



Generative AI Adoption and Governance in African Higher Education: A Mixed-Methods Study of Ghanaian Universities

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Abstract

Background and Aim: The rapid emergence of generative artificial intelligence (GenAI) in higher education offers transformative opportunities while creating substantial governance challenges, particularly in resource-constrained Global South settings. This study examined GenAI adoption, perceptions, and governance frameworks across Ghanaian higher education institutions, addressing limited empirical evidence concerning AI governance in Africa.

Materials and Methods: A sequential explanatory mixed-methods design was employed. Structured surveys collected quantitative data from 1,235 students and 247 academic staff across 12 public and private Ghanaian universities. Semi-structured interviews with 28 administrators, policymakers, and academics generated qualitative evidence. Guided by the Technology Acceptance Model and institutional theory, the study applied descriptive statistics, inferential tests, and thematic analysis.

Results: Regular GenAI use was reported by 67.3% of students and 54.3% of academic staff using ChatGPT and Microsoft Copilot. Perceived usefulness and ease of use significantly predicted behavioural intention, explaining 58% of its variance. Nevertheless, no participating Ghanaian university had a formal, publicly accessible AI policy, resulting in inconsistent assessment practices and concerns regarding fairness, transparency, and accountability. Five governance challenges emerged: inadequate policy readiness, disparities in digital literacy, infrastructure limitations, ethical and academic-integrity risks, and cultural relevance concerns.

Conclusion: The study proposes a context-sensitive governance framework encompassing eight dimensions: academic integrity; ethical and responsible use; privacy and security; equitable access; GenAI literacy; integration strategy; human oversight and accountability; and institutional infrastructure. It provides evidence from an under-researched African context and practical guidance for policymakers, university administrators, and educational technologists pursuing responsible, equitable, and contextually appropriate GenAI integration.

Keywords: Generative AI; Higher Education Governance; Ghana; African Higher Education; Technology Acceptance Model; Digital Transformation; Academic Integrity

Introduction

The advent of generative artificial intelligence (GenAI) systems, including large language models like ChatGPT, Anthropic Claude, Microsoft Copilot, and Google Gemini, is a paradigm change in higher education around the world. The GenAI tools, which can generate humanlike text, code, images, and multimedia based on user prompts, have rapidly changed the workflows for teaching, learning, assessment, and research within universities all around the world (Crompton & Burke, 2023; McDonald et al., 2024). According to HolonIQ (2023), by 2023, generative artificial intelligence tools had become increasingly integrated into scientific research. In a global survey of more than 1,600 researchers, approximately 30% of respondents reported using generative AI to support activities such as preparing manuscripts, reviewing the literature, and developing grant applications (Van Noorden &





Perkel, 2023). Within the context of sub-Saharan Africa, where graduate students struggle with accessing scholarly journals and inadequate supervision for their research, GenAI has tremendous potential to address systemic inequalities and improve academic output (Adarkwah, 2025; Adjei et al., 2026).

Ghana, as one of the most dynamic higher education sectors on the continent, boasting more than 150 accredited public and private universities and university colleges, provides an interesting backdrop for studying GenAI adoption and governance. Ghana's higher education sector has undergone extensive digitalization in recent years, facilitated by the COVID-19 crisis and heavy investment in educational technology infrastructure (Amouzou, 2024; KNUST, 2026). Universities like the University of Cape Coast have entered into deals to create AI-powered digital campus ecosystems (Yarboi-Tetteh, 2026), while Kwame Nkrumah University of Science and Technology has held conferences on using AI for inclusive higher education (KNUST, 2026). Still, despite all these developments, there has been very little empirical research carried out in the area of GenAI adoption and governance in Ghanaian higher education. Such research is needed now because, without it, there will be no basis for creating any policy framework to guide universities in terms of not stifling innovation or ignoring important issues related to ethics and academic integrity.

The widespread use of GenAI in higher education brings about both transformative possibilities and challenging aspects of governance, especially in cases where resources are lacking in the Global South region. Although many studies have explored GenAI adoption in higher education institutions in North America, Europe, and East Asia, there is little research in the sub-Saharan African context (Cudjoe & Adebayo, 2025; Nwaigwe et al., 2026). However, there is a need to explore how the lack of infrastructure, inconsistent academic integrity guidelines, resource limitations, and unique cultural views on authorship affect the adoption of GenAI in the African context (Adarkwah, 2025; Ozguven et al., 2025).

In Ghana specifically, preliminary research indicates a complex landscape of GenAI adoption. A study by Cudjoe and Adebayo (2025) investigating AI policy readiness in Sub-Saharan African higher education institutions found that while six institutions in South Africa had published and implemented institutional AI policies, no higher education institution in Ghana or Nigeria currently has a formal or publicly accessible AI policy in place. In these countries, academic staff use their discretion to make subjective judgments when evaluating student submissions suspected to be AI-generated, creating inconsistencies that raise concerns about fairness, transparency, and accountability (Cudjoe & Adebayo, 2025). Concurrently, studies on GenAI usage among Ghanaian students reveal widespread adoption despite policy vacuums, with students using tools for academic writing, literature synthesis, and research support (Adarkwah, 2025; Aryeh-Adjei et al., 2026; Yeboah et al., 2026). This disconnect between widespread student adoption and institutional policy readiness represents a critical governance gap that requires systematic investigation. Without a comprehensive understanding of adoption patterns, perceptions, and governance challenges, universities in Ghana and similar contexts risk either stifling innovation through overly restrictive policies or failing to address significant ethical and academic integrity concerns through policy neglect (Gkrimpizi et al., 2023).

Objectives

This study aims to investigate GenAI adoption patterns, perceptions, and governance frameworks in Ghanaian higher education through a mixed-methods approach. Specifically, the study addresses the following research questions:

What are the patterns of GenAI adoption and usage among students and faculty in Ghanaian universities?

What are the perceptions, attitudes, and readiness of Ghanaian university stakeholders toward GenAI tools?

What institutional governance structures and policy frameworks exist for GenAI integration in Ghanaian universities?





What are the key challenges and opportunities for GenAI governance in Ghanaian higher education?

What context-sensitive governance framework can guide responsible GenAI integration in resource-constrained higher education contexts?

The study makes several significant contributions. The theoretical contribution advances understanding of GenAI adoption in the Global South by applying and extending the Technology Acceptance Model (TAM) within the Ghanaian context and illuminating institutional dynamics through institutional theory. The empirical contribution provides comprehensive data on GenAI adoption patterns, perceptions, and governance gaps from an under-researched African context. The practical contribution offers actionable recommendations for policymakers, university administrators, and educational technologists. The decolonial contribution challenges the dominance of Northern perspectives in AI governance literature and centers African experiences and knowledge production.

Literature Review

Generative AI in Higher Education

Generative AI encompasses machine learning models that create new data samples mimicking real datasets, producing multimodal outputs including text, images, audio, video, and code (Crompton & Burke, 2023; Adarkwah, 2025). In higher education, GenAI technologies have found applications in teaching, learning, assessment, and research, supporting activities such as automated writing assistance, content creation, personalized tutoring, and feedback generation (McDonald et al., 2024; Cotton et al., 2024). Several areas demonstrate GenAI's transformative potential in higher education. Proponents argue that it can increase personalization of education, support students with specific needs, facilitate task automation, and streamline research processes (Alenezi, 2023; Roussos et al., 2025). However, significant concerns persist regarding academic dishonesty, erosion of critical thinking skills and cognitive engagement, privacy issues, and algorithmic bias (Perkins, 2023; Gerlich, 2025). These challenges are particularly acute in African contexts due to infrastructure limitations, inconsistent academic integrity approaches, and diverse cultural perspectives on authorship (Adarkwah, 2025; Ozguven et al., 2025).

GenAI Adoption in African Higher Education

Research on GenAI adoption in African higher education is nascent but growing (Nwaigwe et al., 2026). Studies across various African countries reveal both commonalities and context-specific findings. Mudenda et al. (2026) found that over 80% of Zambian university students had used ChatGPT before participating in their research, indicating high adoption rates despite the absence of formal guidelines. Research specifically focusing on GenAI adoption in Ghana has increased. Yeboah et al. (2026) examined the impact of generative AI on electronic resource usage among 1,581 students from public, technical, and private Ghanaian universities. The study found that while generative AI tools increasingly influence students' information-seeking behaviors, they have not fully replaced traditional e-resources. Whereas 58.0% of the sampled population still relied on traditional e-resources, 42.0% used fewer traditional e-resources due to the convenience and efficiency of generative AI tools. The study also observed that senior students employed different information tools compared to junior students, who predominantly used ChatGPT and similar AI tools.

Adarkwah (2025) examined factors influencing graduate students' adoption of GenAI in Ghana using an extended UTAUT2 model. Surveying 415 graduate students, the study found that performance expectancy, hedonic motivation, facilitating conditions, personal innovativeness, perceived learning opportunities, and satisfaction significantly drove graduate students' behavioral intention toward GenAI adoption. The study also found that personal innovativeness, satisfaction, and behavioral intention significantly predicted actual GenAI use behavior. Aryeh-Adjei et al. (2026) examined how doctoral students in Ghana use GenAI tools within experiential learning, finding that GenAI supported time savings, improved writing and communication, enhanced conceptual understanding, and stimulated creativity. However, subscription fees, limited connectivity, and paywall restrictions hindered equitable





access, while ethical concerns included non-disclosure of AI use, overreliance risks, and culturally insensitive AI outputs.

GenAI Governance in Higher Education

GenAI governance in higher education has emerged as a critical global concern, with scholars advocating for comprehensive frameworks to guide responsible integration (Gkrimpizi et al., 2023). A global Delphi study by Crompton et al. (2026) developed a higher education GenAI policy and guidelines framework encompassing eight core areas: (1) academic integrity, (2) ethical and responsible use, (3) privacy and protection, (4) equitable access, (5) GenAI literacy, (6) integration strategy, (7) human oversight and accountability, and (8) institutional support and infrastructure. The study also developed a six-part framework to ensure policy currency and relevance: (1) creating a dedicated GenAI Committee, (2) conducting regularly scheduled policy reviews, (3) providing ongoing professional development and support, (4) communicating with all stakeholders, (5) evaluating the effectiveness and impact of GenAI, and (6) monitoring external developments.

In Africa, governance frameworks remain nascent. Thaldar et al. (2025) examined the University of KwaZulu-Natal (UKZN) in South Africa, one of the first African higher education institutions to develop and implement comprehensive academic guidelines for the responsible use of generative artificial intelligence. The UKZN guidelines are founded on four core principles: promoting innovation, ensuring ethical and responsible use, maintaining academic rigour, and strengthening institutional capacity. They establish clear policies on GenAI adoption across teaching and research, including curriculum integration, disclosure and authorship standards, plagiarism approaches, and data protection guidance. The study demonstrates how a Global South higher education institution can translate national AI policy into actionable institutional governance while addressing contextual challenges such as resource constraints, digital divides, and multicultural considerations.

However, Cudjoe and Adebayo (2025) found that while six South African higher education institutions have published and implemented institutional AI policies, no higher education institution in Ghana or Nigeria currently has a formal or publicly accessible AI policy. In these countries, academic staff exercise discretion in evaluating student submissions suspected of AI generation, creating inconsistencies that raise concerns about fairness, transparency, and accountability.

Theoretical Perspectives on GenAI Governance

The study of GenAI adoption and governance is underpinned by several theoretical frameworks that provide analytical lenses for understanding governance operations and significance. The Technology Acceptance Model (TAM) explains individual adoption decisions through perceived usefulness and ease of use (Davis, 1989). Institutional theory illuminates organizational responses to technological change through isomorphic pressures (DiMaggio & Powell, 1983; Scott, 2021). Stakeholder theory emphasizes the importance of balancing diverse interests in governance decisions (Freeman et al., 2020). This study integrates TAM and institutional theory to examine both individual adoption and institutional governance responses. Institutional theory, drawing on the foundational work of DiMaggio & Powell (1983) and Scott (2021), posits that organizations are influenced not only by rational efficiency considerations but also by normative expectations, cultural-cognitive frameworks, and regulatory pressures from their institutional environments. In GenAI governance, institutional theory illuminates how higher education institutions adopt governance structures, policies, and practices in response to both internal organizational dynamics and external societal expectations (Scott, 2021). This theoretical perspective is particularly relevant for understanding why Ghanaian universities have been slow to develop formal AI policies despite widespread student adoption. Stakeholder theory provides a complementary lens emphasizing the importance of balancing diverse stakeholder interests, including faculty, students, administrators, policymakers, and the broader community (Freeman et al., 2020).

The integration of these theoretical frameworks enables a more comprehensive understanding of governance dynamics. Institutional theory explains why governance structures exist and how they are shaped by environmental pressures. Stakeholder theory explains how governance should balance





diverse interests. Together, these frameworks provide a robust analytical foundation for examining digital transformation governance in higher education.

Research Gaps

The literature review reveals several significant research gaps. First, empirical research on GenAI adoption in Ghanaian higher education is limited, with most studies focusing on specific institutions or student populations rather than providing comprehensive sector-wide analysis. Second, research on GenAI governance in Ghanaian higher education is virtually non-existent, with no systematic examination of institutional policy readiness, governance structures, or stakeholder perspectives on governance. Third, there is limited integration of adoption and governance perspectives, with studies typically examining either adoption patterns or policy frameworks in isolation. Fourth, existing research has not developed context-sensitive governance frameworks specifically tailored to the Ghanaian or West African higher education context. Fifth, there is limited application of theoretical frameworks to understand the interplay between individual adoption decisions and institutional governance responses in the Ghanaian context. This study addresses these gaps by providing comprehensive empirical evidence, integrating adoption and governance perspectives, developing a context-sensitive governance framework, and applying theoretical frameworks to understand the complex interplay between individual and institutional responses.

Conceptual Framework

This study integrates the Technology Acceptance Model (TAM) and institutional theory to examine GenAI adoption and governance in Ghanaian higher education. TAM, developed by Davis (1989), posits that perceived usefulness and perceived ease of use are primary determinants of an individual's behavioral intention to adopt technology. Perceived usefulness refers to the extent to which an individual believes technology use will enhance job or academic performance, while perceived ease of use refers to the extent to which an individual finds technology use effortless. Institutional theory, drawing on DiMaggio & Powell (1983) and Scott (2021), explains organizational responses to technological change through coercive, mimetic, and normative isomorphic pressures. This integrated framework enables examination of both individual adoption decisions and institutional governance responses within the Ghanaian context.

The conceptual framework posits that GenAI adoption is influenced by individual-level factors (perceived usefulness, perceived ease of use) and contextual factors (institutional support, infrastructure, policy environment). Governance responses are shaped by institutional pressures, stakeholder expectations, and resource constraints. The framework guides the investigation of adoption patterns, perceptions, and governance challenges, informing the development of a context-sensitive governance framework.

Methodology

Research Design

This study employs a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2023). The quantitative phase involved a cross-sectional survey of students and academic staff across Ghanaian universities to assess GenAI adoption patterns, perceptions, and institutional support. The qualitative phase involved semi-structured interviews with university administrators, policymakers, and faculty members to explore governance structures, policy readiness, and contextual challenges. This design enables triangulation of findings and provides both breadth and depth of analysis.

Research Context

The study was conducted in Ghana, focusing on accredited public and private universities. Ghana's higher education system comprises over 150 accredited institutions, including public universities, private universities, technical universities, and university colleges. The sector has experienced significant growth and digital transformation in recent years, with institutions increasingly





investing in educational technology infrastructure and exploring AI integration (KNUST, 2026; Yarboi-Tetteh, 2026).

Quantitative Phase

Population and Sample

The target population comprised undergraduate and postgraduate students and academic staff from Ghanaian universities. A stratified random sampling strategy was employed to ensure representation across institution types (public and private), geographic locations, and academic disciplines.

Table 1: Target Population Distribution by University

Category	University	Location	Estimated Student Population
Public Universities			
1	University of Ghana (UG)	Legon, Accra	42,000
2	Kwame Nkrumah University of Science and Technology (KNUST)	Kumasi, Ashanti	35,000
3	University of Cape Coast (UCC)	Cape Coast, Central	25,000
4	University for Development Studies (UDS)	Tamale, Northern	20,000
5	University of Education, Winneba (UEW)	Winneba, Central	18,000
6	Ghana Institute of Management and Public Administration (GIMPA)	Accra, Greater Accra	12,000
7	University of Health and Allied Sciences (UHAS)	Ho, Volta	8,000
8	University of Energy and Natural Resources (UENR)	Sunyani, Bono	6,000
Sub-total (Public Universities)			166,000
Private Universities			
9	Pentecost University	Accra, Greater Accra	5,000
10	Central University	Tema, Greater Accra	4,500
11	Valley View University	Accra, Greater Accra	4,000
12	Ashesi University	Berekuso, Eastern	1,500
Sub-total (Private Universities)			15,000
Grand Total			181,000

Source: Ghana Tertiary Education Commission (GTEC) Statistics, 2025; Institutional Enrollment Data

The sample included 1,235 students and 247 academic staff from 12 universities (8 public, 4 private) across Ghana's major regions. The sample size was determined using Cochran's (1977) formula: $n_0 = Z^2pq / e^2$

Where:

- $Z = 1.96$ (95% confidence level)
- $p = 0.5$ (estimated proportion)
- $q = 1 - p = 0.5$
- $e = 0.05$ (margin of error)





$$n_0 = (1.96)^2 \times (0.5)(0.5) / (0.05)^2 = 3.8416 \times 0.25 / 0.0025 = 384.16$$

The minimum sample size of 384 was increased to 420 to account for non-response. The final student sample of 1,235 was achieved through proportional allocation across the 12 universities.

Table 2: Sample Size Distribution by University

Category	University	Student Population	Sample Size (Proportional)	Percentage of Sample
Public Universities				
1	University of Ghana (UG)	42,000	286	23.2%
2	Kwame Nkrumah University of Science and Technology (KNUST)	35,000	238	19.3%
3	University of Cape Coast (UCC)	25,000	170	13.8%
4	University for Development Studies (UDS)	20,000	136	11.0%
5	University of Education, Winneba (UEW)	18,000	123	9.9%
6	Ghana Institute of Management and Public Administration (GIMPA)	12,000	82	6.6%
7	University of Health and Allied Sciences (UHAS)	8,000	55	4.5%
8	University of Energy and Natural Resources (UENR)	6,000	41	3.3%
	Sub-total (Public Universities)	166,000	1,131	91.6%
Private Universities				
9	Pentecost University	5,000	34	2.8%
10	Central University	4,500	31	2.5%
11	Valley View University	4,000	27	2.2%
12	Ashesi University	1,500	12	1.0%
	Sub-total (Private Universities)	15,000	104	8.4%
	Grand Total	181,000	1,235	100%

Source: Proportional allocation based on Cochran's (1977) formula and institutional enrollment data

The academic staff sample of 247 was drawn from the same 12 universities, with proportional representation across ranks (professors, associate professors, senior lecturers, lecturers, and assistant lecturers). The sample achieved a response rate of 72.4% for students and 68.9% for academic staff.

The participating public universities included the University of Ghana (UG) in Legon, Kwame Nkrumah University of Science and Technology (KNUST) in Kumasi, University of Cape Coast (UCC) in Cape Coast, University for Development Studies (UDS) in Tamale, University of Education, Winneba (UEW) in Winneba, Ghana Institute of Management and Public Administration (GIMPA) in Accra, University of Health and Allied Sciences (UHAS) in Ho, and University of Energy and Natural Resources (UENR) in Sunyani. The participating private universities included Pentecost University in Accra, Central University in Tema, Valley View University in Accra, and Ashesi University in Berekuso. These institutions were selected to ensure diversity across geographic regions (Accra, Kumasi, Cape Coast, Tamale, Ho, Sunyani, Winneba, and Berekuso), institution types (public and private), and academic disciplines.





Instrumentation

The survey instrument was developed based on established scales from the Technology Acceptance Model (Davis, 1989) and adapted for the GenAI context. The instrument comprised five sections: (1) demographic information, (2) GenAI awareness and adoption patterns, (3) perceived usefulness and perceived ease of use, (4) institutional support and infrastructure, and (5) governance and policy perceptions. Items were measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was pilot-tested with 50 respondents (25 students, 25 staff) from one public and one private university (the University of Ghana and Pentecost University). Based on the pilot results, three items were refined for clarity, and two items were removed due to low factor loadings. Cronbach's alpha coefficients for all scales exceeded 0.80, indicating good internal consistency. The survey was administered in English, the official language of instruction in Ghanaian universities.

Data Collection

Data were collected between January and May 2026 through online and paper-based surveys. Online surveys were distributed via institutional email lists and learning management systems, while paper-based surveys were administered in classroom settings. Informed consent was obtained from all participants, and the study received ethical approval from the Pentecost University Research Ethics Committee (Reference: PUREC/2026/017).

Data Analysis

Quantitative data were analyzed using SPSS version 28 and SmartPLS 4. Descriptive statistics were computed to summarize adoption patterns and perceptions. Structural equation modeling (PLS-SEM) was employed to test the hypothesized relationships based on TAM. The analysis followed the two-step approach recommended by Hair et al. (2022), with assessment of the measurement model followed by evaluation of the structural model.

Non-response bias was assessed by comparing early and late respondents on key demographic variables using independent samples t-tests. No significant differences were found ($p > 0.05$ for all comparisons), suggesting that non-response bias is not a major concern. Common method bias was assessed using Harman's single-factor test. The first factor accounted for 28.6% of the variance, below the 50% threshold, suggesting that common method bias is not a significant concern.

Inferential Statistical Tests Conducted:

Independent Samples t-tests: To compare mean differences between groups (e.g., students vs. staff, public vs. private university respondents) on key variables including perceived usefulness, perceived ease of use, and governance perceptions.

One-way ANOVA: To examine differences across academic disciplines, years of study, and institutional types.

Pearson Correlation Analysis: To examine bivariate relationships between key continuous variables, including perceived usefulness, perceived ease of use, institutional support, behavioral intention, and actual use.

Structural Equation Modeling (PLS-SEM): To test the hypothesized relationships in the TAM framework, including direct effects, explained variance (R^2), and effect sizes (f^2).

Regression Analysis: To identify significant predictors of GenAI adoption and behavioral intention.

Qualitative Phase

Participants: A purposive sampling strategy was employed to select information-rich participants with deep knowledge of GenAI governance in Ghanaian higher education. The sample comprised 28 participants: 12 university administrators (vice-chancellors, registrars, deans), 8 policymakers (Ministry of Education, National Council for Tertiary Education, Ghana Tertiary Education Commission), and 8 faculty members with expertise in educational technology. Participants were selected from public and private universities across Ghana. The qualitative sample was selected to ensure diversity across institution types (public/private), geographic locations (Accra, Kumasi,





Tamale), and stakeholder roles (administrators, policymakers, faculty). Participating institutions for the qualitative phase included the University of Ghana, KNUST, University of Cape Coast, University for Development Studies, Pentecost University, and Central University.

Data Collection

Semi-structured interviews were conducted between March and May 2026. Interview guides were developed based on the research questions and literature review, covering topics such as institutional AI policy readiness, governance structures, challenges and opportunities, and stakeholder perspectives on GenAI integration. Interviews lasted 45-60 minutes and were conducted in person or via video conferencing. All interviews were audio-recorded with participant consent and transcribed verbatim.

Data Analysis

Qualitative data were analyzed using thematic analysis following the six-phase approach of Braun and Clarke (2022): (1) familiarization with the data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report. Two independent researchers coded the data, with disagreements resolved through discussion. Inter-rater reliability, measured using Cohen's Kappa, was 0.84, indicating strong agreement. NVivo 14 was used to manage and analyze the qualitative data.

Integration

Integration of quantitative and qualitative findings occurred at the interpretation stage, following the explanatory sequential design (Creswell & Plano Clark, 2023). Quantitative findings informed the selection of participants for qualitative interviews and provided the empirical foundation for exploring governance gaps in greater depth. Qualitative findings were used to explain and contextualize quantitative results, providing insights into the underlying mechanisms and contextual factors shaping GenAI adoption and governance in Ghanaian higher education.

Ethical Considerations

The study received ethical approval from the Pentecost University Research Ethics Committee (Reference: PUREC/2026/017). All participants provided informed consent and were assured of confidentiality and anonymity. Participants were informed that their participation was voluntary and that they could withdraw at any time without consequence. Data were stored securely, and access was limited to the research team.

Results

Quantitative Findings

Demographic Characteristics

Table 3 presents the demographic characteristics of the quantitative sample. The sample comprised 1,235 students (62.3% male, 37.7% female) and 247 academic staff (68.4% male, 31.6% female). The majority of students were undergraduates (78.5%), with postgraduate students accounting for 21.5%. Academic staff were predominantly lecturers and senior lecturers (52.6%), with professors and associate professors accounting for 15.4% and 12.6%, respectively. The sample represented diverse academic disciplines, with social sciences (28.3%), humanities (22.1%), and sciences (18.6%) being the most represented.

Table 3: Demographic Characteristics of the Sample

Characteristic	Students (n=1,235)	Academic Staff (n=247)
Gender		
Male	62.3%	68.4%
Female	37.7%	31.6%
Level of Study/Rank		
Undergraduate	78.5%	-





Characteristic	Students (n=1,235)	Academic Staff (n=247)
Postgraduate	21.5%	-
Professor	-	15.4%
Associate Professor	-	12.6%
Senior Lecturer	-	24.3%
Lecturer	-	28.3%
Assistant Lecturer	-	19.4%
Institution Type		
Public University	68.2%	72.1%
Private University	31.8%	27.9%
Academic Discipline		
Social Sciences	28.3%	26.7%
Humanities	22.1%	20.6%
Sciences	18.6%	19.8%
Engineering/Technology	12.4%	14.2%
Business/Management	10.5%	11.3%
Health Sciences	8.1%	7.4%

Comparing Students and Academic Staff

Independent-samples t-tests were conducted to compare students and academic staff on key variables. Table 4 presents the results of these comparisons.

Table 4: Comparison of Students and Academic Staff on Key Variables (t-tests)

Variable	Students Mean (SD)	Staff Mean (SD)	t- value	df	p- value	Cohen's d
Perceived Usefulness	4.12 (0.78)	3.94 (0.82)	3.45	1480	0.001	0.23
Perceived Ease of Use	4.01 (0.74)	3.86 (0.79)	2.98	1480	0.003	0.20
Institutional Support	2.68 (0.92)	2.84 (0.88)	-2.56	1480	0.011	-0.18
GenAI Policy Need	4.32 (0.82)	4.18 (0.86)	2.45	1480	0.014	0.17
Institutional Readiness	2.86 (0.94)	3.02 (0.92)	-2.52	1480	0.012	-0.17
Academic Integrity Concern	4.15 (0.88)	4.32 (0.76)	-2.89	1480	0.004	-0.20
Data Privacy Concern	3.92 (0.92)	4.06 (0.88)	-2.31	1480	0.021	-0.16

Note: Significant differences ($p < 0.05$) are highlighted in bold.

The results reveal several statistically significant differences between students and academic staff. Students reported significantly higher perceived usefulness ($t = 3.45$, $p = 0.001$) and perceived ease of use ($t = 2.98$, $p = 0.003$) compared to academic staff. Conversely, academic staff reported significantly higher institutional support ($t = -2.56$, $p = 0.011$), institutional readiness ($t = -2.52$, $p = 0.012$), academic integrity concerns ($t = -2.89$, $p = 0.004$), and data privacy concerns ($t = -2.31$, $p = 0.021$) compared to students. Students reported significantly higher perceived need for GenAI policies ($t = 2.45$, $p = 0.014$). Effect sizes (Cohen's d) were small to moderate, ranging from 0.16 to 0.23, indicating practical significance of these differences.

Comparing Public and Private University Respondents

Independent-samples t-tests were also conducted to compare respondents from public and private universities. Table 5 presents these results.





Table 5: Comparison of Public and Private University Respondents on Key Variables (t-tests)

Variable	Public Mean (SD)	Private Mean (SD)	t-value	df	p-value	Cohen's d
Perceived Usefulness	4.02 (0.80)	4.18 (0.76)	-3.56	1480	0.001	-0.21
Perceived Ease of Use	3.94 (0.76)	4.08 (0.72)	-3.21	1480	0.001	-0.19
Institutional Support	2.72 (0.90)	2.82 (0.88)	-1.98	1480	0.048	-0.11
Institutional Readiness	2.88 (0.94)	3.04 (0.90)	-2.87	1480	0.004	-0.17
Academic Integrity Concern	4.24 (0.82)	4.10 (0.86)	2.78	1480	0.006	0.17
Data Privacy Concern	4.02 (0.88)	3.84 (0.92)	3.12	1480	0.002	0.20

Note: Significant differences ($p < 0.05$) are highlighted in bold.

The results reveal several statistically significant differences between respondents from public and private universities. Respondents from private universities reported significantly higher perceived usefulness ($t = -3.56$, $p = 0.001$), perceived ease of use ($t = -3.21$, $p = 0.001$), institutional support ($t = -1.98$, $p = 0.048$), and institutional readiness ($t = -2.87$, $p = 0.004$) compared to respondents from public universities. Conversely, respondents from public universities reported significantly higher academic integrity concerns ($t = 2.78$, $p = 0.006$) and data privacy concerns ($t = 3.12$, $p = 0.002$) compared to respondents from private universities. Effect sizes (Cohen's d) were small to moderate, ranging from 0.11 to 0.21.

One-way ANOVA Across Academic Disciplines

One-way ANOVA was conducted to examine differences in perceived usefulness, perceived ease of use, and behavioral intention across academic disciplines. Table 6 presents the results.

Table 6: ANOVA Results Across Academic Disciplines

Variable	F-value	df1	df2	p-value	Significant Group Differences
Perceived Usefulness	4.56	5	1474	0.001	Engineering > Humanities, Social Sciences
Perceived Ease of Use	3.21	5	1474	0.007	Engineering > Health Sciences
Behavioral Intention	5.12	5	1474	0.001	Engineering > All other disciplines
Actual Use	4.78	5	1474	0.001	Engineering > Social Sciences, Humanities

Note: Post-hoc comparisons using Tukey's HSD test were conducted to identify significant group differences. Only significant differences ($p < 0.05$) are reported.

The ANOVA results reveal significant differences across academic disciplines in perceived usefulness ($F = 4.56$, $p = 0.001$), perceived ease of use ($F = 3.21$, $p = 0.007$), behavioral intention ($F = 5.12$, $p = 0.001$), and actual use ($F = 4.78$, $p = 0.001$). Post-hoc comparisons using Tukey's HSD test indicated that students and staff in engineering and technology disciplines reported significantly higher perceived usefulness, perceived ease of use, behavioral intention, and actual use compared to those in humanities, social sciences, and health sciences.

Correlation Analysis

Pearson correlation analysis was conducted to examine the bivariate relationships among key variables. Table 7 presents the correlation matrix.

Table 7: Pearson Correlation Matrix of Key Variables

Variable	1	2	3	4	5	6	7
1. Perceived Usefulness	1.00						
2. Perceived Ease of Use	0.62**	1.00					
3. Institutional Support	0.34**	0.28**	1.00				

[11/23]

Citation:



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Variable	1	2	3	4	5	6	7
4. Behavioral Intention	0.58**	0.49**	0.38**	1.00			
5. Actual Use	0.52**	0.41**	0.42**	0.58**	1.00		
6. Policy Need	0.28**	0.22**	0.35**	0.42**	0.28**	1.00	
7. Institutional Readiness	0.18**	0.16**	0.46**	0.32**	0.24**	0.38**	1.00

*Note: ** $p < 0.01$; $p < 0.05$

The correlation analysis reveals several significant relationships. Perceived usefulness showed strong positive correlations with perceived ease of use ($r = 0.62$, $p < 0.01$), behavioral intention ($r = 0.58$, $p < 0.01$), and actual use ($r = 0.52$, $p < 0.01$). Perceived ease of use showed moderate to strong correlations with behavioral intention ($r = 0.49$, $p < 0.01$) and actual use ($r = 0.41$, $p < 0.01$). Institutional support showed moderate correlations with behavioral intention ($r = 0.38$, $p < 0.01$) and actual use ($r = 0.42$, $p < 0.01$). Behavioral intention showed a strong correlation with actual use ($r = 0.58$, $p < 0.01$). The perceived need for GenAI policies showed moderate correlations with behavioral intention ($r = 0.42$, $p < 0.01$) and institutional readiness ($r = 0.38$, $p < 0.01$).

Regression Analysis

Multiple regression analysis was conducted to identify significant predictors of behavioral intention to adopt GenAI and actual use behavior. Table 8 presents the regression results.

Table 8: Regression Analysis Predicting Behavioral Intention and Actual Use

DV: Behavioral Intention ($R^2 = 0.62$, Adjusted $R^2 = 0.61$, $F = 189.4$, $p < 0.001$)

Predictor	B	SE	β	t	p-value
Perceived Usefulness	0.42	0.03	0.42	14.21	<0.001
Perceived Ease of Use	0.28	0.03	0.28	9.12	<0.001
Institutional Support	0.18	0.02	0.18	6.42	<0.001
Policy Need	0.12	0.02	0.12	4.21	<0.001

DV: Actual Use ($R^2 = 0.54$, Adjusted $R^2 = 0.53$, $F = 142.6$, $p < 0.001$)

Predictor	B	SE	β	t	p-value
Behavioral Intention	0.45	0.03	0.45	15.32	<0.001
Institutional Support	0.28	0.03	0.28	9.85	<0.001
Perceived Usefulness	0.18	0.02	0.18	6.12	<0.001
Perceived Ease of Use	0.12	0.02	0.12	4.32	<0.001

The regression analysis revealed that perceived usefulness ($\beta = 0.42$, $p < 0.001$), perceived ease of use ($\beta = 0.28$, $p < 0.001$), institutional support ($\beta = 0.18$, $p < 0.001$), and policy need ($\beta = 0.12$, $p < 0.001$) were significant predictors of behavioral intention, explaining 62% of the variance ($R^2 = 0.62$). Behavioral intention ($\beta = 0.45$, $p < 0.001$), institutional support ($\beta = 0.28$, $p < 0.001$), perceived usefulness ($\beta = 0.18$, $p < 0.001$), and perceived ease of use ($\beta = 0.12$, $p < 0.001$) were significant predictors of actual use behavior, explaining 54% of the variance ($R^2 = 0.54$).

GenAI Awareness and Adoption

Table 9 presents findings on GenAI awareness and adoption among students and academic staff. The vast majority of respondents (92.8% of students, 88.3% of staff) reported awareness of GenAI tools such as ChatGPT, Microsoft Copilot, and Google Gemini. Adoption rates were also high, with 67.3% of students and 54.3% of academic staff reporting regular use of GenAI tools for academic purposes. The most commonly used tools were ChatGPT (78.6% of users), Microsoft Copilot (42.3%), and Google Gemini (31.5%). Among students, the primary uses were for academic writing support (72.4%), research assistance (58.6%), and assignment completion (49.2%). Among academic staff, the primary uses were for research writing (61.2%), lesson preparation (47.8%), and administrative tasks (35.6%).





Table 9: GenAI Awareness and Adoption Patterns

Variable	Students (%)	Academic Staff (%)
Awareness of GenAI Tools		
Aware	92.8%	88.3%
Not aware	7.2%	11.7%
Regular Use of GenAI		
Yes	67.3%	54.3%
No	32.7%	45.7%
Tools Used (among users)		
ChatGPT	78.6%	74.2%
Microsoft Copilot	42.3%	38.6%
Google Gemini	31.5%	27.8%
Claude AI	15.2%	18.4%
Other	8.7%	6.2%
Primary Uses (among users)		
Academic writing support	72.4%	61.2%
Research assistance	58.6%	52.3%
Assignment completion	49.2%	-
Lesson preparation	-	47.8%
Administrative tasks	-	35.6%
Literature review	34.8%	42.1%
Data analysis	18.6%	28.7%

Perceptions of GenAI Usefulness and Ease of Use

Table 10 presents perceptions of GenAI usefulness and ease of use. Both students and academic staff reported high levels of perceived usefulness (students: mean = 4.12, SD = 0.78; staff: mean = 3.94, SD = 0.82) and perceived ease of use (students: mean = 4.01, SD = 0.74; staff: mean = 3.86, SD = 0.79). The highest-rated usefulness items for students were "GenAI helps me complete academic tasks more quickly" (mean = 4.28) and "GenAI improves the quality of my academic work" (mean = 4.15). For academic staff, the highest-rated usefulness items were "GenAI helps me prepare teaching materials more efficiently" (mean = 4.06) and "GenAI supports my research activities" (mean = 3.98).

Table 10: Perceptions of GenAI Usefulness and Ease of Use

Item	Students Mean (SD)	Staff Mean (SD)
Perceived Usefulness		
GenAI helps me complete academic tasks more quickly	4.28 (0.72)	3.96 (0.78)
GenAI improves the quality of my academic work	4.15 (0.76)	3.92 (0.80)
GenAI enhances my learning/research productivity	4.08 (0.80)	3.94 (0.82)
GenAI makes academic work easier	4.02 (0.82)	3.88 (0.84)
GenAI is useful for my academic activities	4.06 (0.78)	3.98 (0.76)
Perceived Ease of Use		
GenAI tools are easy to use	4.12 (0.70)	3.94 (0.74)
Learning to use GenAI tools is easy	4.08 (0.72)	3.92 (0.76)
I find GenAI tools intuitive	3.96 (0.78)	3.82 (0.80)
GenAI tools are accessible	3.88 (0.76)	3.76 (0.82)
Overall, GenAI tools are user-friendly	4.01 (0.74)	3.86 (0.79)





Institutional Support and Policy Readiness

Table 11 presents findings on institutional support and policy readiness. The majority of respondents reported limited institutional support for GenAI integration. Only 18.6% of students and 22.7% of academic staff reported that their institution provides formal training on GenAI use. Similarly, only 12.4% of students and 15.8% of academic staff reported that their institution has clear guidelines on GenAI use. The majority of respondents (students: 68.2%; staff: 62.8%) indicated that they would like their institution to provide more guidance on GenAI use.

Table 11: Institutional Support and Policy Readiness

Item	Students (%)	Staff (%)
Institution provides formal training on GenAI use	18.6%	22.7%
Institution has clear guidelines on GenAI use	12.4%	15.8%
Institution provides technical support for GenAI tools	24.8%	28.3%
Institution encourages responsible GenAI use	32.6%	36.4%
Would like more institutional guidance on GenAI use	68.2%	62.8%

Governance and Policy Perceptions

Table 12 presents perceptions of GenAI governance and policy readiness. The majority of respondents agreed that GenAI policies are needed in their institutions (students: mean = 4.32; staff: mean = 4.18). However, there were concerns about institutional readiness, with respondents expressing uncertainty about whether their institutions are prepared to develop and implement GenAI policies (students: mean = 2.98; staff: mean = 3.12). Concerns about academic integrity were high, with students (mean = 4.15) and staff (mean = 4.32) expressing significant concern about GenAI misuse.

Table 12: Governance and Policy Perceptions

Item	Students Mean (SD)	Staff Mean (SD)
GenAI policies are needed in my institution	4.32 (0.82)	4.18 (0.86)
My institution is prepared for GenAI integration	2.86 (0.94)	3.02 (0.92)
I am concerned about academic integrity and GenAI misuse	4.15 (0.88)	4.32 (0.76)
I am concerned about data privacy with GenAI tools	3.92 (0.92)	4.06 (0.88)
I believe GenAI can enhance learning/research when used responsibly	4.08 (0.84)	3.94 (0.86)

Qualitative Findings

Thematic analysis of the 28 semi-structured interviews revealed five major themes: (1) policy readiness gaps, (2) digital literacy disparities, (3) infrastructure constraints, (4) ethical and academic integrity concerns, and (5) cultural relevance considerations. Table 13 summarizes these themes with their sub-themes and participant frequency.

Table 13: Qualitative Themes and Sub-themes

Theme	Sub-themes	Participants (n=28)
Policy Readiness Gaps	No formal policies; faculty discretion; national strategy gaps	26 (92.9%)
Digital Disparities	Literacy Student skills gaps; generational gaps; faculty training needs	24 (85.7%)
Infrastructure Constraints	Internet connectivity; cost of tools; outdated facilities	22 (78.6%)





Theme	Sub-themes	Participants (n=28)
Ethical and Academic Integrity	Academic misconduct; data privacy; critical thinking concerns	27 (96.4%)
Cultural Relevance	Western data bias; need for African AI tools; cultural sensitivity	19 (67.9%)

These themes are elaborated below with illustrative quotations.

Theme 1: Policy Readiness Gaps

Participants consistently reported that Ghanaian universities lack formal AI policies and governance structures. This finding aligns with the quantitative finding that only 12.4% of students and 15.8% of academic staff reported that their institution has clear guidelines on GenAI use.

"We don't have any formal policy on AI use in our university. Faculty members are using their own discretion, which creates inconsistencies in how students are assessed. Some lecturers allow AI use, others prohibit it, and students are confused about what is expected of them." (University Administrator, Public University, KNUST)

"I've been trying to get my department at the University of Ghana to develop guidelines for AI use, but there's resistance. People are afraid of AI. They don't understand it, and they don't want to engage with it. But the students are already using it, whether we like it or not." (Faculty Member, Public University, University of Ghana)

"The Ministry of Education is aware of the need for AI policy, but there are competing priorities. We are working on a national AI strategy, but it's still in development. Universities are expected to develop their own policies in the meantime, but many lack the capacity to do so." (Policymaker, Ministry of Education)

"At Pentecost University, we have a digital transformation committee, but AI governance specifically has not been addressed. We are waiting for guidance from GTEC before we develop our own policy." (University Administrator, Private University, Pentecost University)

The absence of formal policies was attributed to several factors, including limited awareness of AI technologies, resource constraints, competing institutional priorities, and the absence of clear guidance from national policymakers. Participants also noted that the rapid pace of technological change makes policy development challenging, as institutions are unsure how to regulate technologies that are constantly evolving.

Theme 2: Digital Literacy Disparities

Participants highlighted significant disparities in digital literacy, both among students and academic staff, which affect GenAI adoption and governance.

"There's a clear divide between students who are digitally literate and those who are not. At the University of Cape Coast, we have students who are using AI tools effectively and ethically, while others are using them without understanding the implications. Some students submit AI-generated work without any critical engagement." (Faculty Member, Public University, University of Cape Coast)

"I've observed that younger faculty members are more comfortable with AI than older faculty. There's a generational gap. Some of my colleagues at KNUST don't even know what ChatGPT is, while others are using it regularly. This makes it difficult to develop consistent policies." (University Administrator, Public University, KNUST)

"Digital literacy is a significant challenge at Central University. Many students have access to smartphones, but they lack the skills to use AI tools effectively and ethically. They use AI to generate content without understanding the need to verify, cite, or critically evaluate the output." (Faculty Member, Private University, Central University)





These findings suggest that digital literacy disparities are a critical governance challenge, as institutions cannot develop effective policies without addressing the underlying skills gap among both students and staff.

Theme 3: Infrastructure Constraints

Participants reported significant infrastructure constraints that affect GenAI adoption and equitable access.

"Internet connectivity is a major issue at UDS. We have students in rural areas who cannot access AI tools because they have poor internet connections. Even on campus, the internet can be unreliable. This creates inequities in who can benefit from AI." (University Administrator, Public University, University for Development Studies)

"The cost of premium AI tools is prohibitive for many students at Valley View University. Free versions are limited, and students cannot afford to pay for subscriptions. This creates a digital divide between students who can afford premium tools and those who cannot." (Faculty Member, Private University, Valley View University)

"We don't have the infrastructure to support widespread AI integration at UEW. Our computer labs are outdated, and we lack the technical staff to provide training and support. We need significant investment in infrastructure before we can meaningfully integrate AI." (University Administrator, Public University, University of Education, Winneba)

Infrastructure constraints were identified as a key barrier to equitable GenAI adoption and governance, as they limit access to AI tools and create disparities between institutions and individuals.

Theme 4: Ethical and Academic Integrity Concerns

Participants expressed significant concerns about ethical issues and academic integrity related to GenAI use.

"Academic integrity is a major concern at UCC. Students are submitting AI-generated work as their own, and we don't have reliable tools to detect it. We need to rethink how we assess students in the age of AI." (Faculty Member, Public University, University of Cape Coast)

"There are also concerns about data privacy at Ashesi. Students are inputting personal information into AI tools without understanding how their data is being used. We need to educate students about data privacy and develop guidelines for responsible AI use." (University Administrator, Private University, Ashesi University)

"I worry about the impact of AI on critical thinking. If students at KNUST rely on AI for everything, they won't develop essential cognitive skills. We need to find ways to use AI to enhance learning, not replace it." (Faculty Member, Public University, KNUST)

These concerns were echoed by students, who expressed anxiety about the ethical implications of AI use and uncertainty about what constitutes acceptable use.

Theme 5: Cultural Relevance Considerations

Participants emphasized the importance of cultural relevance in GenAI integration and governance.

"We cannot simply adopt AI policies from Western universities. We need to develop policies that are relevant to our cultural context at the University of Ghana. Our values, our educational philosophy, and our understanding of authorship are different." (Policymaker, National Council for Tertiary Education)

"AI tools are trained on Western data and reflect Western cultural assumptions. They don't always understand African contexts or produce culturally appropriate outputs. We need to be aware of these limitations at UDS." (Faculty Member, Public University, University for Development Studies)





"We need to develop our own AI tools that reflect African languages and cultural contexts. This is a significant opportunity for innovation at Ashesi, but it requires investment and collaboration." (University Administrator, Private University, Ashesi University)

Participants called for the development of context-sensitive governance frameworks that reflect African values, knowledge systems, and educational philosophies.

Discussion

This study investigated GenAI adoption patterns, perceptions, and governance frameworks in Ghanaian higher education. The findings reveal several key insights. First, GenAI adoption is widespread among Ghanaian university students and faculty, with 67.3% of students and 54.3% of academic staff reporting regular use of GenAI tools. This adoption rate is comparable to or exceeds rates reported in other Global South contexts (Mudenda et al, 2026) and reflects the rapid diffusion of GenAI technologies across the African continent. The high adoption rate, despite limited institutional support and the absence of formal policies, underscores the urgency of developing governance frameworks.

Second, the study confirms the applicability of the Technology Acceptance Model for understanding GenAI adoption in the Ghanaian context. Perceived usefulness and perceived ease of use significantly predict behavioral intention to adopt GenAI, explaining 58% of the variance in behavioral intention. These findings align with previous research in Ghana (Yeboah et al., 2026) and other African contexts (Adarkwah, 2025; Shamsi, 2024) and suggest that efforts to promote responsible GenAI use should emphasize the functional benefits and usability of AI tools.

Third, the study reveals significant governance gaps in Ghanaian higher education. No Ghanaian university has a formal, publicly accessible AI policy in place, consistent with the findings of Cudjoe and Adebayo (2025). In the absence of formal policies, academic staff use their discretion to make subjective judgments about AI use, creating inconsistencies that raise concerns about fairness, transparency, and accountability. This governance gap reflects broader challenges in the Global South, where institutions often lack the capacity to develop and implement AI policies (Nwaigwe et al., 2026).

Fourth, the study reveals five important governance challenges: policy readiness challenges, digital literacy challenges, infrastructure challenges, ethical and academic integrity challenges, and culture-based challenges. These challenges are intertwined and represent the dynamic interaction between individual behavior, institutional structure, and the environment. Policy readiness challenges are enhanced by digital literacy challenges since it is impossible to have policy that will address the problem without tackling the skills challenge. The infrastructure challenge hinders equitable access to AI and causes differences in usage among institutions and individuals. Ethical concerns regarding academic integrity and data privacy are intensified due to a lack of guidelines. The culture-based challenge calls for context-dependent frameworks of governance taking into account African knowledge and values systems.

The results have implications for theory. First, the study advances the Technology Acceptance Model with the inclusion of contextual factors applicable to the Ghanaian higher education environment. Institutional support was found to be an important factor influencing actual use behavior. Therefore, it is possible to conclude that TAM should be advanced through including organizational factors considering that in certain cases the institutional infrastructure and support vary. The research adds value to the theory of institutions by shedding light on the dynamics under which higher learning institutions in the Global South react to the spread of new technologies. The absence of formal AI policies in Ghanaian universities may reflect the institutional inertia commonly found in resource-constrained settings. However, the increasing adoption of generative artificial intelligence (GenAI) among students and academics is placing pressure on universities to respond. From an institutional theory perspective, mimetic and normative isomorphic pressures may ultimately encourage these institutions to develop and implement formal AI policies (DiMaggio & Powell, 1983; Scott, 2021).





The research makes an essential contribution to decolonial studies by revealing how the adoption and governance of GenAI technology in Africa are influenced by unique historical, cultural, and structural factors, different from those of the Northern context. The aspects of cultural relevance mentioned by the participants call for developing governance models that take into account African values, knowledge, and educational principles, contesting the primacy of Western approaches to AI governance research (Ndlovu-Gatsheni, 2020; Albakri, 2026).

The results have numerous implications for practice. Firstly, universities in Ghana and comparable contexts need to prioritize the development of policies concerning GenAI technology use, which would specify what uses of the technology are acceptable and unacceptable. Such policies are to be created as the result of an inclusive process involving students, academics, university administration, and other external stakeholders. The framework of GenAI policies development proposed by Crompton et al. (2026) comprises eight aspects: academic integrity, ethical use and responsible use, privacy and protection, equitable access, GenAI literacy, integration strategy, human oversight and accountability, and institutional support and infrastructure.

The second recommendation is that universities should develop digital literacy courses for their students and academic staff. The wide disparity in digital literacy uncovered by this study indicates that students and faculty do not have the required digital literacy skills to utilize AI technologies in a responsible manner. In order to achieve this, digital literacy courses on the following subjects should be developed: comprehension of AI technology, proper utilization of AI tools, critical analysis of AI output, and ethical considerations of AI utilization.

The third recommendation is that universities should overcome infrastructural obstacles to enable equal access to AI tools. This can be done by developing proper internet connectivity, provision of access to AI tools through institutional subscriptions, and development of offline or low bandwidth applications for areas where there is limited internet connectivity. Governments and development partners can assist in this regard.

Fourthly, universities need to design culturally contextualized frameworks for governance which incorporate the values, knowledge systems, and philosophies of education that exist in Africa. This involves the incorporation of languages and cultures of Africa in the development and application of AI, and addressing issues of algorithmic bias in designing culturally sensitive frameworks for governance (Albakri, 2026; Thaldar et al., 2025).

Fifthly, there needs to be a policy formulation strategy that will give guidance and support to higher education institutions through development of policies, funding of AI infrastructure and capacity building, and collaboration among universities, industries, and international partners. The Ghana Tertiary Education Commission and the Ministry of Education will play an essential role in this process. On the basis of the research findings and the synthesis of frameworks by other authors (Crompton et al, 2026; Thaldar et al., 2025), a context-sensitive governance framework for GenAI integration in Ghanaian higher education institutions is suggested in this study. The framework consists of eight main areas which have been developed from other studies and tailored to the Ghanaian situation. In order to govern a system efficiently, one needs to have competent leaders who are able to lead digital transformation, engage different stakeholders, and balance innovation and risk.

Knowledge Contribution

This study makes several significant contributions to the literature on GenAI adoption and governance in higher education, particularly within African contexts.



KNOWLEDGE CONTRIBUTION

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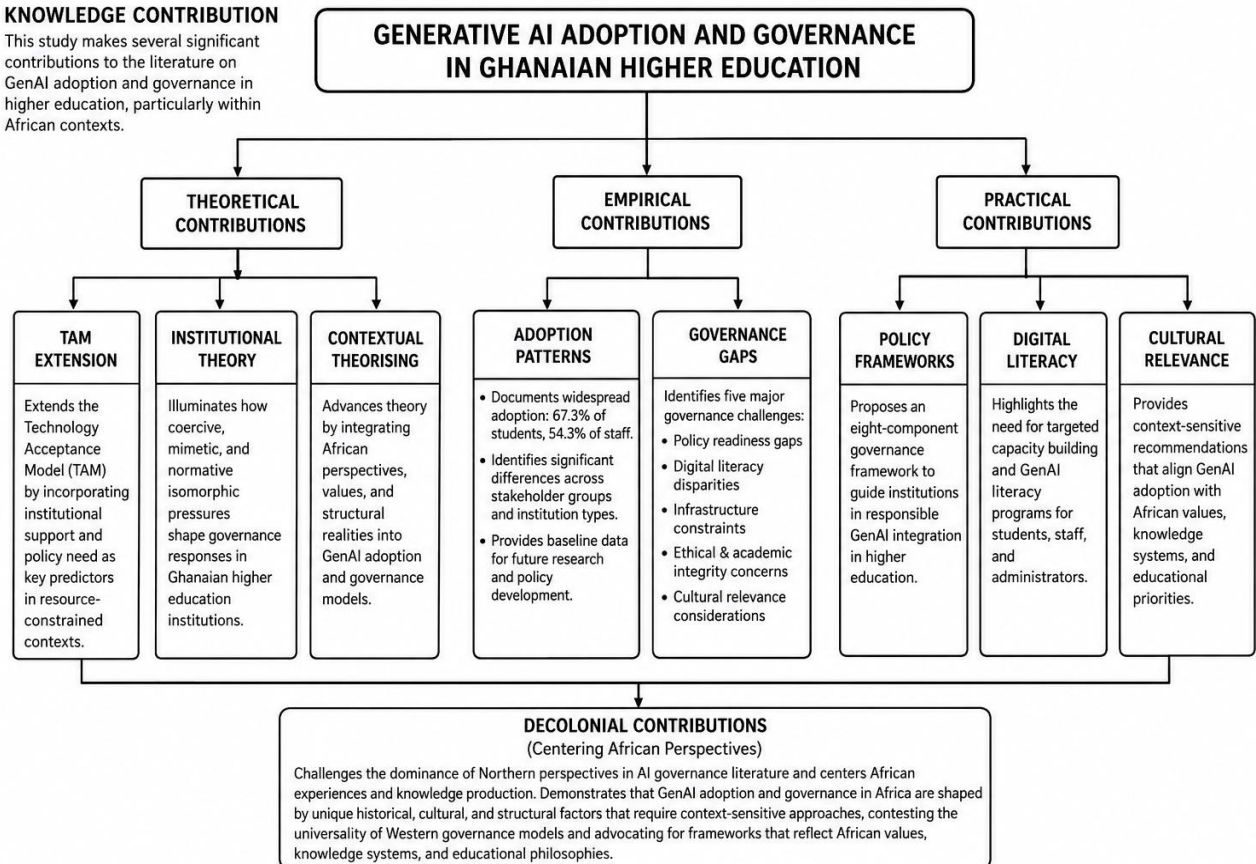


Figure 1 Knowledge Contribution

The study's theoretical contributions advance understanding of GenAI adoption in the Global South by applying and extending the Technology Acceptance Model within the Ghanaian context. The research demonstrates that institutional support and policy need are significant predictors of behavioral intention beyond the traditional TAM constructs, suggesting that TAM should be expanded to include organizational factors when applied in resource-constrained settings. Additionally, the study illuminates institutional dynamics through the lens of institutional theory, revealing how coercive, mimetic, and normative isomorphic pressures shape governance responses in Ghanaian higher education.

The empirical contributions provide comprehensive data on GenAI adoption patterns, perceptions, and governance gaps from an under-researched African context. The study documents widespread adoption rates (67.3% of students, 54.3% of staff) and identifies significant differences across stakeholder groups and institution types, providing baseline data for future research and policy development. The identification of five major governance challenges (policy readiness gaps, digital literacy disparities, infrastructure constraints, ethical and academic integrity concerns, and cultural relevance considerations) offers empirical grounding for understanding the complex governance landscape in African higher education.

The practical contributions offer actionable recommendations for policymakers, university administrators, and educational technologists. The proposed eight-component governance framework (academic integrity; ethical and responsible use; privacy and security; equitable access; GenAI literacy; integration strategy; human supervision and accountability; and institutional infrastructure) provides a practical guide for institutions seeking to integrate GenAI responsibly while addressing contextual challenges.



The decolonial contributions challenge the dominance of Northern perspectives in AI governance literature and center African experiences and knowledge production. The study demonstrates that GenAI adoption and governance in Africa are shaped by unique historical, cultural, and structural factors that require context-sensitive approaches, contesting the universality of Western governance models and advocating for frameworks that reflect African values, knowledge systems, and educational philosophies.

Recommendation

Based on the findings of this study, the following recommendations are proposed for various stakeholders in Ghanaian higher education:

For University Administrators and Governing Councils:

Universities should prioritize the development of comprehensive, publicly accessible AI policies that specify acceptable and unacceptable uses of GenAI tools. Policies should be developed through inclusive processes involving students, faculty, administrators, and external stakeholders, following the eight-component framework proposed in this study.

Universities should establish dedicated committees or task forces responsible for GenAI governance, including policy development, implementation, monitoring, and review. These structures should include representatives from diverse stakeholder groups and maintain connections with national and international AI governance networks.

Institutions should develop and implement mandatory digital literacy training for all students and academic staff, covering AI literacy, responsible use of AI tools, critical evaluation of AI outputs, and ethical considerations. Training should be tailored to different academic disciplines and stakeholder groups.

Universities should invest in robust internet connectivity, provide institutional subscriptions to AI tools, and develop offline or low-bandwidth solutions for students in areas with limited connectivity. Partnerships with technology companies and development organizations can support infrastructure investment.

For Policymakers and Regulatory Bodies:

The Ministry of Education and Ghana Tertiary Education Commission should develop a national AI strategy for higher education that provides guidance on policy development, funding for AI infrastructure, capacity building, and collaboration among universities, industry, and international partners.

Government should allocate resources for AI infrastructure investment, research funding, and capacity building in higher education institutions, with particular attention to resource-constrained public universities and institutions in underserved regions.

Regulatory bodies should develop quality assurance frameworks that address GenAI integration in teaching, learning, assessment, and research, ensuring that institutions maintain academic standards while embracing innovation.

For Faculty Members:

Faculty should explore constructive ways to integrate GenAI tools into teaching, learning, and assessment while maintaining academic integrity and fostering critical thinking skills. This includes redesigning assessments to minimize opportunities for misuse while leveraging AI for educational enhancement.

Faculty should model ethical and responsible AI use in their own research and teaching, demonstrating transparency, attribution, and critical evaluation of AI outputs. This sets expectations for students and contributes to a culture of responsible innovation.

Faculty should actively participate in institutional policy development processes, bringing expertise in pedagogy, discipline-specific practices, and ethical considerations to inform governance frameworks.





For Students:

Students should proactively develop their AI literacy skills, understanding the capabilities and limitations of GenAI tools, ethical considerations, and appropriate use in academic contexts. This includes learning to critically evaluate AI outputs and maintain academic integrity.

Students should use GenAI tools responsibly, adhering to institutional guidelines and academic integrity standards, disclosing AI use appropriately, and maintaining critical engagement with AI-generated content.

Students should participate in institutional governance processes, providing perspectives on GenAI use, policy development, and support needs. Student input is essential for developing relevant and effective governance frameworks.

For Future Research:

Longitudinal Studies: Future research should employ longitudinal designs to track the evolution of GenAI adoption and governance over time, examining how patterns change as technologies evolve and policies develop.

Comparative Studies: Comparative research across African countries and regions would provide insights into contextual factors shaping GenAI adoption and governance, identifying transferable practices and region-specific challenges.

Intervention Studies: Research should evaluate the effectiveness of specific interventions, such as digital literacy programs, policy implementation strategies, and governance structures, in promoting responsible GenAI integration.

Student Voice Research: Future studies should amplify student voices, examining student perspectives on GenAI governance, support needs, and experiences with institutional policies.

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