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Artificial Intelligence, Academic Workload and Institutional Readiness in African Higher Education: A Rapid Need Assessment

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Abstract

This study examined artificial intelligence use, academic workload, and institutional readiness among higher education stakeholders in selected African contexts. It was guided by the rapid emergence of generative artificial intelligence in universities and the need to assess whether institutional policy, training, and governance structures are keeping pace with its adoption. A descriptive rapid needs assessment design was employed. Data were collected using a structured online questionnaire covering respondent characteristics, academic workload, AI use, training needs, preferred AI support functions, ethical concerns, governance priorities, pedagogy, and local relevance. Data were analysed descriptively. Findings indicate that respondents experience substantial workload pressures across research writing, lecture preparation, postgraduate supervision, examination duties, reporting, grading, feedback, and accreditation-related responsibilities. While 80.0% of respondents reported current use of AI tools, fewer than one-quarter (23.3%) had received formal training in AI or digital tools. Nevertheless, nearly all respondents (96.7%) expressed interest in generative AI training. The most preferred AI support functions included research assistance, academic content drafting, grading and assessment support, personalised learning, and curriculum planning. Key concerns identified were academic integrity, data privacy, accuracy, reliability, insufficient training, and *potential job displacement. The study concludes that AI adoption in African higher education should be guided by robust institutional policies, structured staff training, human oversight, data protection mechanisms, contextual relevance, and strong ethical safeguards.*

Keywords: Academic Workload, African Higher Education, Artificial Intelligence (AI), Institutional Readiness, Responsible AI, Generative AI (Gen AI)

Introduction

Artificial intelligence (AI) is no longer a distant technological prospect for higher education. It is increasingly embedded in the daily practices of teaching, learning, research writing, assessment, administration, and institutional management. In particular, generative artificial intelligence (GenAI) tools now support users in drafting text, summarising documents, generating learning resources, analysing data, producing feedback, and assisting decision-making processes. In higher education, these capabilities present new opportunities for academic productivity, personalised learning, and instructional support. At the same time, they raise critical questions regarding academic integrity, equity, data privacy, authorship, institutional accountability, and the evolving nature of academic work (Adamakis & Rachiotis, 2025; Akpareva *et al*., 2026; Bacalso *et al*., 2026).

In African higher education contexts, the debate on AI adoption is particularly urgent. Universities across the continent operate under conditions of expanding student enrolments, limited staffing, infrastructure constraints, digital inequality, and increasing demands for quality assurance, research output, and administrative efficiency. These structural pressures significantly shape how AI tools are introduced, interpreted, and utilised. They also determine whether AI functions as a meaningful support system for academic work or becomes another unevenly distributed technological layer within already strained institutional environments. Recent studies indicate that while African higher education institutions are engaging with AI through policy discussions, pedagogical innovation, student use, and institutional experimentation, levels of readiness remain uneven across contexts (Maina & Kuria, 2024; Maluleke, 2025; Cudjoe & Adebayo, 2025; Thaldar *et al.*, 2025).

The emerging literature further suggests that AI adoption in higher education extends beyond technological access and must be understood as a socio-institutional and governance issue. Factors such as AI literacy, digital competence, leadership preparedness, training opportunities, infrastructural capacity, and institutional support systems significantly shape how AI is adopted and used (Asghar *et al*., 2025; Kabanda, 2026; Ul Haq *et al.*, 2026). In many settings, AI adoption appears to be progressing faster than formal institutional policy development, resulting in a situation where individuals independently experiment with AI tools while institutions gradually develop governance frameworks, ethical safeguards, and capacity-building strategies. In this regard, Cudjoe and Adebayo (2025) highlight the importance of assessing the existence and adequacy of AI policies in Sub-Saharan African higher education institutions, while Thaldar *et al*. (2025) emphasise the need for context-sensitive AI governance frameworks.

Another important dimension of the AI adoption discourse is academic workload. Higher education staff are expected to manage a wide range of responsibilities, including teaching, assessment, supervision, research, publication, committee participation, student support, curriculum development, reporting, and accreditation-related documentation. AI tools are frequently positioned as potential solutions to reduce this workload burden; however, the relationship between AI and academic labour requires careful empirical investigation. Acosta-Enriquez *et al*. (2025) suggest that academic overload may influence the adoption of AI systems, particularly in contexts characterised by high performance demands and work-related stress. Similarly, Adamakis and Rachiotis (2025) note that AI can enhance academic productivity through support for grading, content generation, feedback provision, and administrative optimisation, although these benefits are contingent upon AI literacy, ethical awareness, and institutional integration.

Within African contexts, responsible and locally relevant AI adoption is particularly critical. Existing studies highlight the influence of infrastructural constraints, digital divides, language diversity, institutional capacity, and cultural relevance on AI implementation (Kahenya, 2026; Msomi & Behara, 2026; Zlotnikova & Hlomani, 2025). The potential benefits of AI are therefore closely intertwined with structural realities such as connectivity, electricity supply, language of instruction, staffing capacity, assessment traditions, and resource limitations. For instance, Kondoro (2025), in examining AI writing assistants in Tanzanian universities, identifies both opportunities and challenges associated with AI-supported academic writing. Similarly, Asghar *et al*. (2025) demonstrate that AI literacy among academics in Ghanaian and Nigerian universities encompasses cognitive, behavioural, affective, and ethical dimensions, underscoring that AI adoption is not merely technical but also pedagogical and institutional in nature.

Ethical concerns further complicate AI integration in higher education. Issues of academic integrity, plagiarism, authorship, intellectual ownership, bias, accountability, transparency, and data protection have become central to current debates. Maduka *et al*. (2025) explore authorship and ethical challenges associated with AI-generated research in Nigerian academia, while Zlotnikova and Hlomani (2025) frame generative AI as both a potential crisis and opportunity for African universities. Akpareva *et al*. (2026) similarly argue for a balanced approach that recognises AI's capacity to reduce workload while addressing risks related to privacy, surveillance, accountability, and academic integrity.

Despite the expanding body of literature, a key gap remains. Much existing research focuses on general AI adoption trends, student usage patterns, policy analyses, or conceptual and ethical debates. Less attention has been given to how higher education stakeholders in African contexts empirically connect AI adoption to academic workload, institutional readiness, training needs, governance expectations, and local relevance. This study addresses this gap by conducting a needs assessment among higher education stakeholders in selected African contexts. It explores the workload pressures they experience, their level of AI use and readiness, the AI support functions they consider most valuable, and the ethical and institutional conditions they believe should guide AI adoption.

The study was guided by the following research questions: a) What academic and administrative workload pressures are reported by higher education stakeholders in the selected African contexts? b) What is the level of AI readiness, current AI use, and training exposure among respondents? c) What AI support functions do respondents consider most useful for academic and institutional work? d) What concerns and governance priorities shape academics views on AI adoption in higher education? e) How important are pedagogy, local relevance, and African contextual realities in the adoption of AI tools?

Materials and Methods

Research Design

The study employed a quantitative research design, specifically a descriptive rapid needs assessment. This design was considered appropriate as the study aimed to identify workload patterns, AI readiness, training needs, preferred AI support functions, ethical concerns, and governance priorities among higher education stakeholders.

Study Context and Participants

This study was conducted among higher education stakeholders within African contexts. Respondents were drawn from Nigeria, Cameroon, Burkina Faso, Uganda, Zambia, and Zimbabwe. The sample comprised a broad range of academic and administrative stakeholders, including faculty members, registrars and academic officers, heads of departments, deans, lecturers, postgraduate students, researchers, consultants, ICT and quality assurance personnel, as well as senior institutional administrators. This diversity of participants enabled the study to capture a wide spectrum of academic and administrative perspectives on artificial intelligence adoption, institutional readiness, and academic workload within higher education settings.

Instrument

Data were collected using a structured online questionnaire. The instrument captured respondents’ demographic and professional characteristics, including country, institutional role, and years of experience. It further assessed academic workload and identified repetitive or demanding tasks, alongside measures of AI confidence, current AI use, and prior training exposure. Additional sections explored respondents' interest in generative AI training, preferred AI support functions, ethical concerns, governance priorities, pedagogical considerations, assessment practices, and perceptions of local relevance.

Sampling and Data Collection Procedure

This study employed a rapid needs assessment design to obtain timely insights into the current state of artificial intelligence (AI) readiness, pedagogical practices, governance, and capacity needs across higher education institutions in selected African countries. Given the exploratory nature of the study and its objective of informing institutional capacity development rather than producing nationally representative estimates, a pragmatic sampling approach was adopted. Participants were recruited from diverse stakeholder groups.

The questionnaire was administered online to facilitate broad geographical participation and timely data collection. A total of 62 respondents completed the survey. Participants were informed that their participation was voluntary, their responses would remain anonymous, and the information collected would be used solely for research purposes.

The sample size is considered appropriate for a rapid, exploratory needs assessment intended to identify emerging priorities, perceived challenges, and capacity gaps across diverse institutional contexts. The inclusion of respondents occupying different roles within higher education institutions and representing multiple African countries enhances the breadth of perspectives captured and provides valuable evidence to inform subsequent, more comprehensive investigations and institutional interventions.

Data Analysis

Data were analysed using Python, specifically the pandas library for data cleaning, tabulation, descriptive statistics, frequencies, percentages, and mean workload estimates. Matplotlib was used for data visualisation, while openpyxl was used to export the analysed tables into an Excel workbook. For workload-related items, categorical responses were converted into approximate midpoint values in order to compute estimated mean weekly hours. This approach allowed for standardisation of ordinal workload categories into continuous estimates suitable for descriptive analysis. For multiple-response items, analysis involved the computation of frequencies and percentages based on the number of respondents selecting each option, rather than the total sample size, to accurately reflect item-specific response distributions. Open-ended responses were systematically coded and grouped into pre-defined and emergent response categories. These categories were then quantified through frequency counts to identify the most commonly reported issues. Examples of categories included workload reduction needs, research support, teaching support, administrative support, ethical concerns regarding AI use, and training needs. All findings were presented using tables and figures to enhance clarity, facilitate comparison across variables, and minimise repetition in the presentation of results.

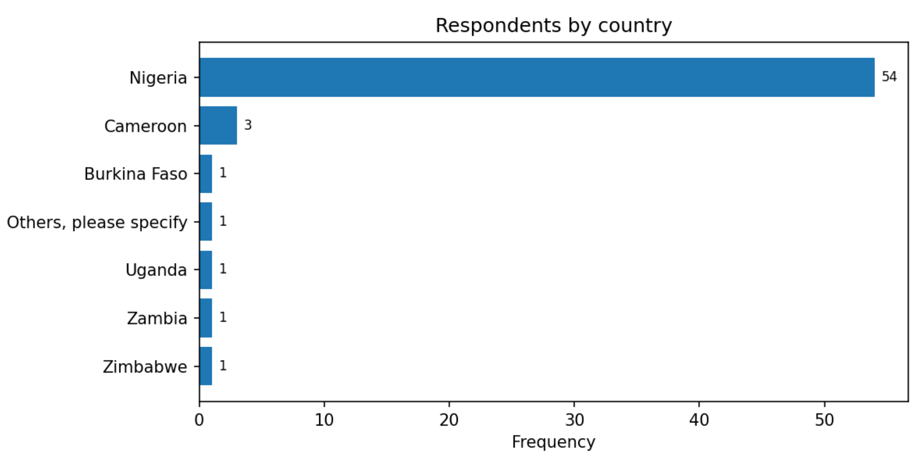
Ethical Considerations

The study utilised anonymised survey data. Participation was entirely voluntary, and respondents were informed that their responses would be used solely for research purposes. No personally identifiable information was collected or reported in the analysis. To further protect confidentiality, all results were presented in aggregated form. Particular attention was given to country-level reporting, where small numbers of respondents in some categories necessitated careful aggregation to minimise the risk of indirect identification.

Results

Respondent Characteristics

The respondents were drawn from Nigeria (87.1%), Cameroon (4.8%), Burkina Faso, Uganda, Zambia and Zimbabwe (1.6% each). In terms of institutional roles, faculty staff constituted the largest group (54.8%), followed by registrars or academic officers (17.7%) and heads of department or deans (12.9%). The remaining respondents were distributed across other institutional roles, including postgraduate students, researchers, consultants, and quality assurance or ICT personnel. Regarding professional experience, a substantial proportion of respondents reported mid- to high-level experience within higher education. Those with 6–10 years of experience formed the largest group (41.9%), followed by those with 11–20 years of experience (25.8%). Overall, the sample largely reflects individuals with considerable experience in higher education systems and institutional practice.



Academic Workload and Repetitive Tasks

The workload analysis indicates that respondents were engaged in a broad range of academic and administrative responsibilities, including teaching, research, assessment, administration, reporting, student support, and quality assurance activities. Among these, research and academic writing accounted for the highest mean weekly workload at 4.38 hours. This was followed by the preparation of lectures and teaching materials (mean = 3.57 hours). Graduate and postgraduate supervision accounted for 3.12 hours, while examination preparation and invigilation accounted for 3.10 hours. Institutional and departmental reporting also reflected substantial time demands, with a mean of 3.08 hours per week.

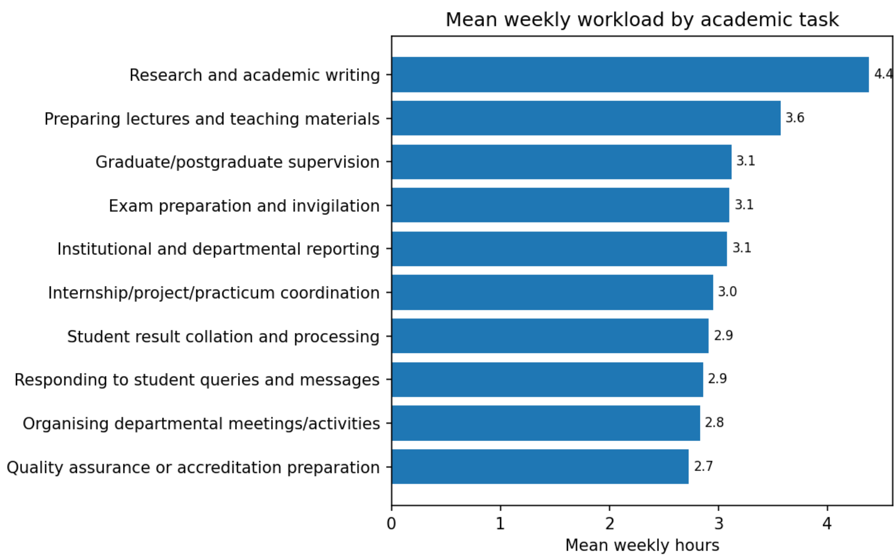


Figure 2: Mean Weekly Workload by Academic Task

Respondents were further asked to identify tasks they perceived as repetitive, time-consuming, or particularly draining. Grading and providing feedback emerged as the most frequently reported task, selected by 37 respondents (61.7%), representing nearly two-thirds of the sample. This was followed closely by drafting lecture materials, reported by 35 respondents (58.3%), and manual computation of results, reported by 34 respondents (56.7%). Other commonly cited tasks included research documentation (26 respondents; 43.3%) and preparation of accreditation documents (22 respondents; 36.7%).

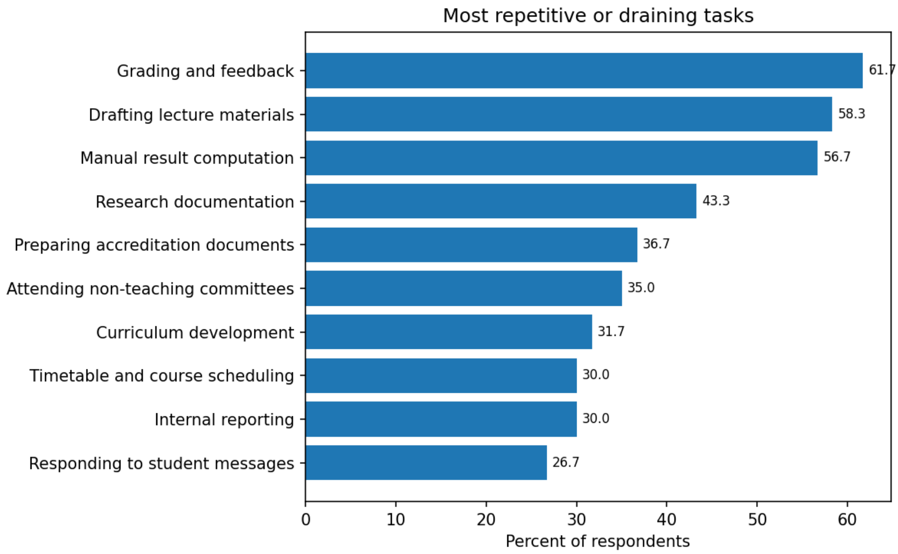


Figure 3: Most Repetitive Academic Tasks

Overall, the findings suggest that academic workload pressures extend beyond classroom teaching and research activities. Rather, they are distributed across a wide ecosystem of responsibilities, including assessment, documentation, reporting, accreditation processes, student support, and broader institutional administrative duties. This pattern highlights the cumulative nature of academic workload and its implications for staff time allocation and productivity.

AI Readiness, Current Use and Training Needs

Respondents reported moderate but uneven levels of confidence in using AI tools. The mean AI confidence score was 2.92 on a five-point scale. In terms of distribution, 40.3% reported being moderately confident. This was followed by 27.4% who indicated slight confidence, while 6.5% reported no confidence at all. A further 19.4% described themselves as confident, and 6.5% reported being very confident. Overall, these findings suggest a concentration around mid-level confidence, with relatively fewer respondents at the extremes of high or no confidence.

Furthermore, 80.0% indicated that they currently use AI tools in their academic or professional activities. However, formal training in AI or related digital tools remains limited, with only 23.3% reporting prior exposure to structured training. Despite this gap, demand for capacity building was extremely high, as 96.7% expressed interest in receiving training on generative AI.

Table 1: AI Readiness and Training

Indicator	Percentage
Currently use AI tools	80.0%
Have received AI or digital tools training	23.3%
Interested in generative AI training	96.7%
Mean AI confidence score	2.92/5

These findings suggest that while AI tools are already in active use among respondents, formal training and capacity development have lagged behind this adoption. Thus, highlighting a clear gap between AI adoption and structured training, with respondents increasingly using AI tools despite limited access to formal capacity-building opportunities.

Preferred AI Academic Companion Functions

Respondents identified multiple functions they would like an AI Academic Companion to support. Research assistance, including literature review and data analysis support, emerged as the most preferred function, selected by 66.7%, representing about two-thirds of respondents. This was followed by drafting academic content (60.0%).

Support for grading and assessment, as well as personalised learning for students, were each preferred by 50.0%, indicating that half of the respondents viewed these as key areas where AI could add value. Curriculum planning was preferred by 40.0%, while administrative task automation was identified by 36.7%. The least selected function was policy or report generation (23.3%).

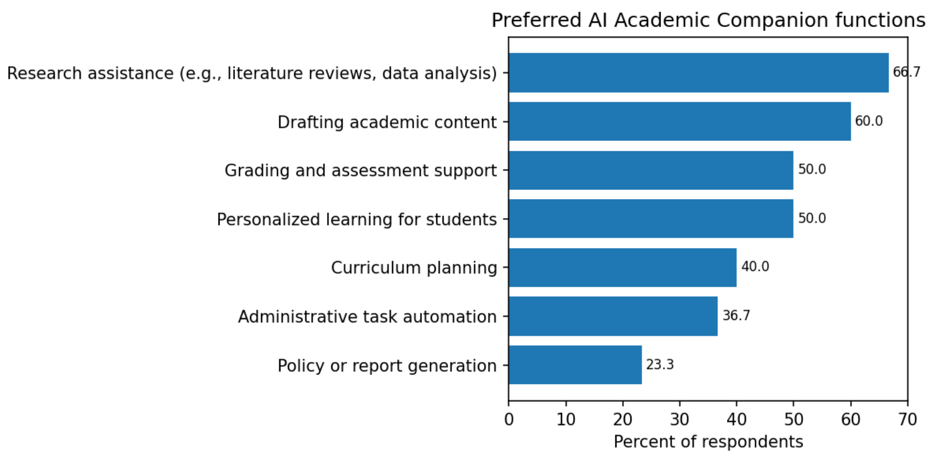


Figure 4: Preferred AI Academic Companion functions

Overall, the findings suggest that respondents envision AI as a dual-purpose tool that can support both core academic activities and selected administrative functions. However, the strongest demand is concentrated in research support, academic writing, assessment processes, and personalised learning, indicating that respondents prioritise AI applications that directly enhance teaching, learning, and scholarly productivity.

AI Concerns and Governance Priorities

Respondents identified several concerns that may influence the adoption and integration of AI in higher education. Ethical use and academic integrity emerged as the most prominent concern (73.3%). This was followed by data privacy and security (66.7%), and concerns about accuracy and reliability of AI outputs (60.0%). Other notable concerns included lack of adequate training or institutional support (53.3%) and potential job displacement (46.7%).

There was near-universal support for formal institutional governance of AI use, with 96.7% of respondents indicating that their institutions require formal policies to guide AI integration. One respondent was unsure, and none opposed the development of institutional policy frameworks, reflecting strong consensus on the need for governance structures.

In terms of guiding principles for institutional AI use, academic integrity was the most frequently endorsed principle (93.3%). This was followed by transparency (86.7%) and data protection (80.0%). Institutional accountability was selected by 70.0% of respondents, while local relevance was selected by 60.0%. Equity and inclusion, as well as human oversight, were each endorsed by 56.7% of respondents.

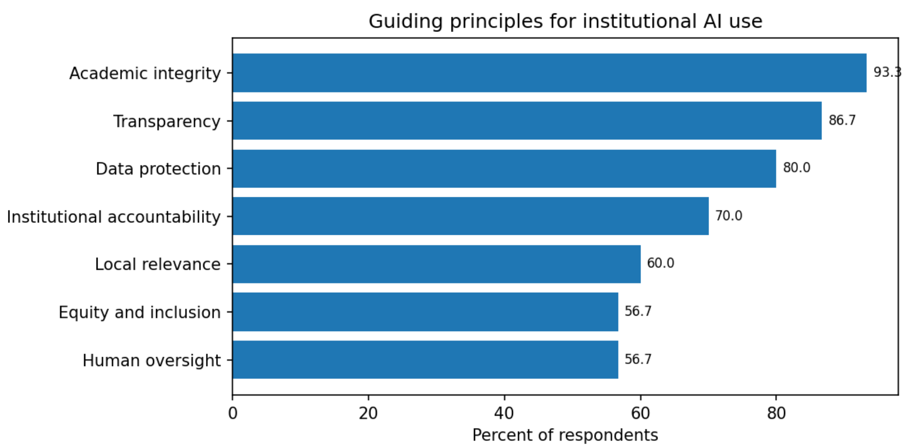


Figure 5: Guiding Principles for Institutional AI use

Overall, the findings suggest that while respondents are broadly open to AI adoption in higher education, they strongly emphasise the need for robust governance frameworks anchored in academic integrity, transparency, data protection, institutional accountability, and contextually relevant, equitable, and human-centred oversight.

Pedagogical Context and Local Relevance

The pedagogy section indicates that blended instruction was the most commonly reported teaching mode (43.3%), followed by face-to-face teaching (36.7%) and online teaching (20.0%). This distribution suggests a predominantly hybrid instructional environment across respondents.

Respondents identified several key challenges affecting effective pedagogy. Large class sizes (66.7%) and limited student digital literacy (66.7%) emerged as the most frequently reported constraints. These were followed by lack of infrastructure (63.3%) and time constraints (60.0%). Curriculum rigidity was also noted as a challenge by 43.3% of respondents, indicating structural limitations within institutional teaching frameworks.

Despite these constraints, there was strong openness to the integration of AI in teaching and learning. A substantial majority (90.0%) indicated willingness to adopt AI-supported pedagogy, and an equivalent proportion expressed interest in training on how to use AI tools effectively in curriculum delivery. However, concerns regarding academic integrity remain salient, with 80.0% of respondents agreeing or strongly agreeing that students may misuse AI tools for cheating or plagiarism.

Local relevance and contextual alignment of AI tools were also strongly emphasised. A majority of respondents rated local academic and cultural alignment as very important (60.0%), with a further 16.7% considering it extremely important. In addition, 70.0% agreed or strongly agreed that AI tools should be adapted to reflect African contexts and learning cultures, underscoring the importance of contextual sensitivity in AI integration.

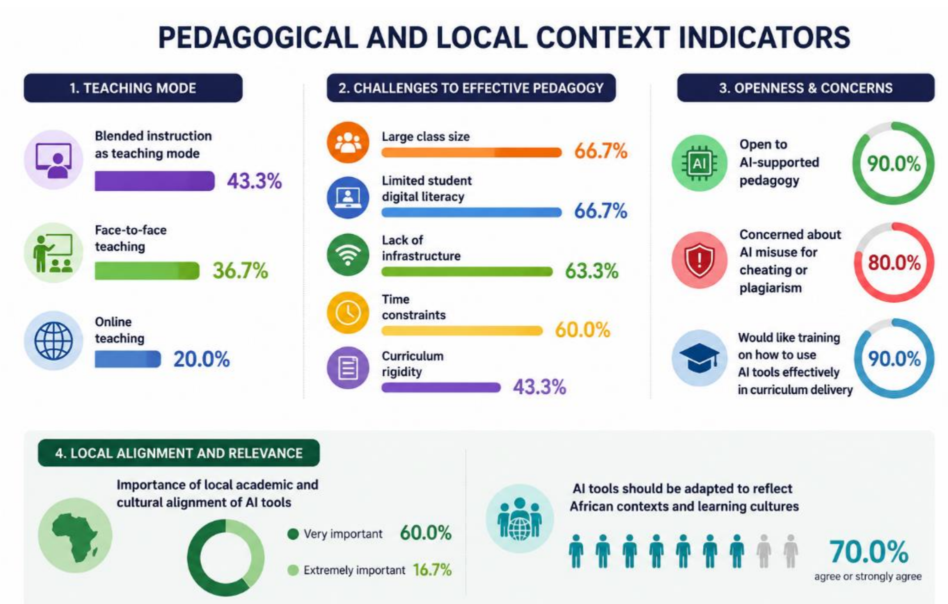


Figure 6: Pedagogical and Local Context Indicators

Summary of Results

The findings indicate that respondents experienced substantial workload pressures across multiple academic responsibilities, including research, lecture preparation, assessment, student support, reporting, and accreditation-related tasks. Although the use of artificial intelligence (AI) tools was already evident among many respondents, formal training in their application remained limited. Nevertheless, there was strong expressed interest in generative AI capacity-building and broad support for the development of institutional policies to guide its use in higher education.

Respondents identified research assistance, academic content development, grading and assessment support, personalised learning, and curriculum planning as the most preferred areas for AI integration. At the same time, several concerns were raised, particularly regarding academic integrity, data privacy, accuracy and reliability of AI outputs, insufficient training, and the potential for job displacement.

Overall, the findings suggest that while AI adoption in African higher education is increasingly accepted, its effective and sustainable integration depends on structured training, robust institutional policy frameworks, contextual relevance, and strong ethical safeguards.

Discussion

The findings of this study indicate that AI adoption in African higher education is shaped by a complex interplay of academic workload pressures, uneven institutional readiness, limited training opportunities, ethical concerns, pedagogical expectations, governance considerations, and the demand for contextual relevance. Rather than being driven solely by technological enthusiasm, AI uptake appears closely tied to the realities of academic labour and institutional constraints.

A central finding is the extent of academic workload pressure experienced by respondents across research and academic writing, lecture preparation, postgraduate supervision, assessment and examination duties, grading and feedback, reporting, result computation, and accreditation-related tasks. Research and academic writing emerged as the most time-intensive activities, while grading, feedback provision, lecture preparation, and manual result computation were identified as particularly repetitive and burdensome. This broad pattern suggests that academic workload in African higher education extends beyond classroom teaching to include extensive invisible and administrative labour. These findings align with Acosta-Enriquez *et al*. (2025), who argue that academic overload significantly shapes the adoption of AI tools, particularly in high-pressure academic environments. Similarly, Adamakis and Rachiotis (2025) highlight the growing role of AI in supporting academic writing, grading, feedback generation, and administrative workflows. In this context, AI is increasingly perceived not merely as an innovation but as a potential mechanism for alleviating academic labour pressures. However, the findings also underscore the need for caution, as AI should complement rather than replace academic judgement, particularly in evaluation, interpretation, mentoring, and decision-making processes.

The study further reveals a notable mismatch between the rapid uptake of AI tools and the level of institutional preparedness. While 80% of respondents reported using AI tools, only 23.3% had received formal training, despite an overwhelming 96.7% expressing interest in generative AI capacity-building. This gap reflects a broader pattern in which AI adoption is occurring ahead of structured institutional support systems. Asghar *et al*. (2025) similarly emphasise that AI literacy is multidimensional, encompassing cognitive, behavioural, affective, and ethical competencies, and cannot be reduced to mere tool usage. Ul Haq *et al*. (2026) also highlights the importance of institutional support and digital literacy in ensuring meaningful AI integration in higher education. The present findings therefore suggest that AI adoption in African universities is currently characterised by individual experimentation rather than coordinated institutional implementation. Kabanda (2026) reinforces this concern by identifying a leadership readiness gap for AI in Sub-Saharan Africa, while Cudjoe and Adebayo (2025) point to the limited development of institutional AI policies. The implication is that without structured governance and training, AI adoption risks becoming uneven, potentially privileging digitally skilled staff while marginalising others. The strong demand for training observed in this study therefore reflects not resistance to AI but a desire for structured, equitable, and responsible integration.

Respondents' preferences regarding AI functionality further illustrate how academic work is being reimagined. The most desired applications included research assistance, academic content drafting, grading and assessment support, personalised learning, and curriculum planning. This reflects an expectation that AI should support both cognitive and administrative dimensions of academic work. The prominence of research assistance aligns with studies showing increasing use of AI tools in academic writing, literature review support, summarisation, and productivity enhancement (Adamakis & Rachiotis, 2025). Kondoro (2025) similarly demonstrates that AI writing assistants are becoming embedded in academic practice in African universities, though concerns remain regarding language, access, and responsible use. The demand for grading and assessment support is consistent with Dagash (2026), who argues that AI can contribute to assessment design, moderation, outcome mapping, and instructional quality improvement. Given that grading and feedback were identified as among the most repetitive tasks, AI is seen as potentially valuable in generating draft feedback, organising rubric-based responses, and supporting formative assessment processes. However, as Dagash (2026) cautions, such applications still require strong faculty oversight to ensure academic standards are maintained.

Interest in curriculum planning and personalised learning further highlights the pedagogical potential of AI. Kusi *et al*. (2026) demonstrate that perceived AI feedback quality and learner trust significantly influence learning outcomes, while Zilundu *et al.* (2026) show that academic staff increasingly recognise the pedagogical benefits of AI integration. These findings suggest that respondents view AI not only as a productivity tool but also as a potential enhancer of teaching design, feedback quality, and learner-centred instruction.

Despite this optimism, ethical concerns remain central to AI adoption. Academic integrity and ethical use emerged as the most pressing concerns, followed by data privacy and security, accuracy and reliability of outputs, lack of training, and potential job displacement. These findings are consistent with Akpareva *et al.* (2026), who argue that while AI offers opportunities for efficiency and inclusion, it simultaneously raises concerns around surveillance, accountability, privacy, and inequity. Maduka *et al*. (2025) further highlight how generative AI complicates established notions of authorship and originality in African academia, reinforcing concerns about scholarly integrity. Zlotnikova and Hlomani (2025) similarly frame generative AI as both a crisis and an opportunity, depending on institutional responses. The present findings reinforce this duality, showing that while AI is widely accepted, its legitimacy is contingent on ethical governance. Concerns about data privacy and reliability also highlight the risk of inaccurate outputs and potential exposure of sensitive institutional or student data, reinforcing the need for structured training and clear institutional policies.

In this regard, institutional governance emerges as a critical prerequisite for sustainable AI adoption. Respondents strongly supported the development of formal institutional AI policies, emphasising principles such as academic integrity, transparency, data protection, accountability, equity, inclusion, local relevance, and human oversight. This aligns with Bacalso *et al*. (2026), whose systematic review highlights diverse institutional approaches to generative AI governance, including policy development, training frameworks, and management strategies. Thaldar *et al*. (2025) similarly emphasise the importance of structured governance in managing generative AI within higher education contexts. Cudjoe and Adebayo (2025) and Maina and Kuria (2024) further stress the need for clear policy direction in shaping Africa's AI future in higher education. The findings therefore suggest that AI governance is not an optional institutional add-on but a foundational requirement for responsible adoption. Importantly, respondents framed governance as a matter of trust, indicating that institutional policies must extend beyond technical regulation to include ethical clarity on authorship, acceptable use, data protection, and accountability mechanisms.

The findings also indicate that while respondents are largely open to AI-supported pedagogy, this openness is accompanied by caution. Although 90% expressed willingness to integrate AI into teaching and curriculum delivery, 80% were concerned about student misuse, particularly cheating and plagiarism. This reflects a tension between innovation and integrity. Adamakis and Rachiotis (2025) argue that successful AI integration requires alignment with pedagogical integrity and institutional policy, while Akpareva *et al*. (2026) caution that benefits must be balanced against risks to academic integrity and competence disparities. These concerns suggest that assessment practices may need to be redesigned in response to AI capabilities rather than relying solely on punitive approaches. Approaches such as oral assessments, reflective tasks, staged submissions, project-based evaluations, supervised assessments, and explicit disclosure of AI use may offer more robust responses to evolving academic realities. At the same time, respondents highlighted structural constraints such as large class sizes, limited digital literacy, inadequate infrastructure, and curriculum rigidity. Msomi and Behara (2026) similarly show that digital divide challenges and institutional support significantly shape perceptions of AI-enabled learning, underscoring the importance of broader systemic investment.

Finally, the study highlights the importance of local relevance in AI adoption. Respondents consistently emphasised that AI tools should be adapted to reflect African academic, linguistic, and cultural contexts. Kahenya (2026) argues that while generative AI may support educational equity in Sub-Saharan Africa, its effectiveness depends on contextual suitability and access. Kondoro (2025) similarly highlights challenges related to language and institutional realities, while Zlotnikova and Hlomani (2025) stress the importance of interpreting generative AI through Africa's specific higher education conditions. This suggests that localisation must go beyond surface adaptation to include alignment with curricula, assessment systems, accreditation frameworks, multilingual realities, and resource constraints. Without such adaptation, AI risks reproducing global inequalities in knowledge production and educational access.

An additional and important finding is the role of AI in supporting accreditation and quality assurance processes, which are often overlooked in discussions of AI in higher education. Respondents identified accreditation-related documentation as a repetitive and burdensome task. This extends the relevance of AI beyond teaching and learning into institutional administration and quality assurance. Gollapalli *et al*. (2026) support this possibility through their proposal of AI-enabled dashboards for accreditation and standards management, including curriculum mapping, reporting, and performance tracking. In African higher education contexts, where accreditation processes are documentation-intensive, AI could potentially enhance efficiency in evidence organisation and reporting. However, such applications must remain subject to human oversight, institutional validation, and strong data governance mechanisms.

Overall, the findings suggest that AI adoption in African higher education is widely welcomed but remains conditional. Its successful integration depends on the alignment of workload realities, institutional readiness, ethical governance, pedagogical redesign, training provision, and contextual relevance. Rather than replacing academic labour, AI is most likely to be effective when positioned as a supportive infrastructure embedded within robust institutional systems that prioritise equity, accountability, and academic integrity.

Study Implications for Institutional Readiness

Taken together, the findings indicate that institutional readiness for artificial intelligence in African higher education is multidimensional and extends beyond technological capacity. It encompasses workload awareness, staff confidence, AI literacy, structured training, leadership preparedness, policy development, ethical safeguards, infrastructural capacity, assessment redesign, and contextual adaptation to local academic realities.

This broader conceptualisation of readiness is strongly supported in the literature. Asghar *et al.* (2025) emphasise that AI literacy is inherently multidimensional, encompassing cognitive, behavioural, affective, and ethical dimensions. Kabanda (2026) highlights persistent leadership readiness gaps in the governance of AI across Sub-Saharan African higher education institutions, while Cudjoe and Adebayo (2025) underscore the centrality of coherent institutional policy frameworks for guiding AI integration. Similarly, Thaldar *et al.* (2025) demonstrate the importance of structured governance systems in managing generative AI responsibly within higher education environments. In addition, Msomi and Behara (2026) draw attention to infrastructural inequalities and digital divide constraints that continue to shape the feasibility of AI-enabled learning. Collectively, these studies reinforce the view that AI readiness is not simply a matter of access to technology, but a complex socio-technical and institutional condition.

This study contributes to this growing body of literature by empirically linking AI adoption to lived academic realities, particularly workload intensity, uneven institutional preparedness, governance expectations, and the demand for contextual relevance in African higher education settings. The findings demonstrate that while respondents are broadly receptive to AI, they do not envision it as a substitute for academic labour. Rather, they anticipate its role as a support system for reducing repetitive workload, enhancing research and teaching efficiency, improving administrative processes, and strengthening institutional effectiveness, provided that appropriate ethical and governance structures are in place.

The central implication is that responsible AI integration in African higher education requires a balanced and deliberately structured approach. Such an approach must combine capacity-building and training with robust policy frameworks, safeguard academic integrity, ensure data protection, preserve human academic judgement, and adapt AI systems to the linguistic, pedagogical, and institutional realities of African universities.

Conclusion and Recommendations

This study examined AI, academic workload, and institutional readiness in selected African higher education contexts. The findings indicate that respondents experience substantial workload pressures across core academic and administrative functions, including research and academic writing, lecture preparation, assessment, postgraduate supervision, reporting, accreditation documentation, and broader institutional responsibilities. While artificial intelligence tools are already in use among many respondents, formal training and structured capacity-building remain limited. Nonetheless, there is strong interest in generative AI training, alongside clear preferences for AI support in areas such as research assistance, academic content development, grading and assessment, personalised learning, and curriculum planning.

The study further reveals that respondents hold significant concerns regarding academic integrity, data privacy, accuracy, reliability of AI-generated outputs, insufficient training, and potential job displacement. At the same time, there is strong institutional demand for formal AI policy frameworks. Respondents emphasised that such policies should be grounded in academic integrity, transparency, data protection, institutional accountability, local relevance, equity, inclusion, and human oversight. These findings underscore that AI adoption in African higher education cannot be understood solely as a technological shift, but must instead be approached as an institutional, ethical, and pedagogical transformation.

Overall, the study contributes to the emerging literature on artificial intelligence in African higher education by demonstrating how AI adoption is shaped by the intersection of academic workload, institutional readiness, governance expectations, and contextual relevance. It highlights that while AI is widely welcomed as a tool for enhancing efficiency and supporting academic work, its sustainable and responsible integration depends on structured training, robust policy frameworks, ethical safeguards, adequate infrastructure, and context-sensitive implementation within African higher education systems.
Based on the findings, the following context-specific recommendations are proposed as priorities for supporting responsible and effective artificial intelligence integration in African higher education.

1) Institutional AI governance should be formally established across African higher education institutions. The study shows strong consensus among respondents on the need for structured AI policy frameworks, particularly to guide issues of academic integrity, transparency, data protection, accountability, equity, inclusion, local relevance, and human oversight. Institutions should therefore move beyond informal or individual-level AI experimentation toward clearly articulated institutional policies that regulate acceptable use and ensure ethical compliance.
2) Targeted staff capacity-building is essential to bridge the gap between widespread AI use and limited formal training. Given that many respondents already use AI tools but lack structured guidance, training programmes should be designed around actual academic work demands. Priority areas should include AI-supported research assistance, academic writing and content development, grading and feedback processes, curriculum planning, responsible and ethical AI use, and the critical evaluation and verification of AI-generated outputs.

3) Workload-focused AI adoption should guide implementation strategies. AI tools should initially be deployed in areas identified as most time-consuming and repetitive, including research writing, lecture preparation, grading and feedback, manual computation of results, reporting tasks, and accreditation-related documentation. These areas represent the most immediate opportunities for efficiency gains and workload relief without undermining core academic judgement.
4) Assessment redesign and academic integrity safeguards are necessary in response to concerns about student misuse of AI. Institutions should revise assessment strategies to reflect the realities of AI-enabled learning environments. This includes introducing explicit AI-use declarations, incorporating staged and process-based submissions, using oral examinations or defences where appropriate, strengthening reflective and applied tasks, and aligning assessment design more closely with learning outcomes to reduce opportunities for academic dishonesty.
5) Finally, local relevance and equity considerations should guide all AI integration efforts. AI tools must be adapted to reflect African higher education contexts, including local curricula, linguistic diversity, infrastructural constraints, accreditation requirements, and unequal access to digital technologies. Ensuring contextual relevance is essential not only for effectiveness but also for fairness, inclusivity, and sustainability of AI adoption across diverse institutional settings.

Future Research Direction

Future research should build on the present study by empirically testing AI-supported workload interventions within African higher education institutions. Specifically, longitudinal and experimental studies are needed to determine whether AI tools meaningfully reduce academic workload, enhance efficiency in teaching and research support, improve administrative processes, and sustain academic quality over time. Such studies should also examine the extent to which AI adoption influences academic integrity, assessment practices, and institutional readiness when implemented at scale rather than at an individual user level.

In addition, future research should adopt mixed-methods approaches, combining quantitative and qualitative designs to generate a more comprehensive understanding of AI adoption in higher education. While quantitative studies can measure patterns of AI use, workload reduction, and institutional readiness, qualitative inquiry can provide deeper insight into lived experiences, perceptions, ethical concerns, and contextual dynamics shaping AI integration. In particular, qualitative approaches such as interviews, focus group discussions, and case studies would be valuable for exploring how academics and students interpret AI use in relation to workload, integrity, pedagogy, and institutional culture.

Future research should also investigate the differential effects of AI adoption across academic roles, disciplines, and institutional types, as well as variations in access, digital literacy, and infrastructure that may shape uneven adoption outcomes. Comparative studies across countries and regions within Africa would further strengthen understanding of contextual influences on AI integration.

Given the strong emphasis on training and governance in the present study, future work should evaluate the effectiveness of AI capacity-building programmes and institutional policy frameworks in enhancing responsible use, ethical compliance, and user confidence. Furthermore, research should explore student perspectives in greater depth, particularly regarding assessment practices, academic integrity, and learning behaviours in AI-enabled environments.

Finally, future studies should examine the development and performance of locally relevant AI systems tailored to African higher education contexts, including linguistic diversity, curriculum alignment, and accreditation requirements. This will help ensure that AI adoption is not only effective, but also equitable, context-sensitive, and sustainable.

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AI Declaration
NotebookLM, Google Scholar Labs, and ChatGPT were used as AI-assisted tools during the preparation of this manuscript. The authors take full responsibility for the final manuscript.

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