

From Innovation Signaling to Governance Readiness: Generative AI Governance in Two Rwandan Universities

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ABSTRACT

Background: Generative artificial intelligence is now part of the ordinary ecology of higher education, but institutional governance has not matured at the same speed as tool adoption. **Purpose:** This article examines how generative AI integration, policy visibility, readiness, opportunities, and risks are publicly documented at the African Leadership University (ALU) and the Adventist University of Central Africa (AUCA) in Rwanda. **Method:** The study uses an interpretivist comparative multiple-case design based on public document analysis. The core corpus comprises publicly retrievable institutional webpages, policy documents, academic regulations, handbooks, e-learning materials, research manuals, national policy texts, and sectoral guidance retrieved and checked through April 2026. Analysis used a directed qualitative codebook aligned with institutional readiness, Diffusion of Innovations, and a rights-based AI governance lens. **Findings:** Both universities publicly signal AI engagement, but in different forms. ALU is more innovation-signaling, with visible AI research, student bootcamp activity, and outward-facing policy discourse. AUCA is more governance-dense, with stronger public visibility of academic regulations, ICT and online-learning policies, plagiarism infrastructure, and AI-and-big-data institutional positioning. Yet neither university publicly presents, within the reviewed corpus, a fully specified institution-level generative AI acceptable-use architecture aligned with Rwanda's emerging sectoral expectations. **Contribution:** The article sharpens a distinction between visible innovation activity and visible governance readiness, showing why AI adoption cannot be inferred from promotional visibility alone. It also offers a replicable public-document method for studying institutional AI governance in underdocumented African higher education contexts while clearly separating documented evidence, analytic inference, and public silence.

Keywords: generative AI; higher education; Rwanda; academic integrity; AI governance; institutional readiness; document analysis; comparative case study

Article history:

Received: April 24, 2026

Accepted: May 03, 2026

Published: May 04, 2026

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Citation:

Dusengumuremyi F., Chukwudi H.J., Ndahimana S., Ndahayo C. & Sangwa S. (2026). From Innovation Signaling to Governance Readiness: Generative AI Governance in Two Rwandan Universities. Open Journal of AI, Ethics & Society, Vol. 2(2). Open Christian Press.

DOI:

[10.65655/OpenChristianPr
ess.2026.108](https://doi.org/10.65655/OpenChristianPress.2026.108)

1. Introduction

1.1 Background and context

Generative artificial intelligence has altered the practical conditions under which universities teach, assess, supervise research, and interpret authorship. Large language models and related tools now support drafting, summarization, coding, translation, feedback, ideation, and data interpretation. Their educational significance therefore cannot be reduced to convenience or productivity. Generative AI changes the evidentiary relationship between submitted work and student learning, because externally generated fluency can obscure the process by which understanding is formed and demonstrated (Dwivedi et al., 2023; Kasneci et al., 2023; Lodge et al., 2023).

The governance challenge is especially acute in higher education systems where policy ambition, digital infrastructure, staff capacity, and classroom practice develop at different speeds. UNESCO's guidance on generative AI in education and research stresses human agency, privacy, equity, validation, and policy capacity as prerequisites for responsible adoption (Miao & Holmes, 2023). OECD's digital education work similarly frames digital transformation as an ecosystem issue, not merely a technology acquisition issue (OECD, 2023). These concerns are directly relevant to Rwanda, where national policy explicitly treats AI as an instrument of inclusive development and where the Higher Education Council (HEC) has issued guidance for virtual learning and AI use in higher learning institutions (Higher Education Council [HEC], 2025; Ministry of ICT and Innovation [MINICT], 2023).

1.2 Problem statement and contribution

The central problem addressed in this article is not whether generative AI will enter Rwandan universities. It already has. The more important question is whether visible institutional activity is accompanied by visible governance readiness: clear permission structures, assessment redesign principles, disclosure expectations, staff and student capacity-building mechanisms, privacy safeguards, and academic-integrity rules adequate to machine-assisted intellectual work. Recent studies show that universities often move from reactive prohibition toward managed integration, but many policy ecosystems remain fragmented, audience-specific, or overly focused on cheating rather than assessment validity and

responsible learning (An et al., 2025; Jin et al., 2025; Luo, 2024; Moorhouse et al., 2023).

This article contributes to the field in three precise ways. First, it provides an exploratory Rwanda-based comparison of publicly documented generative AI governance at two universities operating under the same national policy environment. Second, it conceptualizes the difference between innovation signaling and governance readiness, arguing that publicly visible AI activity does not necessarily equal institutionally mature governance. Third, it demonstrates how public-document analysis can map visible governance architecture in underdocumented contexts while avoiding stronger claims about internal practice that would require interviews, surveys, syllabi, or classroom observation.

1.3 Research objectives and questions

The study has three objectives: to map publicly documented generative AI platforms, activities, and institutional references at ALU and AUCA; to compare visible policy architecture, academic-integrity framing, infrastructure signals, and capacity-building provisions; and to identify opportunities, risks, ambiguities, and evidence gaps that should inform later primary-data research.

The research questions are: RQ1. What generative AI platforms, activities, or institutional references are publicly documented by ALU and AUCA? RQ2. How do the two universities compare in policy architecture, academic-integrity framing, infrastructure signals, and capacity-building provisions? RQ3. What opportunities, risks, and governance gaps emerge from the documentary record, and what remains unknowable without later fieldwork?

1.4 Scope and delimitations

The study is delimited to publicly retrievable documents and webpages available between 2021 and April 2026, with greatest analytic attention to the post-ChatGPT period from 2022 onward. It does not measure actual student use, faculty attitudes, institutional enforcement, or classroom implementation fidelity. The analysis therefore speaks to visible public governance and institutional self-presentation. It does not claim to describe the full internal reality of either university. This distinction is essential because public silence is not institutional absence; it is evidence only of what students, staff,

external stakeholders, and reviewers can publicly locate in the reviewed corpus (Bowen, 2009; Johnston, 2014).

2. Literature and Theoretical Framework

2.1 Conceptualizing generative AI in higher education

Generative AI in higher education is best understood as a socio-technical and institutional phenomenon. It redistributes cognitive labor by allowing users to delegate parts of drafting, summarizing, translating, coding, feedback generation, and exploratory reasoning to machine systems. This redistribution produces educational opportunities, but it also unsettles authorship, accountability, assessment validity, privacy, bias, and evidence of learning (Bond et al., 2024; Dwivedi et al., 2023; Jensen et al., 2025; Kasneci et al., 2023).

The deeper pedagogical question is not simply whether AI-generated text is “original.” It is whether assessment tasks still support valid inferences about student competence when machine assistance may shape the submitted output. Luo (2024) argues that a policy response focused only on originality can miss the more fundamental issue of assessment redesign. Bittle and El-Gayar (2025) likewise show that academic integrity in the generative AI era requires a broader research agenda involving disclosure, prevention, detection limits, pedagogy, and institutional policy.

2.2 Global scholarship on governance, adoption, and risk

The global literature now contains a substantial body of policy scans, institutional guideline analyses, and conceptual frameworks. Chan (2023) proposes a comprehensive university AI policy framework spanning pedagogical, governance, and operational dimensions. Moorhouse et al. (2023) document early and uneven institutional responses to generative AI tools in assessment. An et al. (2025) show that guidance in leading U.S. universities is often distributed across teaching, learning, research, and administrative audiences rather than consolidated in one policy text. Jin et al. (2025), using a global comparative policy sample, demonstrate that institutional adoption is increasingly proactive but still uneven in scope, communication, and role allocation.

Together, these studies show that the emerging policy frontier concerns institutional alignment. Universities need more than generic integrity statements. They need coherent systems that clarify permitted and prohibited uses, protect confidential data, uphold student fairness, support faculty judgment, and redesign assessment to preserve meaningful learning evidence. This literature provides a strong comparative backdrop, but it remains dominated by institutions in North America, Europe, Australia, and East Asia. The African and Global South evidence base remains much thinner.

Table 1. Representative Recent Scholarship on Generative AI Governance in Higher Education and Its Relevance to the Present Study

Study	Context and method	Main contribution	Relevance to this article
Chan (2023)	Hong Kong higher education; mixed-method policy framework development	Identifies pedagogical, governance, and operational AI-policy dimensions.	Supports a multidimensional rather than plagiarism-only policy lens.
Moorhouse et al. (2023)	Global top-ranked universities; guideline/document analysis	Shows rapid and uneven early responses to generative AI and assessment.	Benchmarks the problem of fragmented institutional guidance.
An et al. (2025)	Top 50 U.S. universities; mixed guideline analysis	Shows differentiated guidance across teaching, learning, research, and administration.	Helps interpret distributed governance architecture.
Jin et al. (2025)	Forty universities across six regions; comparative policy analysis	Uses Diffusion of Innovations to interpret global institutional adoption strategies.	Anchors the diffusion lens used in this comparison.

Luo (2024)	Twenty world-leading universities; critical policy review	Argues that policies over-focus on originality and under-address assessment redesign.	Sharpens the article's assessment-validity critique.
Sebihi et al. (2025)	University of Rwanda; survey-informed analysis	Identifies Rwandan readiness potential alongside regulatory, infrastructure, and ethical concerns.	Establishes the immediate Rwandan higher education relevance.
Belkina et al. (2025)	International case studies; systematic review	Finds a shift from commentary toward implementation-focused evidence.	Justifies a first-stage institutional document study in an underdocumented context.

2.3 Generative AI in African and Global South higher education

African higher education research on generative AI remains emergent. Rwandan evidence from the University of Rwanda identifies optimism about AI's educational potential alongside concerns about infrastructure, regulation, training, and ethics (Sebihi et al., 2025). Comparative work involving Rwanda, Lesotho, and Nigeria similarly shows that smart-technology provision, educator preparation, and institutional planning remain significant barriers to fuller AI adoption (Theodorio et al., 2024). Sangwa and Mutabazi (2025) further argue that academic-integrity policy in online and distance learning in the Global South must move from detection-centered thinking toward assessment redesign and policy clarity.

The University of KwaZulu-Natal's 2025 AI academic guidelines are useful because they show that explicit institutional guidance is possible within African higher education, even if such guidance is not yet common across the continent. The lesson is not that African universities should copy any single external model. Rather, institution-level policy must translate global principles into local academic cultures, infrastructure conditions, assessment practices, and student-support systems.

2.4 Rwanda's policy and higher education context

Rwanda is an analytically important setting because national policy ambition is explicit. The National AI Policy positions AI as a driver of inclusive and sustainable socioeconomic transformation and emphasizes skills, infrastructure, responsible innovation, data strategy, ethical principles, and research capacity (MINICT, 2023). For universities, this national policy environment creates an expectation

that AI will be incorporated not only into economic development strategies but also into education, research, and capacity formation.

The sectoral benchmark became more concrete with the HEC guidelines for virtual learning and AI in higher learning institutions. The HEC document calls for responsible AI integration in teaching, learning, assessment, research, and academic governance. It also includes quality-assurance standards covering infrastructure, materials development, staff readiness, student readiness, assessment, policies, and management. Its appendices include international examples of traffic-light permission systems and an AI-use declaration form. This gives Rwandan universities a clearer basis for moving from broad AI ambition to institution-specific rules and evidence of implementation (HEC, 2025).

2.5 Integrated theoretical framework and operationalization

This study uses an integrated framework built around institutional readiness, Diffusion of Innovations, and a rights-based governance lens. Institutional readiness is the primary construct. It is interpreted through the visible presence or absence of policy clarity, leadership attention, digital infrastructure, staff and student support, academic-integrity mechanisms, and ethical safeguards. Diffusion of Innovations helps interpret how institutional practices become observable, compatible with existing systems, triable, and communicable (Rogers, 2003). A rights-based governance lens foregrounds human agency, privacy, fairness, transparency, accountability, and the protection of learners in AI-mediated educational environments (Miao & Holmes, 2023; UNESCO, 2022, 2024, 2025).

The Technology Acceptance Model is not used as a primary framework because perceived usefulness and

perceived ease of use require user-perception data, which this document-based study does not collect (Davis, 1989). TAM is retained only as a limited sensitizing concept for interpreting why adoption

pressure may intensify when tools are perceived as useful and easy to access. Claims about actual acceptance among staff or students are therefore deliberately excluded.

Table 2. Framework-to-Code Alignment Used in the Directed Document Analysis

Analytical construct	Observable document indicators	Coding domain	Boundary condition
Institutional readiness	Policy texts, academic regulations, LMS visibility, ICT policies, staff/student support language, infrastructure signals, capacity-building programs.	Governance clarity; digital-governance density; capacity-building signals.	Visible documentation is not treated as proof of implementation fidelity.
Diffusion of Innovations	Public communication of AI initiatives, partnerships, bootcamps, research forums, institutional positioning, program visibility.	Public AI visibility; observability; compatibility signals.	Promotional material is coded as signaling, not as binding governance.
Rights-based AI governance	References to privacy, data protection, accountability, academic integrity, transparency, disclosure, learner fairness, human oversight.	Ethical safeguards; assessment validity; responsible-use architecture.	Absence of public evidence is reported as non-visibility, not institutional non-existence.
TAM as limited sensitizing concept	No direct user-perception indicators were available in the corpus.	Excluded from primary coding.	No claims are made about perceived usefulness, ease of use, or behavioral intention.

2.6 Conceptual gap

The existing scholarship is now rich in policy commentary, institutional scans, and perception studies, but it still lacks sufficient African comparative case studies that combine institution-level documents, national AI policy context, and readiness theory in a disciplined way. The present study addresses that gap by comparing two Rwandan universities under one national policy environment while calibrating every claim to what the documentary record can reasonably support.

3. Methodology

3.1 Research paradigm and design

The study adopts an interpretivist qualitative paradigm and a comparative multiple-case study design based on document analysis and secondary analysis. An interpretivist stance is appropriate because the study is not estimating prevalence, predicting behavior, or testing causal effects. It interprets how institutions publicly signify AI, formalize governance, and render academic expectations visible through official or institutionally hosted documents. Following Bowen (2009), documents are treated as evidence of formal institutional position, public communication, and governance architecture rather than as weak substitutes for interviews.

3.2 Case selection

ALU and AUCA were selected because they are both universities in Rwanda but differ in mission identity, institutional history, public digital ecosystems, and visible AI-related activity. This makes them suitable for an exploratory paired comparison under a shared national policy environment. The case selection is not intended to represent all Rwandan universities. It is intended to illuminate how different public-facing institutional profiles can coexist under the same macro-policy context.

3.3 Corpus construction and retrieval protocol

The core documentary corpus consisted of 18 institutional and national/sectoral sources: seven ALU sources, nine AUCA sources, and two national or sectoral policy anchors. Public documents were retrieved, checked, and logged through April 2026. For each source, the corpus log recorded the institution or issuing body, document type, URL or public access point, publication year where available, retrieval date, and primary analytic use. PDFs and webpages were treated differently: policy PDFs were interpreted as relatively stable documentary records, while dynamic webpages were treated as dated public signals that may

change over time. The study therefore avoids treating website indicators as permanent institutional facts.

3.4 Inclusion, exclusion, and source appraisal

Documents were included when they were publicly retrievable and institutionally issued, hosted, or clearly connected to teaching, learning, assessment, digital infrastructure, academic integrity, AI, research governance, or national higher education policy. Duplicates, purely ceremonial pages, and promotional pages without analytic substance were excluded. Public-facing communications were retained only when they documented identifiable AI activity, program activity, governance language, or institutional priorities. Each document was appraised for source authority, relevance, retrievability, document stability, and proximity to the research questions.

3.5 Coding procedure and analytic workflow

Analysis proceeded in five stages. First, documents were appraised and entered into a corpus log. Second, relevant passages were extracted into a case-comparison matrix. Third, directed qualitative

content analysis was conducted using six predefined domains: public AI visibility, public academic-integrity specificity, public digital-governance density, AI-specific acceptable-use specificity, capacity-building signals, and national-policy alignment visibility. Fourth, evidence was weighted by distinguishing documented evidence, analytic inference, and absence of public evidence. Fifth, cross-case synthesis was conducted at the level of coded documentary patterns rather than assumed institutional practice (Hsieh & Shannon, 2005).

The primary coding was conducted by the lead authorial team using a shared matrix. Coding consistency was checked through repeated comparison of extracted evidence against domain definitions, discussion of ambiguous cases, and revision of domain notes where a source could plausibly support more than one interpretation. Disagreements or interpretive uncertainties were resolved by returning to the source category and coding rule: binding policy language, documented program activity, general promotional language, and public silence were not treated as equivalent evidence.

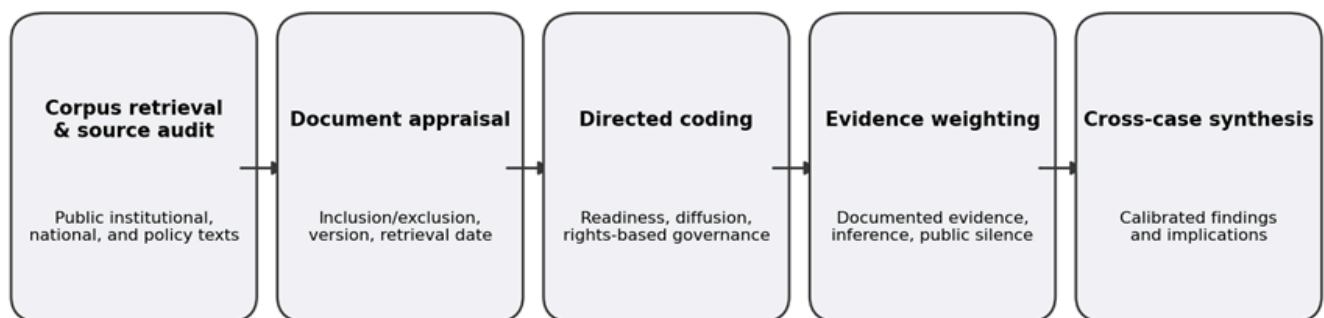


Figure 1. Documentary Analysis Workflow and Audit Trail. The workflow summarizes the study's source-to-claim sequence. It was revised to make the evidentiary chain more transparent and replicable.

3.6 Trustworthiness, positionality, ethics, and design limits

Trustworthiness was strengthened through triangulation across institutional, national, sectoral, and peer-reviewed sources; use of a pre-specified codebook; a corpus log; cross-case comparison; and explicit separation of documented evidence from analytic inference. The analysis also uses cautious language where the evidence concerns public visibility rather than institutional reality. This is crucial because public absence cannot prove internal absence.

The study involved no human participants and relied exclusively on public documents, so formal human-subject ethics approval was not required.

However, the authors recognize an important positionality issue: some members of the author team are institutionally affiliated with the universities being analyzed. This proximity can enrich contextual interpretation, but it can also introduce bias. Safeguards included applying the same coding domains to both cases, privileging publicly retrievable evidence over insider knowledge, avoiding claims unsupported by the public corpus, maintaining an audit trail, and framing comparative judgments as evidence-weighted observations rather than institutional rankings.

4. Findings and Discussion

4.1 Overview of the documentary corpus

The corpus revealed different public documentation ecologies. ALU's retrievable corpus was smaller and more outward-facing, with strong visibility around AI research, AI-related learning opportunities, digital library provision, and public ethics discourse. AUCA's corpus was larger and more rule-heavy, including

academic regulations, a student handbook, ICT policy, online teaching and learning policy, research manual, Moodle-based e-learning infrastructure, and research-center materials. This difference is analytically important because the public document ecology is part of how governance becomes legible to students, staff, reviewers, and external stakeholders.

Table 3. Core Documentary Corpus Used in the Cross-Case Analysis

Corpus cluster	Institution/ source	Document type	Primary analytical use	Evidence status
Policies page and institutional ethics documents	ALU	Institutional webpage	Public governance visibility and general ethics architecture	Documented public evidence
AI in Africa research project and AI in Practice Forum pages	ALU	Research and policy webpages	AI ambition, responsible AI discourse, sectoral framing	Documented public evidence
Synapse Africa AI Bootcamp page	ALU	Student-program webpage	AI capacity-building and student exposure signal	Documented public evidence
Knowledge management/library pages and academic-integrity event page	ALU	Library support webpages	Digital support and integrity programming	Documented public evidence
Software engineering programme page	ALU	Programme webpage	Technological identity and ethical digital-transformation signal	Documented public evidence
Academic regulations, student handbook, and ICT policy	AUCA	Formal policy PDFs	Governance, conduct, academic integrity, and digital-use architecture	Documented public evidence
Online teaching and learning policy and Moodle/e-learning platform	AUCA	Policy PDF and LMS/platform pages	Digital-learning infrastructure, LMS links, plagiarism infrastructure, readiness signals	Documented public evidence and dynamic platform evidence
Research manual and research center pages	AUCA	Research/governance webpages and PDF	Research culture, publication expectations, AI and big-data positioning	Documented public evidence
Homepage AI outreach materials and related public communications	AUCA	Institutional and public-facing webpages	AI training outreach and institutional innovation signal	Documented public evidence
National AI Policy and HEC AI/virtual learning guidelines	Rwanda	Official national/sectoral policy documents	Macro-policy benchmark, sector expectations, acceptable-use and declaration models	Benchmark evidence

4.2 Documented generative AI platforms, uses, and institutional references

ALU's public-facing AI footprint is substantial but primarily developmental and outward-facing rather than regulatory. The AI in Africa Research Project presents ALU as leading research intended to inform policymakers, businesses, and civil society on responsible AI development and deployment in Sub-Saharan Africa, with education among its focal sectors (African Leadership University [ALU], n.d.-b).

The AI in Practice Forum further positions ALU as a convening institution for responsible AI discourse. The Synapse Africa AI Bootcamp page documents a student-facing AI learning experience offered in partnership with Colorado State University and the Global Livingston Institute, with hands-on workshops, intercultural collaboration, and expert-led sessions (ALU, n.d.-c). These documents show that AI is publicly normalized at ALU as a research, learning, and regional policy topic.

AUCA's public-facing AI footprint is also visible, but it appears more institution-internalized. The AUCA Research Center identifies AI and big data as part of its strategic research and innovation profile, including applications and training linked to healthcare, education, agriculture, and digital solutions (Adventist University of Central Africa [AUCA], n.d.-d). AUCA's homepage and public communications also refer to AI and big-data training outreach, connecting the university to Rwanda's broader digital-skills agenda and the One Million Rwandan Coders initiative (AUCA, n.d.-a; One Million Rwandan Coders, n.d.). AUCA's e-learning environment exposes operational digital infrastructure through LMS access, policy links, plagiarism-related resources, and postgraduate analytics-related pathways (AUCA, n.d.-b; AUCA, n.d.-e).

The cross-case difference is therefore not visibility versus invisibility. Both universities are publicly engaged. The difference lies in the form of visibility: ALU is more externally networked and policy-discursive, while AUCA is more internally procedural and platform-linked. This distinction supports the article's main argument: AI visibility alone cannot be equated with AI governance readiness.

4.3 Publicly visible policy architecture at ALU and AUCA

ALU's public policy architecture visibly includes general institutional policies such as ethics, safeguarding, conflict-of-interest, anti-bribery and anti-fraud, and whistleblowing documents (ALU, n.d.-a). These are meaningful governance signals, but the reviewed corpus did not reveal publicly accessible, institution-specific classroom guidance on generative AI use, disclosure, course-level permissions, assessment boundaries, or citation of machine assistance. ALU's library and programme pages show academic support and technological identity, but public guidance on generative AI acceptable use was not retrievable in the corpus. This should be interpreted as public under-visibility, not proof that no internal guidance exists.

AUCA's public policy architecture is denser. Its academic regulations formalize teaching, learning, assessment, and student responsibilities (AUCA, 2023). Its student handbook defines academic dishonesty and plagiarism, including misuse of electronic sources, and specifies sanctions (AUCA,

2021b). Its ICT policy addresses software, cybersecurity, service support, capacity building, and university-wide ICT governance (AUCA, n.d.-c). Its online teaching and learning policy and Moodle environment show stronger public visibility of learning management and platform-based academic support (AUCA, 2021a; AUCA, n.d.-b).

Yet AUCA's stronger rule density does not equal full generative AI policy maturity. The public rules are mostly legacy academic-integrity and digital-governance texts. They provide a stronger governance base than was publicly visible for ALU, but they do not yet publicly specify how generative AI should be used, disclosed, limited, cited, or differentiated across assessment types. Against the HEC 2025 benchmark, both universities remain publicly incomplete in AI-specific acceptable-use architecture.

4.4 Publicly visible readiness signals

ALU's readiness signals are strongest in intellectual orientation, partnership activity, and digital identity. The library describes itself as primarily digital for Rwanda students and reports access to a large body of journals and information resources (ALU, n.d.-d). ALU's software engineering communication emphasizes ethical digital transformation, while its AI research and bootcamp activity make AI visible as an institutional and student-facing priority (ALU, n.d.-b, n.d.-c, n.d.-f). These are significant readiness signals, especially for innovation capacity and observability.

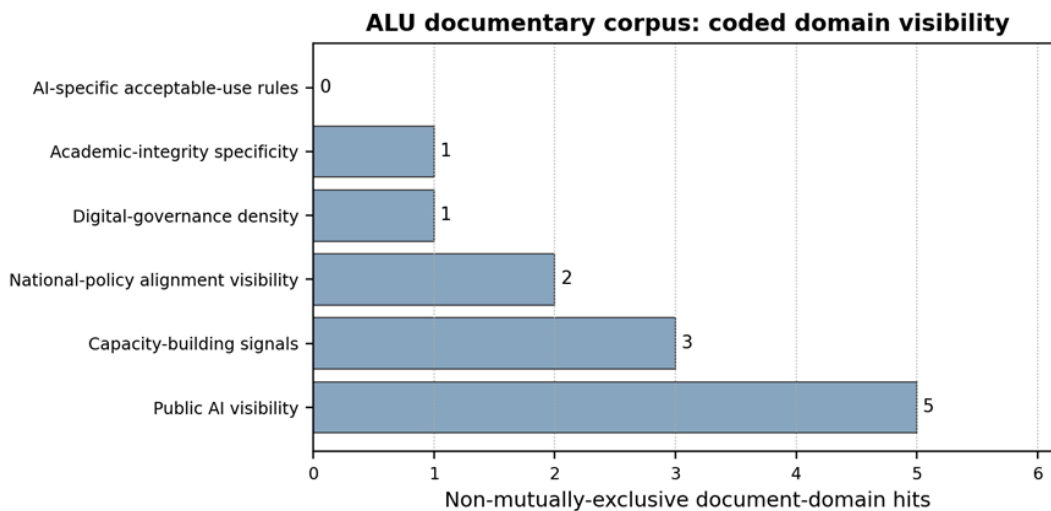
AUCA's readiness signals are more procedural and operational. The ICT policy, online teaching and learning policy, e-learning platform, Turnitin/plagiarism-related infrastructure, research manual, research center, and big-data positioning suggest a more formalized digital and academic governance environment (AUCA, 2021a, 2021b, 2022, 2023, n.d.-b, n.d.-c, n.d.-d). These materials point to institutional structures that could host a generative AI governance framework with less foundational work than would be required in a thinner policy environment. Where LMS and analytics-related pathways are publicly visible, they should be governed as part of a broader learning-support ecosystem rather than treated as neutral infrastructure (Ifenthaler & Yau, 2020).

Figures 2 and 3 summarize coded document-domain hits for each institution. These counts are non-mutually

exclusive and should not be read as performance metrics. A single document could contribute to more

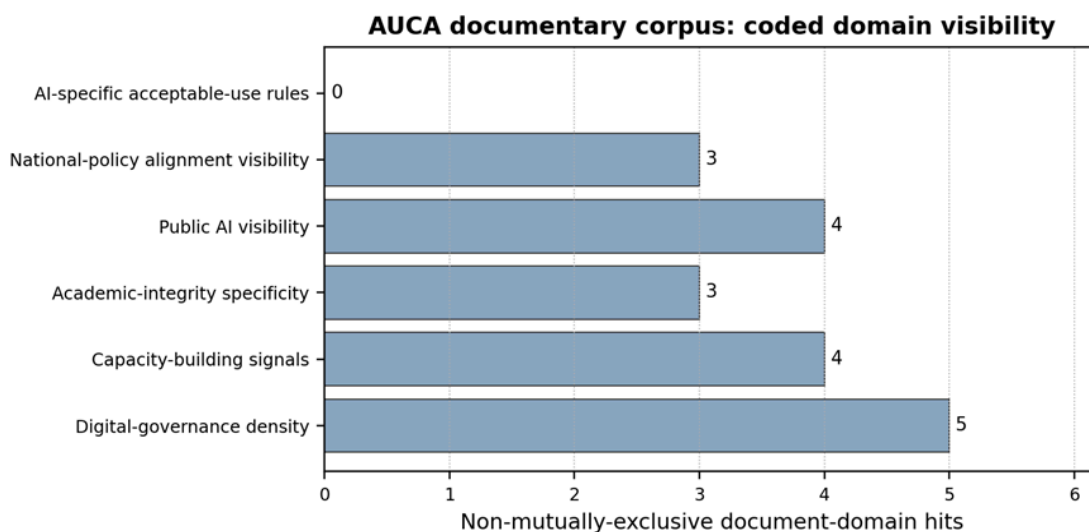
than one domain. The charts are intended to make the evidentiary basis of the comparison visible rather than to rank the institutions numerically.

Figure 2. Distribution of Coding-Domain Hits in the ALU Documentary Corpus



The chart indicates strong public AI signaling and capacity-building visibility, but weaker public rule specificity in the reviewed corpus.

Figure 3. Distribution of Coding-Domain Hits in the AUCA Documentary Corpus



The chart indicates denser public governance and digital-readiness documentation, while also showing that AI-specific acceptable-use rules were not publicly retrievable in the reviewed corpus.

4.5 Cross-case comparison of visible governance readiness

The most important comparative finding is that ALU and AUCA occupy different positions within the same unresolved transition from AI visibility to AI governance readiness. ALU appears more

innovation-forward and outward-facing. AUCA appears more governance-dense and operationally structured. Both profiles contain strengths. Both also contain the same missing endpoint: a publicly visible, institution-specific, generative AI acceptable-use architecture that specifies permission levels, disclosure rules, privacy safeguards, staff responsibilities, assessment implications, and student support.

Table 4. Evidence-Weighted Cross-Case Comparison of Publicly Visible Generative AI Governance Readiness

Analytical domain	ALU: documented evidence and inference	AUCA: documented evidence and inference	Comparative interpretation and confidence
Public AI visibility	AI in Africa project, AI forum, Synapse AI Bootcamp, software-engineering digital identity, library support activity. Inference: high innovation signaling.	AI and Big Data research-center identity, AI outreach, LMS/analytics visibility, innovation-center language. Inference: high institution-internalized AI visibility.	Both visibly engaged. Confidence: high.
Public academic-integrity specificity	Limited publicly retrievable academic-integrity rules in the reviewed corpus, though library support signals exist. Inference: public specificity is thin.	The student handbook defines academic dishonesty and plagiarism, and Moodle links to plagiarism-related resources. Inference: stronger visible integrity architecture.	AUCA is stronger in public integrity architecture. Confidence: high for visibility, moderate for implementation.
Public digital-governance density	Digital library and technology-oriented programme communication are visible, but binding academic digital-governance rules were limited in the reviewed public corpus.	ICT policy, online-learning policy, LMS, academic regulations, and research manual create denser public governance architecture.	AUCA has denser publicly visible digital governance. Confidence: high.
AI-specific acceptable-use rules	No publicly retrievable institution-specific generative AI acceptable-use matrix, disclosure template, or assessment permission model found in the reviewed corpus.	No publicly retrievable institution-specific generative AI acceptable-use matrix, disclosure template, or assessment permission model found in the reviewed corpus.	Shared public governance gap. Confidence: moderate to high; limited by dynamic webpages and possible internal documents.
Capacity-building signals	AI Bootcamp, AI research/forum activity, digital library resources, and academic-support programming.	AI outreach, research center, Moodle/e-learning ecosystem, postgraduate analytics identity, and ICT capacity language.	Both show capacity signals, differently distributed. Confidence: high for visibility.
National-policy alignment visibility	Alignment is largely implicit through responsible AI discourse and innovation orientation.	Alignment appears more institutionally internalized through policies and systems but remains incomplete on AI-specific rules.	Neither publicly demonstrates full alignment with HEC 2025 AI-use expectations. Confidence: moderate.
Overall public-facing readiness profile	Innovation-forward and governance-thin in public documentation.	Governance-denser but still AI-rule incomplete in public documentation.	Different strengths, same AI-specific endpoint gap. Confidence: high at the level of public visibility.

4.6 Governance gaps and areas of ambiguity

Three governance gaps stand out. First, neither university publicly presents an institution-specific generative AI acceptable-use matrix comparable to the HEC's sectoral expectations. The HEC guidance identifies traffic-light permission logics and includes an AI-use declaration form covering students, lecturers, researchers, assignments, teaching materials, research papers, theses, and scholarly outputs (HEC, 2025). No comparably explicit public institutional framework was found for either case.

Second, both universities face the transition from generic academic-integrity language to AI-era integrity language. AUCA has a stronger publicly visible base because it defines plagiarism and academic dishonesty, including electronic sources. However, neither institution's public corpus clarified how AI assistance should be disclosed, what levels of machine contribution are permitted, whether prompts must be retained, how AI-generated citations should be verified, or how rules differ across formative, summative, supervised, and open-book assessments. This is now the crucial frontier because generative AI

challenges the authorship and evidentiary assumptions on which assessment judgments often depend.

Third, systematic faculty and student AI literacy pathways are not yet sufficiently visible. Both institutions show capacity-building signals, but public documentation does not establish a university-wide program for staff development, discipline-specific assessment redesign, student AI literacy, data-protection training, or AI-use support embedded across curricula. This matters because Rwanda's national and sectoral policies link responsible AI adoption to institutional capacity, not only innovation aspiration (HEC, 2025; MINICT, 2023).

4.7 Opportunities for teaching, learning, and institutional innovation

The documentary record also reveals important opportunities. ALU's outward-facing AI research, partnership network, and student-oriented AI exposure could support rapid development of a mission-aligned AI literacy framework for African leadership education. Its existing responsible AI discourse could be translated into course-level guidance, disclosure language, and assessment redesign principles. AUCA's denser academic and digital governance ecosystem could support faster institutionalization of AI guidance through existing academic regulations, ICT policy mechanisms, Moodle, plagiarism infrastructure, research supervision, and faculty development.

For both institutions, generative AI can be framed as more than a threat to integrity. Properly governed, it can support writing development, formative feedback, translation support, coding practice, research discovery, simulation, accessibility, and individualized learning. The condition is that AI use must remain pedagogically bounded, transparent, critically supervised, and aligned with the purpose of assessment and formation. Where students use generative AI without verification, disclosure, or meaningful cognitive engagement, the tool becomes an instrument of substitution rather than learning. Where it is used to scaffold inquiry, critique, revision, and metacognition, it can strengthen learning rather than replace it (Kim et al., 2025; Miao & Holmes, 2023).

4.8 Ethical analysis: human agency, fairness, privacy, truthfulness, and formation

The ethical issue at stake is not merely regulatory compliance. It concerns the kind of intellectual

formation universities are responsible to protect. A responsible governance framework should be organized around at least seven normative principles: transparency, accountability, fairness, privacy, human agency, academic formation, and institutional responsibility. Transparency requires students and staff to know when AI is permitted, prohibited, or required to be disclosed. Accountability requires humans to remain responsible for claims, sources, data, and interpretations. Fairness requires comparable expectations across students, courses, campuses, and assessment types. Privacy requires protection of student data, institutional records, confidential research materials, and third-party intellectual property. Human agency requires that AI assistance does not replace the learner's own judgment. Academic formation requires that fluency does not masquerade as understanding. Institutional responsibility requires universities to align policy, training, technology, and assessment rather than leaving staff and students to improvise.

These principles also resonate with the public-good purposes of higher education. Universities do not only certify outputs; they cultivate judgment, truthfulness, discipline, discernment, and service. This is especially important for faith-informed institutions, where academic excellence and moral formation should not be separated. A modest faith-informed ethical reflection therefore strengthens rather than distracts from the analysis: AI governance should protect human dignity, intellectual honesty, wisdom, and responsibility. Such language must remain connected to the evidence. In this study, the evidence shows that public governance specificity has not yet caught up with public AI visibility. The ethical implication is that ambiguity itself becomes a risk because it can normalize inconsistent practice, unequal enforcement, and unexamined dependence on machine-generated fluency.

4.9 Cross-case discussion through the theoretical framework

Through an institutional-readiness lens, AUCA appears more publicly structured, while ALU appears more publicly catalytic. AUCA's public documents show more formal governance density, especially in academic regulation, ICT policy, online learning, research procedures, and LMS infrastructure. ALU's public materials show stronger observability of AI ambition, external partnership, regional discourse, and

student exposure. Readiness is therefore not one-dimensional. It includes both capacity for innovation and capacity for governance.

Through Diffusion of Innovations, ALU's public AI work increases observability and communicates institutional openness to experimentation. AUCA's documentation suggests greater compatibility work within existing systems and norms. Yet diffusion without governance can produce unmanaged adoption, while governance without innovation can produce policy formalism. Mature institutional AI governance requires alignment between visible experimentation, visible rule architecture, and visible support systems.

Through a rights-based governance lens, the decisive weakness is not lack of AI interest but under-specification of responsibility. Students have a right to fair, intelligible assessment expectations. Faculty have a right to clear institutional backing when redesigning assignments and enforcing disclosure. Institutions have a responsibility to protect privacy, data security, and scholarly reliability. These rights and responsibilities require more precise policy articulation than either institution currently makes publicly visible.

4.10 Implications for Rwandan higher education and comparable African contexts

The most immediate implication is that Rwanda's higher education sector now needs institution-level translation of national AI ambition into enforceable, pedagogically specific, and publicly accessible campus rules. The HEC has already provided a sector benchmark. Universities now need local frameworks that specify acceptable and unacceptable uses, traffic-light permission categories, disclosure forms, privacy safeguards, faculty-development obligations, student AI-literacy pathways, and procedures for monitoring and periodic revision.

For comparable African contexts, the broader implication is that universities do not need perfect infrastructure before they govern AI responsibly. They do need coherence. Governance credibility grows when mission, policy, learning design, digital infrastructure, academic integrity, faculty support, and student formation are aligned. Public-document analysis can help identify where that alignment is visible, where it is ambiguous, and where further primary research is needed.

5. Conclusion and Recommendations

5.1 Summary of core findings

This study compared publicly documented generative AI integration and governance readiness at ALU and AUCA. It found that both universities visibly engage AI, but in different ways. ALU's public presence is marked by AI research ambition, student exposure, regional policy discourse, and digital identity. AUCA's public presence is marked by denser academic and digital governance documents, e-learning infrastructure, academic-integrity language, and AI-and-big-data institutional positioning. Yet neither case publicly presents a fully articulated institution-specific generative AI acceptable-use architecture at the level implied by Rwanda's HEC 2025 guidance. The study therefore supports a calibrated conclusion: visible AI activity is advancing faster than visible AI rule specificity.

5.2 Theoretical and methodological contributions

The theoretical contribution is the distinction between innovation signaling and governance readiness. This distinction helps avoid a common category error: treating public AI visibility as evidence of policy maturity. The methodological contribution is a replicable public-document approach for studying visible institutional governance in fast-moving policy domains. By distinguishing documented evidence, analytic inference, and absence of public evidence, the study offers a fairer way to compare institutions whose internal practices may be richer than their public documentation reveals.

5.3 Policy and institutional recommendations

Both universities should publish institution-specific generative AI frameworks that move beyond generic ethics and legacy plagiarism language. These frameworks should define generative AI, classify uses by assessment context, and specify prohibited, limited, and permitted uses using a clear red-amber-green or equivalent model. They should require transparent AI-use declarations for coursework, instructional materials, research outputs, theses, and publications where machine assistance materially shaped the work. They should also require human verification of AI-assisted claims, references, calculations, code, data analysis, and translations.

Both institutions should formalize faculty development around assessment redesign, discipline-specific AI pedagogy, feedback design, verification practices, and privacy protection. Student AI literacy should include prompt literacy, source verification, bias recognition, data-protection awareness, epistemic humility, and truthful disclosure. Institutional policy should be accompanied by templates, syllabus language, examples of permitted and prohibited use, and a periodic review process tied to national guidance and emerging evidence.

5.4 Limitations

The study's main limitation is its reliance on public documents. Public documents can reveal formal positions and public governance architecture, but they cannot show how staff and students actually interpret, implement, resist, or work around institutional expectations. Public websites are also dynamic, and some internal policies may not be publicly available. The study therefore analyzes visible governance, not total governance. Its claims are exploratory, comparative, and evidence-calibrated rather than generalizable to all Rwandan or African higher education institutions.

5.5 Directions for future primary research

A follow-up primary study should investigate stakeholder awareness of AI-related rules, actual patterns of generative AI use, differences across disciplines and assessment types, faculty confidence in managing AI-assisted work, student perceptions of fairness and disclosure, and the relationship between public policy architecture and lived practice. A mixed-method design combining surveys, interviews, syllabus analysis, LMS policy review, and assignment-level assessment analysis would be especially valuable.

5.6 Concluding reflection

Universities are not merely deciding whether to allow or ban a tool. They are deciding what kind of intellectual formation they intend to defend in an age of machine-generated fluency. Rwanda's policy environment already recognizes that AI governance must be responsible, inclusive, and capacity-building. The challenge now is institutional translation. ALU and AUCA each possess real strengths. The central conclusion is not that one university has succeeded and

the other failed. It is that both currently stand at different points in the same transition from AI visibility to institutionally articulated AI governance.

Declarations

Ethics approval: *This study involved no human participants, interviews, surveys, private institutional records, or personally identifiable research data. It relied exclusively on publicly retrievable documents and webpages. Formal human-subject ethics approval and participant consent were therefore not applicable.*

Positionality and competing interests: *Some members of the author team are institutionally affiliated with the universities analyzed in this study. The authors disclose this institutional proximity because it may shape contextual understanding and interpretive sensitivity. To reduce bias, the analysis relied only on publicly retrievable evidence, applied the same codebook to both cases, separated documented evidence from analytic inference, and avoided comparative claims not supported by the reviewed corpus. No financial competing interests are declared.*

Funding: *No external funding was received for this study.*

Data availability: *The data analyzed in this study consist of publicly accessible institutional webpages, policy documents, national policy texts, sectoral guidance, and peer-reviewed literature. A corpus log with source categories, retrieval dates, and analytic uses is provided in Appendix A. Because websites are dynamic, the findings should be read as a dated analysis of public visibility through April 2026.*

Author contributions: *All authors contributed to conceptualization, documentary review, analysis, interpretation, writing, and critical revision. The corresponding author coordinated manuscript preparation and submission. All authors approved the submitted version.*

AI-tool use disclosure: *Generative AI tools were used only to support language editing, structural refinement, formatting preparation, and non-substantive editorial checking. The authors retained responsibility for source verification, analysis, interpretation, citations, and all final claims.*

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Appendix A. Corpus Log and Retrieval Record

The table below summarizes the public corpus used for the revised analysis. Retrieval dates are provided for dynamic webpages and publicly accessible policy sources. The table is intended to improve replicability and to make clear that the study analyzes public visibility rather than private institutional practice.

Table A1. Public Corpus Log

No.	Source	Institution/body	Type	Publication or status	Retrieval/check date	Primary use
1	ALU policies	ALU	Institutional webpage	n.d.	April 29, 2026	General governance visibility
2	About the AI in Africa research project	ALU	Research webpage	n.d.	April 29, 2026	Responsible AI discourse and sector focus
3	AI in Practice Forum	ALU	Forum/project webpage	2025/2026 page	April 29, 2026	AI convening and regional policy visibility
4	Synapse Africa AI Bootcamp/global learning experiences	ALU	Student-program webpage	2025 offering visible	April 29, 2026	AI capacity-building signal
5	Knowledge management/library home	ALU	Library webpage	n.d.	April 29, 2026	Digital support and library infrastructure
6	Knowledge management upcoming events	ALU	Library events webpage	n.d.	April 29, 2026	Academic-integrity support signal
7	BSc. (Hons) software engineering	ALU	Programme webpage	n.d.	April 29, 2026	Technology identity and ethical digital transformation
8	Online teaching and learning policy	AUCA	Policy PDF	2021	April 29, 2026	Online-learning governance
9	Student handbook 2018-2021	AUCA	Handbook PDF	2021 public upload	April 29, 2026	Academic integrity and conduct rules
10	AUCA research manual revised June 2022	AUCA	Research manual PDF	2022	April 29, 2026	Research governance and documentation norms
11	AUCA academic rules and regulations	AUCA	Policy PDF	2023	April 29, 2026	Academic regulation and assessment architecture
12	AUCA ICT policy	AUCA	Policy PDF	n.d. public policy PDF	April 29, 2026	ICT governance and digital readiness
13	AUCA e-learning	AUCA	LMS/platform page	Dynamic page	April 29, 2026	LMS and plagiarism-related infrastructure
14	E-learning platform page	AUCA	Institutional webpage	n.d.	April 29, 2026	Digital-learning visibility
15	Research center	AUCA	Research webpage	Dynamic page	April 29, 2026	AI and big-data positioning
16	AUCA homepage/outreach materials	AUCA	Institutional webpage	Dynamic page	April 29, 2026	AI outreach and institutional communication
17	The National AI Policy for the Republic of Rwanda	MINICT	National policy	2023	April 29, 2026	National AI policy benchmark
18	Guidelines and assessment tools for virtual learning and AI in Rwanda's higher learning institutions	HEC	Sectoral guidance	2025	April 29, 2026	Higher education AI governance benchmark

Appendix B. Codebook and Evidence Matrix

The codebook below was used to ensure that the same interpretive criteria were applied to both cases. The categories are descriptive and interpretive. They are not ordinal ratings, institutional rankings, or measures of actual practice.

Table B1. Directed Coding Codebook

Code	Definition	Examples of qualifying evidence	Non-qualifying evidence
Public AI visibility	Publicly retrievable evidence that the institution communicates AI activity, AI research, AI training, or AI-related institutional positioning.	AI research projects, AI bootcamps, AI outreach, research-center AI and big-data language.	Generic technology language without identifiable AI connection.
Public academic-integrity specificity	Publicly visible rules or guidance about plagiarism, dishonesty, authorship, originality, sanctions, or integrity support.	Handbook plagiarism rules, academic-dishonesty sanctions, plagiarism-checking resources, integrity workshops.	General values language without academic-integrity content.
Public digital-governance density	Publicly visible governance texts or systems covering LMS, online learning, ICT, cybersecurity, software, digital support, or platform operations.	ICT policy, online teaching and learning policy, LMS links, e-learning platform descriptions.	Standalone marketing claims about being innovative.
AI-specific acceptable-use specificity	Publicly visible institution-specific rules on permitted, limited, or prohibited generative AI use, disclosure, prompt retention, citation, privacy, and assessment variation.	Traffic-light AI permission model, AI-use declaration form, course-level acceptable-use guidance.	General statements that AI is important or useful.
Capacity-building signals	Publicly visible programs, resources, training, workshops, support structures, or curricula that build AI, digital, research, or integrity capabilities.	AI bootcamps, outreach programs, library training, LMS support, research-center training.	Unspecified claims of excellence without program detail.
National-policy alignment visibility	Public evidence that institutional documentation aligns with or could operationalize Rwanda's AI policy and HEC higher education AI guidance.	References to responsible AI, AI literacy, research capacity, AI-use guidance, data protection, virtual-learning standards.	General innovation language without visible governance translation.

Table B2. Condensed Evidence Matrix by Case

Domain	ALU public evidence	AUCA public evidence	Claim calibration
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AI visibility	AI in Africa research project, AI in Practice Forum, Synapse AI Bootcamp, software engineering digital identity.	AI & Big Data research-center identity, Innovation Center, AI outreach, LMS and analytics-related program visibility.	Documented high visibility in both cases.
Integrity specificity	Integrity support visible mainly through library/event-level material; binding public academic-integrity rules not prominent in corpus.	Student handbook, regulations, LMS/plagiarism resources, and research manual provide stronger visible architecture.	AUCA stronger publicly; ALU under-visible publicly.
Digital governance	Digital library and technology communication visible; formal public academic digital-governance rules limited in corpus.	ICT policy, online-learning policy, Moodle, academic regulations, and research manual visible.	AUCA governance denser publicly.
AI acceptable use	No institution-specific public generative AI use matrix or declaration form found.	No institution-specific public generative AI use matrix or declaration form found.	Shared public gap, not proof of internal absence.
Capacity building	Bootcamp, AI research/forum ecosystem, library support, digital resources.	Outreach, research center, LMS, ICT capacity language, analytics-related pathways.	Both present capacity signals with different emphases.
Policy alignment	Implicit alignment through responsible AI discourse and innovation activity.	Stronger procedural base but AI-specific translation still incomplete.	Neither visibly demonstrates full alignment with HEC 2025.