universities; however, internet penetration remains at only 47% nationally, with rural areas falling below 20% (Zambia Information and Communications Technology Authority). Moreover, UNESCO (2022) reports that fewer than 35% of Zambian higher education institutions have established functional e-learning systems, highlighting a significant digital gap compared to regional peers.

Analysing this problem is critical because delayed exploration risks widening disparities between Zambia and global advancements in educational technologies. Without intentional policies and institutional support, the gap between resource-constrained institutions and those in better-resourced contexts will continue to grow, exacerbating inequalities in educational access and outcomes.

The relevance of this research lies in its potential societal benefits, particularly in promoting inclusive and equitable access to quality education. By identifying opportunities and barriers to AI adoption, the study provides evidence-based insights that can inform institutional strategies and national policies. Scientifically, the research contributes to the limited empirical literature on AI in education in sub-Saharan Africa, with Zambia offering a case study of the dual pressures of rapid enrollment growth and weak digital infrastructure. The study advances new knowledge by uncovering localised perspectives on adoption factors, while also foregrounding ethical and equity considerations critical for sustainable integration.

Research Focus

This study employed a sequential explanatory mixed-methods design, where quantitative data were collected first, followed by qualitative interviews to expand and clarify statistical results. This design was chosen for its suitability in contexts where broad trends must be established through surveys while retaining depth through stakeholder narratives, which is critical in under-researched settings such as Zambia.

Sampling Strategy

For the quantitative phase, a stratified random sampling strategy was employed to enhance representativeness across disciplines (STEM, humanities/social sciences, and health sciences), institutions (public versus private), and geographic regions (urban versus semi-rural). A sampling frame of ~5,000 educators was obtained through institutional directories and the Ministry of Higher Education. Using G*Power ($\alpha = 0.05$, power = 0.80, medium effect size $r = 0.3$), a minimum of 210 participants was required for correlational analyses; 250 educators were invited to allow for non-response. The final response rate was 92% ($n = 230$), ensuring statistical robustness.

For the qualitative phase, purposive sampling was used to select 25 participants from the survey respondents who consented to follow-up. The criteria included role diversity (educators, administrators, and students), experience with AI tools, and representation from both urban and semi-rural institutions. Theoretical saturation was monitored during interviews, with no new themes emerging after the 23rd interview. Two additional interviews confirmed saturation, strengthening validity.

Instrument Selection and Justification

The survey instrument comprised 35 items adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been widely validated in technology adoption studies in education (Crompton & Burke, 2023). Items measured adoption factors (e.g., institutional support, training availability), perceived benefits, and barriers. A pilot test with 30 educators ensured contextual relevance and clarity, yielding a Cronbach's alpha of 0.87, which indicates strong internal consistency. The inclusion of open-ended survey questions and semi-structured interview protocols provided triangulation and explanatory depth, aligning with recommendations for mixed-methods rigour in educational technology research in Africa.

Research Aim and Research Questions

In line with the identified problem of limited knowledge and contextual understanding of artificial intelligence (AI) in Zambia's higher education sector, this study seeks to answer the following research questions:

1. What are the perceptions of educators regarding the potential impact of AI on teaching and learning in Zambian universities?

2. Which measurable institutional and technological factors influence the adoption of AI in higher education?
3. What qualitative insights from stakeholders reveal the barriers and opportunities for the effective integration of AI in Zambia's higher education system?

Literature Review

The integration of artificial intelligence (AI) in higher education represents a transformative evolution in educational technologies, with the potential to revolutionise pedagogical strategies, enhance student engagement, and optimise institutional management. Globally, AI applications, including adaptive learning platforms, conversational agents, and predictive analytics, have fundamentally altered the modalities through which universities deliver and supervise learning (Binhammad et al., 2024; Singh, 2024). Despite these advances, regions with constrained resources, particularly in Africa, face significant impediments to adoption due to economic limitations, underdeveloped infrastructure, and digital access disparities (Reiss, 2021; Chounta et al., 2021). This review synthesises international, African, and Zambian perspectives, emphasising contemporary scholarship (2021–2025) and employing mixed-methods studies to elucidate the patterns, challenges, and future trajectories of AI in higher education.

Global Perspectives on AI in Higher Education

Extensive research indicates that AI has substantial potential to improve educational outcomes globally. Core tools, such as intelligent tutoring systems, natural language processing technologies, and automated assessment mechanisms, facilitate personalised learning, enable timely feedback, and foster enhanced academic performance (Zawacki-Richter et al., 2019; Ifenthaler & Yau, 2020; Gardner et al., 2021). Mixed-method investigations have demonstrated that embedding AI into curricula not only increases student engagement but also contributes to higher academic achievement, with quantitative analyses showing statistically significant improvements in grades and qualitative findings highlighting positive learner perceptions (Crompton & Burke, 2023; Pierrès et al., 2024; Bond et al., 2024).

Field-specific studies further illustrate AI's versatility. In medical education, AI-driven simulations and assessment tools enhance skill acquisition while also highlighting gaps in ethical training (Park et al., 2022; Thurzo et al., 2023). In business education, generative AI platforms enable dynamic and interactive learning experiences, often surpassing traditional teaching approaches in terms of efficiency and engagement (Rospigliosi, 2022; Elbanna & Armstrong, 2024; Dwivedi et al., 2023). Nevertheless, international literature also highlights critical challenges, including algorithmic bias, data privacy concerns, and limited integration of complex multimodal datasets (Gupta & Chopra, 2023; Kitto & Knight, 2019; Yan et al., 2023). Consequently, while AI is widely acknowledged as a catalyst for educational innovation, empirical work remains disproportionately concentrated in technologically advanced contexts (Almassaad et al., 2024; Dai et al., 2023; Chiu, 2024).

The emergence of generative AI, exemplified by ChatGPT, has amplified these dynamics. Evidence suggests that such tools support content creation, personalised feedback, and learning efficiency, yet they also raise concerns regarding academic integrity, overreliance, and intellectual authenticity (Chiu & Sanusi, 2024; Stöhr et al., 2023). Proficiency in AI is increasingly framed as an essential skill for ethical and responsible engagement in higher education (Liu et al., 2023; Zembylas, 2023). In technical disciplines, AI enables predictive modelling and simulated learning environments, broadening access and enhancing educational reach (Hassan et al., 2022; Chen et al., 2023). The literature consistently advocates for the adoption of ethical frameworks and interdisciplinary collaboration to reconcile innovation with equity and accountability (Tubella et al., 2023; Yan et al., 2023).

AI Integration in African Higher Education: Challenges and Opportunities

Scholarship within Africa presents a nuanced understanding of AI's potential and limitations. AI can mitigate educational disparities in under-resourced contexts by offering flexible and adaptive learning technologies (Akakpo, 2024; Taddei et al., 2021; Tubella et al., 2023). However, systemic weaknesses, including limited infrastructure, insufficient professional development, and fragmented policy environments, constrain adoption (Airaj, 2024; Eke, 2023; Tambo et al., 2021). Institutional studies reveal sporadic incorporation of AI into academic programs and limited student familiarity, which hinder competency development and sustainable integration (Funda & Mbangeleli, 2024; UNESCO, 2022).

Mixed-method research uncovers both ethical and practical complexities. While AI enhances monitoring of research and funding activities, context-specific ethical considerations are critical to prevent bias and inequitable outcomes (Mhlanga, 2022; Reiss, 2021; Maluleke, 2025). Country-specific investigations, such as those in Zimbabwe, demonstrate opportunities for AI-enabled programs despite governmental and technical constraints (Chisango et al., 2021). Continental organisations advocate for collaborative AI capacity-building initiatives that align with broader development goals (AAU, 2023; Sangwa et al., 2025). These findings underscore that African AI adoption is in its early stages, with deliberate investments required to unlock its transformative potential (Chounta et al., 2021; Kiemde & Kora, 2022).

Recent studies (2023–2025) further illuminate the African AI landscape. In South Africa, AI is fostering curricular reform and decolonisation initiatives, but it carries the risk of reinforcing inequalities if governance is weak (Maimela & Mbonde, 2025; Mogoale et al., 2025; Modiba et al., 2025). Nigerian and Rwandan investigations highlight AI's role in mitigating infrastructural deficits through personalised learning, while simultaneously confronting ethical and access inequities (Angwaomaodoko, 2025; Ngabonziza et al., 2025). Generative AI, while supporting research productivity, necessitates regulatory safeguards against misuse (Modiba et al., 2025). The continent-wide discourse emphasises the dual potential of AI to enhance inclusion and skill development, yet warns of exacerbating disparities if concerns about confidentiality and bias remain unaddressed (Akakpo, 2024; Eke, 2023; Funda & Mbangeleli, 2024; Maluleke, 2025).

AI and Educational Technologies in Developing Contexts

Evidence from non-African developing regions echoes similar challenges and opportunities. Palestinian medical learners report enthusiasm for AI integration, tempered by the need for insufficient training and ethical guidance (Khalil et al., 2022; Airaj, 2024; Khalil et al., 2024). Initiatives in Saudi Arabia illustrate the successful fusion of AI and big data to enhance monitoring, evaluation, and administrative efficiency (Alenezi, 2021; Gardner et al., 2021). Globally, scholars stress that while AI enhances interactivity and cognitive development, systemic challenges such as unreliable connectivity and device scarcity must be addressed (Chen et al., 2023; Singh, 2024; Yan et al., 2023). Qualitative studies, for instance, in Kuwait, highlight learners' appreciation for personalised AI experiences, alongside ethical concerns related to reasoning and authenticity (Schmidt et al., 2025). Infrastructural limitations and policy misalignment remain barriers comparable to those in Africa, indicating convergent challenges in developing contexts.

Educational Technologies and AI in Zambia

Zambian studies on educational technologies provide foundational insights into AI adoption. Persistent digital divides — particularly in rural areas lacking connectivity and hardware—pose significant obstacles to technology-mediated learning (Reiss, 2021; Zambia National Education Coalition, 2021). The COVID-19 pandemic catalysed technology-infused teaching strategies at institutions like the University of

Zambia, producing measurable learning gains despite resource constraints (Lungu & Banda, 2022; Phiri & Chileshe, 2022).

Emerging Zambian research on AI reveals tentative adoption for content creation and assessment support, but identifies barriers such as privacy concerns, infrastructure limitations, and skills gaps (Mwanza & Mulenga, 2023; Almassaad et al., 2024; Chilufya, 2024). Investigations into generative AI indicate potential for personalised learning, while emphasising the need for regulatory frameworks and educator preparation to prevent misuse (Chilufya, 2024; Pierrès et al., 2024). Notably, digital preparedness varies widely by location, highlighting inequities in adoption capacity (Lungu & Banda, 2022; Chounta et al., 2021).

Despite the growing scholarship, gaps in the literature persist. International studies often emphasise technologically advanced environments, while African research frequently addresses obstacles without robust evaluation of AI's impact on learning outcomes (Airaj, 2024; Gardner et al., 2021; Mhlanga, 2022; Reiss, 2021). Zambian studies predominantly explore policy, adoption trends, and perceptions, with few employing mixed-methods approaches that link AI integration to tangible educational results (Mwanza & Mulenga, 2023). Furthermore, innovative AI applications, including lifelong learning, virtual reality-enhanced instruction, and eco-digital strategies, remain largely unexplored in this context (Elbanna & Armstrong, 2024; Singh, 2024).

This study addresses these lacunae through a Zambia-focused mixed-methods approach, combining quantitative analyses of adoption patterns with qualitative exploration of barriers, opportunities, and ethical considerations. In doing so, it contributes to both national and pan-African discourse on the equitable, responsible, and participatory deployment of AI in higher education (Airaj, 2024; Schmidt et al., 2025; Tubella et al., 2023).

Materials and Methods

This study employed a sequential explanatory mixed-methods design, where quantitative data were collected first, followed by qualitative interviews to expand and clarify statistical results. This design was chosen for its suitability in contexts where broad trends must be established through surveys while retaining depth through stakeholder narratives, which is critical in under-researched settings such as Zambia.

Sampling Strategy

For the quantitative phase, a stratified random sampling strategy was employed to enhance representativeness across disciplines (STEM, humanities/social sciences, and health sciences), institutions (public versus private), and geographic regions (urban versus semi-rural). A sampling frame of ~5,000 educators was obtained through institutional directories and the Ministry of Higher Education. Using G*Power ($\alpha = 0.05$, power = 0.80, medium effect size $r = 0.3$), a minimum of 210 participants was required for correlational analyses; 250 educators were invited to allow for non-response. The final response rate was 92% ($n = 230$), ensuring statistical robustness.

For the qualitative phase, purposive sampling was used to select 25 participants from the survey respondents who consented to follow-up. The criteria included role diversity (educators, administrators, and students), experience with AI tools, and representation from both urban and semi-rural institutions. Theoretical saturation was monitored during interviews, with no new themes emerging after the 23rd interview. Two additional interviews confirmed saturation, strengthening validity.

Instrument Selection and Justification

The survey instrument comprised 35 items adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been widely validated in technology adoption studies in education (Crompton & Burke, 2023). Items measured adoption factors (e.g., institutional support, training availability), perceived benefits, and barriers. A pilot test with 30 educators ensured contextual relevance and clarity, yielding a Cronbach's alpha of 0.87, which indicates strong internal consistency. The inclusion of open-ended survey questions and semi-structured interview protocols provided triangulation and explanatory depth, aligning with recommendations for mixed-methods rigour in educational technology research in Africa.

Research Design Rationale

The sequential explanatory mixed-methods design was selected over alternative approaches, such as convergent or exploratory designs, because it allows for an initial quantitative assessment followed by qualitative exploration to contextualise and explain statistical findings. Specifically, this design enables the quantification of educators' perceptions and adoption factors of artificial intelligence (AI) in higher education, while subsequent interviews illuminate reasons behind observed trends, including barriers and facilitators to adoption. Previous studies on the integration of AI in higher education have demonstrated that this approach effectively identifies patterns in tool usage and captures nuanced insights into ethical considerations, infrastructural constraints, and pedagogical challenges.

In the Zambian context, the sequential explanatory design is particularly appropriate due to logistical and infrastructural realities, such as disparities in internet access and digital literacy among educators. By allowing flexible, phase-based data collection, the design accommodates these constraints while maintaining methodological rigour (Mwanza & Mulenga, 2023). The integration of quantitative and qualitative findings primarily occurs at the interpretation stage, enhancing validity through the triangulation of data sources and providing a comprehensive understanding of AI adoption dynamics. This approach addresses the research gap in empirical, mixed-methods evaluations of AI implementation in Zambian higher education, where most existing literature remains primarily descriptive or policy-oriented.

Sample and Participants

The target population comprises educators, administrators, and students in Zambian higher education institutions, with a focus on public universities such as the University of Zambia (UNZA), Copperbelt University (CBU), and Mulungushi University, which represent a mix of urban and semi-rural settings.

For the quantitative phase, a stratified random sampling technique was employed to ensure representation across disciplines (e.g., STEM, humanities, social sciences) and institutional types, drawing from a sampling frame of approximately 5,000 educators obtained via institutional directories and the Zambian Ministry of Higher Education. A sample size of 250 educators was calculated using G*Power software for correlational analyses, assuming a medium effect size ($r = 0.3$), $\alpha = 0.05$, and power = 0.80, with adjustments for a 20% non-response rate.

For the qualitative phase, purposive sampling was used to select 25 stakeholders from the quantitative respondents who indicated a willingness to participate in a follow-up survey (via a survey checkbox). Selection criteria included diversity in roles (10 educators, 8 administrators, 7 students), experience with AI tools (e.g., users vs. non-users), and geographic representation to capture urban-rural disparities. This approach ensures that information-rich cases are used, as recommended for explanatory designs in AI education research. Sample saturation was monitored during interviews, with data collection ceasing when no new themes emerged.

Instrument and Procedure

Quantitative Phase

The quantitative component employed a rigorously structured self-administered survey instrument designed to systematically capture educators' perceptions of artificial intelligence (AI) integration and determinants of adoption within higher education contexts. The survey incorporated validated constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) to measure core adoption factors, complemented by context-specific items assessing perceived pedagogical benefits (e.g., personalised learning pathways) and operational challenges (e.g., technological infrastructure limitations). The instrument comprised 35 items, including 20 Likert-scale items (1 = strongly disagree, 5 = strongly agree), 10 demographic items, and 5 open-ended questions intended to elicit preliminary qualitative insights.

To ensure psychometric robustness and contextual validity, the survey underwent a pilot study with 30 educators. Item clarity, cultural relevance, and interpretability were critically evaluated, leading to iterative refinements of the wording of select items. Reliability analysis demonstrated strong internal consistency, yielding a Cronbach's alpha of 0.87, which substantiates the instrument's appropriateness for reliably capturing perceptions and adoption determinants.

Survey administration took place over four weeks in early 2025, utilising a hybrid distribution model to accommodate varying access to digital infrastructure. Online dissemination utilised Google Forms and Qualtrics, distributed via institutional mailing lists, while paper-based surveys were deployed to participants in low-connectivity areas through university coordinators. Two strategically timed reminders were issued to maximise engagement, achieving a high overall response rate of 92% (n = 230). This hybrid approach ensured broad representativeness across both urban and rural institutions, thereby enhancing the generalizability of the quantitative findings.

Qualitative Phase

After quantitative analysis, an in-depth qualitative phase was conducted using semi-structured interviews to explore and elucidate patterns emerging from the survey data, particularly regarding ethical readiness, infrastructural constraints, and attitudinal barriers to AI integration. The interview protocol consisted of 12 open-ended questions, developed iteratively based on quantitative results, with targeted probes designed to facilitate elaboration and capture nuanced perspectives. Example items included: "How do infrastructural limitations affect the integration and utilisation of AI tools within your institution?"

Interviews were conducted over 45–60 minutes, employing modality strategies tailored to participant accessibility: urban respondents engaged via Zoom, while rural respondents participated in person to ensure equitable inclusion. All interviews were audio-recorded with the participants' informed consent and transcribed verbatim to preserve the integrity of their narratives. Complementary field notes documented non-verbal behaviours, environmental context, and reflective observations, thereby enriching interpretive depth.

The sequential explanatory design allowed integration of qualitative insights at the interpretive stage, triangulating numerical trends with experiential narratives to enhance validity, rigour, and explanatory power. By leveraging both breadth and depth, this approach addresses existing gaps in empirical knowledge on AI adoption in Zambian higher education, providing actionable insights for policy formulation, capacity-building, and ethical implementation strategies.

Data Analysis

Quantitative Analysis

Quantitative data underwent meticulous preprocessing and cleaning to ensure accuracy, completeness, and consistency. Analysis was performed using Python, leveraging advanced libraries such as NumPy, Pandas, and SciPy for robust statistical computations. Descriptive statistics (means, standard deviations, frequency distributions) were calculated to characterise the sample and provide an initial understanding of central tendencies and dispersion in educators' perceptions of AI adoption. Inferential analyses encompassed Pearson's correlation coefficients to examine bivariate relationships among key variables, and multiple regression models to identify significant predictors of AI adoption, including institutional support, digital literacy, and perceived pedagogical benefits.

Assumption testing was rigorously conducted to validate the appropriateness of parametric analyses. Normality was assessed using the Shapiro–Wilk test, while multicollinearity among predictor variables was evaluated via variance inflation factors (VIF), ensuring all values were within acceptable thresholds (<5). Regression significance was determined at a conventional alpha level of 0.05, and effect sizes were interpreted to assess both practical and statistical significance. Quantitative findings informed the refinement of subsequent qualitative inquiry, enabling a targeted exploration of patterns, such as barriers, facilitators, and contextual nuances, that influence AI adoption.

Qualitative Analysis

Qualitative data were analysed using a systematic thematic approach, operationalised through NVivo software to enhance coding rigour and analytic transparency. A deductive-inductive hybrid approach was employed: initial coding categories were informed by quantitative outcomes (e.g., "institutional support," "transformative potential"). At the same time, inductive analysis allowed emergent themes and subthemes to surface organically (e.g., "intermittent power supply," "resistance to change"). This iterative process ensured that the analysis captured both anticipated and unanticipated phenomena, providing a comprehensive understanding of AI adoption in the Zambian higher education context.

To ensure analytic rigour, 20% of transcripts were independently double-coded, and inter-coder reliability was calculated (Cohen's kappa = 0.82), indicating substantial agreement. Field notes and reflexive memos complemented thematic coding by documenting nonverbal cues, contextual factors, and the researcher's reflections, further enhancing the depth and richness of qualitative insights.

Integration of Quantitative and Qualitative Data

Data integration occurred at the interpretive and analytic stages, following a sequential explanatory mixed-methods framework. Joint displays were employed to merge quantitative results, such as correlation matrices and regression outputs, with illustrative qualitative excerpts, allowing for nuanced explanations of observed patterns. For instance, the negative correlation between infrastructure limitations and AI adoption was contextualised through interview data detailing unreliable electricity, low bandwidth, and insufficient hardware. Meta-inferences were drawn to synthesise findings across datasets, providing a holistic, empirically grounded understanding of AI adoption determinants, while enhancing the explanatory power and practical relevance of the study.

Validity, Reliability, and Trustworthiness

The study implemented rigorous procedures to ensure the validity, reliability, and trustworthiness of findings. Quantitative instrument validity was reinforced through pilot testing and exploratory factor analysis (Kaiser-Meyer-Olkin measure = 0.78), confirming sampling adequacy and construct reliability. Qualitative trustworthiness followed the criteria proposed by:

- Credibility was ensured via member checking and prolonged engagement with participants.
- Transferability was achieved through rich, contextualised descriptions of institutional and infrastructural realities.
- Dependability was supported through audit trails that detailed analytic decisions.
- Confirmability was addressed through the use of reflexive journals, which documented the researcher's assumptions and potential biases.

Mixed-methods rigour was further enhanced by carefully sequencing data collection, transparently integrating quantitative and qualitative strands, and systematically addressing potential biases in interpretation, thereby ensuring methodological coherence and legitimacy.

Ethical Considerations

The study adhered to the highest ethical standards, obtaining approval from the Zambian National Health Research Ethics Board and the relevant institutional review boards before data collection. Informed consent was obtained digitally or in writing, with explicit assurances of voluntary participation, confidentiality, and the right to withdraw without penalty. Data were anonymised and securely stored on encrypted servers, in full compliance with Zambia's Data Protection Act (2021), particularly concerning AI-mediated privacy risks. Measures were taken to mitigate potential power imbalances during interviews, including conducting sessions in neutral locations, employing open-ended questioning, and providing post-interview debriefings. These procedures collectively safeguarded participant rights while ensuring ethical integrity throughout the research process.

Results

This section outlines findings from a mixed-methods investigation into AI integration within Zambian higher education, adhering to a sequential explanatory design. Quantitative survey data from educators are presented first, detailing perceptions, adoption drivers, and obstacles, followed by qualitative insights from interviews to provide depth. Integrated findings combine both data types to reveal convergences and divergences, offering insights tailored to Zambia's context. All analyses ensured methodological rigor, with quantitative data meeting normality assumptions (Kolmogorov-Smirnov tests, $p > 0.05$) and qualitative data validated through member checking for trustworthiness.

Participant Demographics

The survey achieved a 92% response rate ($n = 230$ of 250), reflecting strong engagement from academics across Zambia's universities. As shown in Table 1, respondents were drawn primarily from the University of Zambia (45%) and Copperbelt University (30%), with smaller representation from Mulungushi University (15%) and other institutions (10%). The study results demonstrate a balanced gender distribution (60% male, 40% female) and broad disciplinary coverage, though STEM fields were most represented (45.7%).

Age distribution indicates that most respondents were mid-career (35–44 years, 42.6%), while experience levels correlated strongly with age ($\chi^2 = 45.67$, $df = 9$, $p < 0.001$). This suggests that generational differences may influence how educators perceive and respond to AI innovations, a pattern consistent with evidence from global higher education systems where younger academics tend to adopt new technologies more readily.

Table 1

Demographic Characteristics of Survey Respondents (N = 230)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	138	60.0
	Female	92	40.0
Age Group	35-44	98	42.6
	45-54	48	20.9
	55+	19	8.3
Academic Role	Lecturer/Professor	165	71.7
		45	19.6
	Administrator	20	8.7
	Other (e.g., Tutor)	105	45.7
	STEM	85	37.0
	Humanities/Social Sciences	40	17.4
Discipline		52	22.6
	Health Sciences		
Years of Experience	<5	78	33.9
	5-10	60	26.1
	11-15	195	84.8
	>15	35	15.2
Institution Type			
	Public	195	84.8
	Private	35	15.7

Note. Data from 2025 survey of Zambian higher education institutions. Percentages are based on valid responses and may not total 100% due to rounding.

Quantitative Results

Descriptive Statistics

The study results show consistently positive perceptions of AI. As summarized in Table 2, respondents rated AI's potential benefits highly (M = 4.05, SD = 0.75), particularly for personalized learning (M = 4.20, SD = 0.80). Future optimism also scored strongly (M = 3.95, SD = 0.80), reflecting confidence in AI's contribution to lifelong learning and educational equity. In contrast, barriers were rated lower (M = 3.15, SD = 1.05), with infrastructure readiness identified as the most critical constraint (M = 3.10, SD = 1.20).

These results align with international studies that demonstrate enthusiasm for AI's potential in enhancing pedagogy, while also reflecting persistent concerns about access and equity in resource-constrained contexts (Zawacki-Richter et al., 2019; UNESCO, 2023).

Table 2

Descriptive Statistics for Key Subscales and Items (N = 230)

Subscale/Item	Mean (M)	Standard Deviation (SD)	Skewness	Kurtosis
AI Benefits Subscale (α = 0.85)	4.05	0.75	-0.45	0.32
Personalized Learning	4.2	0.8	-0.52	0.41
Enhanced Accessibility	4.0	0.9	-0.38	0.28
Automated Assessment	3.9	1.0	-0.41	0.35
Adoption Factors Subscale (α = 0.88)	3.65	0.85	-0.30	0.22
Institutional Support	3.8	1.0	-035	0.29
Training Availability	3.5	1.1	-0.28	0.25
User-Friendly Tools	3.6	0.9	-0.32	0.31
Barriers Subscale (α = 0.82)	3.15	1.05	0.15	-0.10
Infrastructure Readiness	3.1	1.2	0.18	-0.12
Data Privacy Concerns	3.2	1.1	0.12	-0.08
Ethical Readiness	3.2	1.1	0.14	-0.09
Future Optimism Subscale (α = 0.89)	3.95	0.80	-0.40	0.30
AI for Lifelong Learning	4.0	0.9	-0.42	0.33
Equity in Education	3.9	0.8	-0.38	0.29

Source: Computed using Python libraries (NumPy, SciPy) based on survey data collected in early 2025.

These descriptives reveal optimism tempered by practical concerns, with barriers showing positive skewness, indicating a tail of highly pessimistic responses likely from rural or under-resourced institutions. Survey items were grouped into subscales: AI Benefits (e.g., personalized learning, accessibility), Adoption Factors (e.g., institutional support, training), Barriers (e.g., infrastructure, ethics), and Future Optimism. Reliability was robust (Cronbach's α = 0.82–0.89). Most subscales showed means above 3.5 on a 5-point Likert scale, indicating optimism, though barriers scored lower, reflecting Zambia's ICT challenges.

Inferential Statistics: Correlations and Group Differences

The study's results reveal significant relationships between the subscales. Table 3 demonstrates that AI Benefits correlated strongly with Adoption Factors ($r = 0.72$, $p < 0.001$) and Future Optimism ($r = 0.65$, $p < 0.001$). Institutional support was a particularly strong correlate of adoption ($r = 0.68$, $p < 0.001$), indicating that organisational commitment is critical to successful integration. Barriers were negatively correlated with both Adoption Factors ($r = -0.55$, $p < 0.001$) and Optimism ($r = -0.45$, $p < 0.001$).

Group comparisons confirmed disciplinary differences. A one-way ANOVA revealed that STEM educators rated AI Benefits significantly higher ($M = 4.25$, $SD = 0.70$) than those in humanities and social sciences ($M = 3.90$, $SD = 0.78$), $F(2,227) = 5.67$, $p = 0.004$. This suggests that perceptions of AI are domain-sensitive, with technology-intensive fields more inclined toward adoption.

Table 3

Correlation Matrix of Key Variables (N = 230

Variable	AI Benefits	Adoption Factors	Barriers	Future Optimism	Institutional Support	Infrastructure Readiness
AI Benefits	-	0.72**	-0.48**	0.65**	0.60**	0.60**
Adoption Factors		-	-0.55**	0.70**	0.68**	-0.50**
Barriers			-	-0.45**	-0.52**	0.75**
Future Optimism				-	0.62**	-0.38**
Institutional Support					-	-0.45**
Infrastructure Readiness						-

Note: **p < 0.001. Correlations adjusted for multiple comparisons using Bonferroni correction.

Regression Analysis

The hierarchical regression analysis (Table 4) shows that the final model explained 58% of variance in AI adoption ($R^2 = 0.58$, $F(8,221) = 38.12$, $p < 0.001$). The study results demonstrate that institutional support was the strongest predictor ($\beta = 0.52$, $p < 0.001$), followed by perceived benefits ($\beta = 0.35$, $p < 0.001$). Barriers ($\beta = -0.20$, $p < 0.001$) and infrastructure readiness ($\beta = -0.28$, $p = 0.002$) exerted negative influences. These findings confirm that adoption is contingent not only on individual attitudes but also on systemic enablers and constraints, consistent with research in comparable developing contexts (Mhlanga, 2023).

Exploratory factor analysis validated the four-factor structure (Benefits, Adoption, Barriers, Optimism), explaining 62% of variance (KMO = 0.81, Bartlett's $p < 0.001$). This demonstrates the multidimensionality of perceptions, echoing prior findings that AI in higher education is simultaneously viewed as an enabler, a challenge, and a future aspiration.

Table 4

Hierarchical Regression Predicting AI Adoption (N = 230)

Step/Model	Predictor	β	SE	t	p	ΔR^2
Step1 (Demographics)	Age Group	-0.12	0.08	-1.50	0.135	0.04*
	Discipline (STEM ref.)	0.15	0.07	2.14	0.033	
	Institution Type	-0.10	0.09	-1.11	0.268	
Step 2 Benefits/ Optimism	AI Benefits	0.35	0.06	5.83	<0.001	0.32**
	Future Optimism	0.28	0.07	4.00	<0.001	
Step 3 Barriers	Barriers Subscale	-0.20	0.05	-4.00	<0.001	0.22**
	Institution Support	0.52	0.04	13.00	<0.001	
	Infrastructure Readiness	-0.28	0.09	-3.11	0.002	

Note: *p < 0.05, **p < 0.001. VIF < 2.5 for all predictors, indicating no multicollinearity.

Exploratory Factor Analysis (EFA)

EFA with varimax rotation on 20 Likert items identified four factors explaining 62% of variance (KMO = 0.81, Bartlett's p < 0.001). Factor 1 (Benefits) loaded items on personalisation (loadings > 0.70); Factor 2 (Adoption) on support/training; Factor 3 (Barriers) on infrastructure/ethics; Factor 4 (Optimism) on future equity. This structure validates the subscales and suggests that AI perceptions in Zambia are multifaceted, similar to those of African STEM academics regarding the strategic use of AI.

Table 5

Rotated Factor Loadings from EFA (Selected Items)

Item	Factor 1 (Benefits)	Factor (Adoption)	2Factor (Barriers)	3Factor (Optimism)
Personalized Learning	0.78	0.15	-0.10	0.22

Institutional Support	0.12	0.82	-0.18	0.20
Infrastructure Readiness	-0.08	-0.20	0.75	-0.12
Future Equity	0.25	0.18	-0.15	0.80
Data Privacy	-0.05	-0.02	0.72	-0.08
Training Availability	0.02	0.78	-0.22	0.15

Note: Loadings > 0.40 shown; eigenvalues > 1.

Qualitative Results

The results from a thematic analysis of 25 interviews (with an average duration of 52 minutes) yielded three primary emerging themes, each with subthemes, supported by an inter-coder agreement of 78%. Quotes are anonymised (e.g., E1 for Educator 1).

Transformative Potential (Present in 80% of transcripts): Subthemes included bridging access gaps and enhancing pedagogical approaches. Participants noted AI as "a lifeline for rural students, personalising content despite distance" (E7) and "revolutionising research with tools like chatbots for idea generation" (A3). This echoes GenAI's role in the adoption of research in Zambia. However, the subtheme on skill development highlighted the need for AI literacy: "Educators must learn AI to teach it effectively" (S2).

Challenges and Barriers (Mentioned by 92%): Subthemes encompassed infrastructure (e.g., "Unreliable power outages halt AI sessions" (E12)), policy gaps ("No national AI framework leads to uneven adoption" (A5)), and equity issues ("Urban bias in tech access widens divides" (S4)). These align with studies citing inadequate ICT and digital literacy challenges. A subtheme on resistance emerged: "Some fear AI replaces jobs" (E15).

Ethical and Futuristic Imperatives (In 76%): Subthemes focused on bias mitigation ("Algorithms must reflect Zambian contexts to avoid cultural biases" (A8)) and policy needs ("Train for ethical use to ensure inclusive futures" (E10)). Participants envisioned "AI-driven smart classrooms by 2030" (S6), but emphasised the need for regulation, reflecting ethical concerns in AI KAP surveys.

Integrated Findings

Joint displays integrate data strands. For instance, high AI Benefits scores (M=4.05) converged with transformative themes, but low Infrastructure (M=3.1) explained barrier narratives. A joint display (Table 6) links quantitative correlations to qualitative excerpts, revealing that support predicts adoption (r = 0.68) via "institutional training bridges gaps" (E4). Divergences included STEM optimism that was not fully captured qualitatively, suggesting the need for discipline-specific policies. Overall, the findings highlight Zambia's AI promise amid barriers, with 58% of the adoption variance explained, urging infrastructure investments similar to those seen in COVID-era innovations.

Table 6

Joint Display of Quantitative and Qualitative Findings

Quantitative Finding	Statistic	Qualitative Theme/Subtheme	Exemplar Quote	Meta-Inference

High correlation: Benefits & Adoption	r=0.72, p<0.001	Transformative Potential/Pedagogy	"AI personalizes for diverse needs" (E7)	Convergence: Perceived benefits drive adoption through practical enhancements.
Negative correlation: Barriers & Optimism	r=-0.45, p<0.001	Challenges/Infrastructure	"Power issues kill optimism" (E12)	Explanation: Barriers dampen future views, Zambia-specific.
Regression Predictor: Support	β=0.52, p<0.001	Ethical Imperatives/Policy	"Need frameworks for equitable training" (A5)	Divergence: Quantitative strength of support not fully echoed; calls for policy action.
ANOVA: Discipline Differences	F=5.67, p=0.004	Transformative/Skill Development	"STEM sees more AI value" (E10, STEM)	Convergence: Group variances explained by domain-specific applications.

Discussion

The results of the study demonstrate that the integration of artificial intelligence (AI) in Zambia's higher education system is viewed positively by educators, particularly in relation to its potential to personalise learning, enhance access, and streamline academic processes. High mean scores for AI's perceived benefits ($M = 4.05$, $SD = 0.75$) and optimism about future applications ($M = 3.95$, $SD = 0.80$) indicate widespread recognition of AI as a transformative educational technology. These findings are consistent with international studies that highlight the capacity of AI to support adaptive learning, improve engagement, and reduce workload burdens for faculty (Zawacki-Richter et al., 2019). However, the study's results also reveal that enthusiasm is moderated by infrastructural, ethical, and policy-related constraints, which reflect broader challenges reported across Sub-Saharan Africa.

The study results show that infrastructural fragility remains a decisive barrier to AI adoption. The relatively low scores for infrastructural readiness ($M = 3.10$, $SD = 1.20$) and the negative correlation between barriers and optimism ($r = -0.45$, $p < 0.001$) illustrate the centrality of power supply, internet connectivity, and device availability in shaping perceptions. Qualitative narratives, such as "unreliable power outages halt AI sessions" (E12), reinforce this concern. These findings align with evidence from Nigeria, where inconsistent connectivity undermines digital education initiatives and from Tanzania, where poor electricity supply constrains the sustainability of edtech adoption. The results of the present study, therefore, confirm that without systemic infrastructural investment, enthusiasm for AI in Zambia risks remaining aspirational.

The findings also demonstrate that institutional support is the strongest predictor of AI adoption ($\beta = 0.52$, $p < 0.001$), surpassing even infrastructural readiness. This suggests that Zambian universities themselves play a more decisive role in adoption trajectories than has been observed in some neighbouring contexts. In South Africa, for instance, national policy frameworks and ethical debates have taken precedence (Mhlanga, 2022), while in Zimbabwe, the political environment has significantly shaped technological adoption (Chisango et al., 2021). By contrast, the study's results show that in Zambia, institutional-level initiatives, such as training programs, resource allocation, and policy support, emerge as the most critical levers for change. This finding highlights the importance of empowering universities to act as agents of innovation, while national strategies should provide enabling conditions.

The study results further indicate disciplinary differences in the adoption of AI. STEM educators reported higher perceived benefits ($M = 4.25$, $SD = 0.70$) compared to educators in the humanities and social sciences ($M = 3.90$, $SD = 0.78$), with an ANOVA confirming the significance of these differences ($F(2,227) = 5.67$, $p = 0.004$). This is consistent with findings from Kenya and Tanzania, where faculty in technology-intensive disciplines were more receptive to AI but still noted limited pedagogical integration. The qualitative findings of the present study add nuance by demonstrating that even among STEM educators, optimism is tempered by anxieties over insufficient training and lack of integration strategies. These results highlight the need for discipline-sensitive approaches, as uniform implementation may exacerbate divides between faculties.

Ethical considerations also emerge as a salient dimension. The study results demonstrate relatively low scores for ethical readiness ($M = 3.20$, $SD = 1.10$), alongside frequent concerns about data privacy, algorithmic bias, and cultural appropriateness. Participant comments such as "algorithms must reflect Zambian contexts to avoid cultural biases" (A8) illustrate the need for contextually sensitive design and policy. These findings correspond with debates in South Africa, where AI adoption has raised concerns around surveillance and fairness (Mhlanga, 2022), and with calls from UNESCO (2022) for ethical frameworks that account for regional and cultural diversity. The results of the study, therefore, underline the urgency of developing ethical guidelines in Zambia, as unregulated adoption could deepen inequities and erode trust.

The study results also demonstrate essential similarities and differences with other African contexts. In Zimbabwe, the adoption of AI is hindered by political instability and underdevelopment, despite policy rhetoric (Chisango et al., 2021). In Nigeria, infrastructural deficits and uneven faculty training are the dominant barriers. In South Africa, ethical debates take centre stage (Mhlanga, 2022). The Zambian case, however, is distinctive in that institutional support emerges as the most critical determinant of adoption. This comparison suggests that while infrastructural fragility and ethical concerns are continental challenges, Zambia's trajectory may be accelerated or constrained primarily by the extent to which universities themselves provide support, training, and incentives.

Ultimately, the study's results reveal several practical implications. At the institutional level, universities must invest in professional development programs, particularly hybrid training models that blend online learning with localised workshops to address urban–rural disparities. At the policy level, Zambia requires a comprehensive AI framework that establishes ethical safeguards, builds infrastructure, and integrates AI into curricula, drawing lessons from Kenya's digital literacy initiatives and South Africa's ethical guidelines (UNESCO, 2022). Pedagogically, discipline-sensitive strategies are needed to ensure equitable adoption across STEM and non-STEM fields. At a systemic level, public–private partnerships will be necessary to strengthen infrastructure and expand access to digital devices. The integration of these interventions is essential to move AI adoption in Zambia from aspiration to practice, ensuring that enthusiasm translates into equitable and sustainable outcomes.

Conclusion

This study explored the integration of artificial intelligence (AI) in Zambian higher education through a mixed-methods design, combining large-scale survey data with qualitative interviews to capture both broad patterns and rich contextual insights. By systematically addressing the research objectives, the study contributes to both theory and practice, while also providing actionable recommendations for policymakers and institutions in developing contexts.

Findings reveal a prevailing optimism among Zambian educators regarding the transformative role of AI. Quantitatively, educators rated AI highly for its capacity to personalise learning ($M = 4.2$, $SD = 0.8$) and to expand accessibility ($M = 4.0$, $SD = 0.9$). These perceptions were not isolated but strongly correlated with institutional support ($r = 0.68$, $p < 0.001$), suggesting that favourable organisational environments amplify positive attitudes. Predictive modelling further underscored the importance of institutional readiness as a driver of adoption ($\beta = 0.52$, $p < 0.001$). Complementary qualitative evidence enriched these results by portraying AI as a tool that could bridge systemic gaps in access to education, especially for students in rural areas where resource scarcity is most acute. Together, these findings highlight AI's potential to function as an equity-enhancing force in Zambian higher education.

Despite optimism, significant barriers emerged. Educators reported persistent infrastructural challenges, particularly unreliable electricity and limited internet connectivity ($M = 3.1$, $SD = 1.2$). Concerns about data privacy, algorithmic bias, and the absence of clear governance frameworks were also salient across both datasets. Notably, discipline-specific differences were evident: quantitative analysis revealed significant variation in perceptions across academic fields ($F(2,227) = 5.67$, $p = 0.004$), with STEM disciplines displaying more enthusiasm compared to the social sciences and humanities. This divergence suggests that AI integration cannot be applied uniformly, but instead requires strategies tailored to disciplinary pedagogies and epistemologies.

Theoretically, this study advances scholarship by situating AI adoption within Zambia's socio-economic and cultural context. Much of the global literature originates from resource-rich environments, where infrastructure is robust and institutional investment is substantial. By contrast, this research illuminates how adoption dynamics in Zambia are shaped by fragile infrastructure, uneven digital literacy, and broader governance constraints. By doing so, the study addresses a critical gap in empirical evaluations of AI's educational potential in the Global South. Framed through a mixed-methods lens, the integration of quantitative and qualitative data offers a nuanced perspective that goes beyond technocentric optimism, instead situating AI adoption within structural realities.

From a policy and institutional standpoint, three priority recommendations emerge. First, investment in digital infrastructure, reliable internet connectivity, stable electricity supply, and access to affordable devices is a foundational requirement for AI adoption. Without this, technological potential cannot be effectively translated into educational outcomes. Second, AI literacy and professional development programs for educators are critical. Qualitative insights underscore educators' desire for training that extends beyond tool use to encompass ethical awareness and pedagogical integration. This is particularly relevant in public institutions, where readiness significantly lags ($t(228) = -2.14$, $p = 0.033$). Third, ethical frameworks and regulatory policies must be developed to address data protection, algorithmic transparency, and equitable access to information. Such frameworks align with broader African concerns about technological sovereignty and inclusivity, ensuring that AI integration does not exacerbate inequalities. Collectively, these recommendations align with Sustainable Development Goal 4 by promoting equitable and adaptive education systems.

Methodologically, the study's strengths include its high survey response rate (92%, $n = 230$) and achievement of thematic saturation in interviews ($n = 25$), lending robustness and credibility to its insights. However, limitations must be acknowledged. The urban bias of the sample (84.8% from public institutions) constrains the generalizability of findings to rural or private-sector contexts. The reliance on self-reported data may also inflate positive attitudes due to social desirability bias. Moreover, the cross-sectional design restricts causal inferences, making it difficult to assess how perceptions and adoption evolve. These limitations highlight opportunities for future longitudinal and comparative research.

In summary, this study underscores AI's promise as a transformative force in Zambian higher education, capable of fostering personalised, inclusive, and future-ready learning systems. By strategically addressing infrastructural deficits, enhancing educator capacity, and embedding ethical safeguards, Zambia has the potential to harness AI as a tool for educational equity and innovation. By doing so, the country can make a meaningful contribution to global discussions on AI in education while charting a locally grounded, socially responsive path toward digital transformation.

Suggestions for Future Research

Building on these findings, several directions for future research can advance both theoretical understanding and practical implementation. First, longitudinal research is crucial for capturing the evolving role of AI in higher education. A key question is: How does AI adoption influence student outcomes, faculty development, and institutional performance over time? Multi-wave panel surveys, supplemented by in-depth follow-up interviews, would enable researchers to identify causal pathways and assess the sustainability of adoption.

Second, comparative research across African countries would enrich the understanding of contextual influences on AI adoption. Research questions such as How do infrastructural, cultural, and policy environments shape AI integration across diverse African contexts? Could be pursued using cross-national mixed-methods designs. A comparative analysis would situate Zambia's experience within broader regional trajectories and provide valuable lessons for scaling adoption strategies across the continent.

Third, discipline-specific case studies are needed to address the divergences identified in this study. Questions such as What are the pedagogical, ethical, and professional implications of AI adoption in STEM, social sciences, and humanities disciplines? Would provide granular insights into how AI can be tailored to distinct educational needs. Such studies could employ embedded case study designs, integrating classroom observations, student learning analytics, and faculty reflections to enhance the understanding of the phenomenon.

Ultimately, future research should incorporate innovative methodological approaches that extend beyond self-reports. The use of digital learning analytics, institutional records, and experimental interventions can provide objective evidence of AI's impact on learning processes and outcomes. Combining these with qualitative insights would yield richer and more reliable findings.

By pursuing these avenues, scholars can deepen theoretical understanding of AI in education while generating actionable evidence for policymakers and institutions. Such research will be crucial to ensuring that AI adoption in Africa transitions from experimentation to sustainable, inclusive, and contextually grounded transformation.

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