AFRICA UNIVERSITY

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IMPACT OF AI TOOLS ON STUDENTS' LEARNING AND ACADEMIC INTEGRITY: A CASE STUDY AT AFRICA UNIVERSITY

 \mathbf{BY}

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A DISSERTATION PROPOSAL SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCES HONOURS IN COMPUTER SCIENCE IN THE COLLEGE OF ENGINEERING AND APPLIED SCIENCES.

ABSTRACT

This study examined the impact of artificial intelligence tools on students' learning experiences and academic integrity at Africa University. Using a mixed-methods approach combining quantitative surveys and qualitative interviews, the research investigated AI tool usage patterns, effects on critical thinking skills, and access disparities among students. The findings revealed widespread AI adoption across all academic disciplines, with 77.1% of students using these technologies weekly or daily and 89.4% reporting improved academic performance. However, 63.5% simultaneously expressed concerns about negative impacts on critical thinking development, revealing a significant tension between performance enhancement and cognitive skill development. Substantial disciplinary variations emerged, with engineering students showing the highest usage rates (57.9% daily) compared to social sciences students (22.7%), reflecting different epistemological traditions. Concerning academic integrity, 47.1% of students reported using AI detection evasion tools despite limited awareness of institutional policies. Qualitative analysis uncovered sophisticated metacognitive strategies employed by high-achieving students to balance AI benefits with cognitive development, while also documenting concerning patterns of unequal access to AI tools based on socioeconomic factors. The study contributes to the emerging literature on AI in higher education by providing empirical evidence from an African context and concludes with strategic recommendations for educational institutions, emphasizing comprehensive policy development, disciplinespecific pedagogical approaches, enhanced digital literacy initiatives, and equitable resource distribution to ensure AI tools serve as facilitators of educational innovation within an ethical, inclusive framework.

Keywords: Artificial Intelligence, Academic Integrity, Higher Education, Critical Thinking, Digital Equity

Declaration

I declare that this dissertation is my original work except where sources have been cited and acknowledged. The work has never been submitted, nor will it ever be submitted to another university for the award of a degree.

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Dedication

Thank you, God for the gift of life and the strength to contribute to the world. I dedicate this work to my beloved mother, Epiphania Silika, whose unwavering support has been my guiding light; to my aunt, Noster Gomo, and my uncle, Tawanda Mapako, who have raised me as their own and helped shape the person I am today; and in loving memory of those who have passed away, whose enduring spirit and lessons continue to inspire me every day.

Not everyone is granted the opportunity to write these words. Many come close, but only a few truly achieve it, and I am deeply grateful for this moment. This dissertation is more than just an academic accomplishment it is a milestone in my journey.

And this is just the beginning. The road ahead is long, but I embrace it with gratitude and determination. This dissertation represents the challenging 1%—the foundation that will carry me through the next 99% of my career. The journey ahead will demand even more, but with faith, perseverance, and the lessons I have learned, I am ready for what's to come.

List of Acronyms and Abbreviations

Acronym/Abbreviation

Full Form

AI Artificial Intelligence

ACT Adaptive Control of Thought

ACT-R Adaptive Control of Thought-Rational

ALEKS Assessment and Learning in Knowledge Spaces

ANOVA Analysis of Variance

API Application Programming Interface

AR Augmented Reality

Archiv für Technik, Lebenswelt und Alltagssprache

ATLAS.ti (Archive for Technology, Lifeworld and Everyday

Language)

AU Africa University

AUREC Africa University Research Ethics Committee

BB Blackboard (Learning Management System)

BDI Belief-Desire-Intention

BYOD Bring Your Own Device

CAN Controller Area Network

CLT Cognitive Load Theory

CT Cognitive Theory

DE Digital Education

DL Deep Learning

EDA Exploratory Data Analysis

EDM Educational Data Mining

ELSA Ethical, Legal, Social Aspects

FYP Final Year Project

GDPR General Data Protection Regulation

GPU Graphics Processing Unit

HCI Human-Computer Interaction

Acronym/Abbreviation

Full Form

HPC High-Performance Computing

ICANN Internet Corporation for Assigned Names and Numbers

ICT Information and Communication Technology

Information and Communication Technologies for

ICT4D

Development

ICTP International Centre for Theoretical Physics

IPR Intellectual Property Rights

IRB Institutional Review Board

ISO International Organization for Standardization

ITS Intelligent Tutoring Systems

LMS Learning Management System

LOOCV Leave-One-Out Cross-Validation

LTI Learning Tools Interoperability

ML Machine Learning

MLA Machine Learning Algorithm

MOOC Massive Open Online Course

MOODLE Modular Object-Oriented Dynamic Learning Environment

MTBF Mean Time Between Failures

MTTR Mean Time To Repair

NGO Non-Governmental Organization

NIST National Institute of Standards and Technology

NLP Natural Language Processing

NLP4Ed Natural Language Processing for Education

NVivo A qualitative data analysis software (not an acronym)

OED Oxford English Dictionary

OER Open Educational Resources

OECD Organisation for Economic Co-operation and Development

PHI Protected Health Information

Acronym/Abbreviation

Full Form

PISA Programme for International Student Assessment

POE Predictive Outcome Engine

PPC Pay-Per-Click

QoE Quality of Experience

RFP Request for Proposal

RL Reinforcement Learning

ROM Read-Only Memory

SEL Social-Emotional Learning

SEO Search Engine Optimization

SMTP Simple Mail Transfer Protocol

SPSS Statistical Package for the Social Sciences

SRL Self-Regulated Learning

STEM Science, Technology, Engineering, and Mathematics

SVM Support Vector Machine

TAM Technology Acceptance Model

TCP/IP Transmission Control Protocol/Internet Protocol

TELOS Technological, Economic, Legal, Operational, Schedule

TL Transformative Learning

TQM Total Quality Management

UCL University College London

United Nations Educational, Scientific and Cultural

Organization

UNESCO

URL Uniform Resource Locator

UTAUT Unified Theory of Acceptance and Use of Technology

VR Virtual Reality

WAN Wide Area Network

WLAN Wireless Local Area Network

WYSIWYG What You See Is What You Get

Acronym/Abbreviation

Full Form

XML Extensible Markup Language

XSS Cross-Site Scripting

YAML Yet Another Markup Language

ZPD Zone of Proximal Development

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Chapter 1: Background to the Study

1.1 Evolution of AI in Education

The development of artificial intelligence in education has been characterized by profound enhancement and revolutionary innovations but is still in its nascent form. A comparison of the initial stages of development serves to outline how AI technologies have systematically transformed education environments throughout the ages.

Early Developments:

The beginnings of AI in education began with intelligent tutoring systems that would replicate one-on-one interaction between teachers and students. These systems gave individualized instruction and feedback on par with individual tutors taking students through problems. SCHOLAR, developed in the 1970s, used a primitive form of artificial intelligence that involved natural language processing to teach geography (Carbonell, 1970). However, most of the early systems were constrained by a shortage of computation available and low-quality training data.

Rise of Intelligent Tutoring Systems:

During the 1980s and 1990s, there were more advanced Intelligent Tutoring Systems. Cognitive Tutors, based on the ACT theory of John Anderson, were built to understand and predict student activity in the course of learning procedures (Anderson et al., 1995). They provided step-by-step instruction and feedback, notably for mathematics and science instruction. The systems were largely domain-specific and relatively inflexible, so their implementation was difficult in diverse instructional settings.

Integration of Adaptive Learning Technologies:

The beginning of the 2000s witnessed the emergence of a new era characterized by the integration of adaptive learning technologies within conventional education systems. Adaptive learning platforms like Knewton and ALEKS utilized machine learning algorithms to analyze student data and provide personalized content (Oxman & Wong, 2014). These innovations enabled individualized learning experiences responsive to the performance of each student, thereby promoting the scalability and accessibility of AI adoption in eLearning platforms.

Current Applications and Advancements:

In contemporary learning spaces, the utilization of AI ranges from one-on-one learning to administrative support. Edmodo and Coursera utilize artificial intelligence to analyze learning behavior and provide users with recommendations and adaptive quizzes according to individual skill levels (Kizilcec et al., 2017). AI has been incorporated into automated grading systems, virtual teaching assistants, and smart content tools.

Natural language processing algorithms allow for the generation of interactive content, like quizzes and simulations, thereby enhancing both engagement and efficacy in learning materials. Artificial intelligence also facilitates collaborative learning spaces by pairing students with complementary skill sets and learning style preferences (Holstein et al., 2020).

Future Trends and Innovations:

The future of artificial intelligence (AI) in education has great potential for future innovations. Some of the recent advancements involve AI-powered tutors and adaptive textbooks that aim to offer interactive, interesting, and immersive learning experiences (Holmes et al., 2019). Moreover, AI usage is being used more in special education, offering personalized assistance to students with varying learning requirements. AI-based tools have the ability to detect early indications of learning challenges and allow timely interventions.

The integration of AI with other emerging technologies such as virtual reality (VR) and augmented reality (AR) can create even more immersive and interactive learning experiences, simulating real-world environments where students can practice the application of knowledge and develop 21st-century skills (Radianti et al., 2020).

In conclusion, the development of artificial intelligence in education has been marked by an ongoing process of innovation and diversification. From initial research on intelligent tutoring systems to complex adaptive learning systems, this development has had a profound impact on teaching practices by promoting personalization, efficiency, and interactivity in learning methods. Today, AI technology has great potential to remain a transformative force in education in the coming years.

1.1.2 Context of Africa University

The phenomenon of digital transformation has continued to evolve more at Africa University, which is based in Zimbabwe. The institution draws a student population from various African nations, all of whom have varying educational backgrounds and technical competencies. This diversification has advantages as well as challenges for the efficient deployment and use of AI tools (Mhaka, 2024).

Accessibility of AI Tools:

Several factors influenced the accessibility of AI tools at Africa University:

- Technological Infrastructure: The technological infrastructure of Africa
 University, encompassing the computer and internet labs, has experienced
 considerable enhancement. This development is crucial to fully exploit AI
 applications, i.e., ChatGPT, POE, Gamma, Gemini, and Claude. Having
 access to them enables learners to utilize more advanced technologies in
 support of their academic pursuit.
- Digital Literacy: he level of digital literacy among students revealed immense disparity. Some had a level of awareness regarding AI tools, while others required additional training and support. For the sake of students' familiarity and ease of use with such technologies, the university initiated digital literacy programs (Chigwedere, 2024).
- 3. Economic Barriers: Economic differences among students impacted their access to AI facilities. Disadvantaged economic students lacked easy access to such facilities off-campus, as personal equipment and internet connectivity were still costly. Though the university offered such facilities on campus, limitations in access still existed for most students (Ndlovu, 2024).
- 4. **Curricular Integration:** Ndlovu (2024) believes that artificial intelligence tools at Africa University have mostly been utilized by students and lecturers on an individual basis rather than through a structured institutional framework. Incorporation of AI tools into the curriculum through a systematic mechanism has not occurred, leading to wide variations in usage patterns across various courses and programs.

5. **Faculty Support:** Faculty participation was instrumental in facilitating the effective utilization of AI tools. The institution conducted workshops and training to facilitate the supporting of the faculty in integrating AI technologies into pedagogy (Dube, 2023). Nevertheless, the adoption rate of AI tools among the faculty showed significant disparity, which influenced the consistency and effectiveness of such technologies in the classroom setting.

1.1.3 Implications of Unstructured AI Use

The informal application of AI tools within Africa University had various effects on the learning environment, both positive and negative.

Positive Implications:

- Enhanced Learning: Artificial Intelligence technologies enriched learning
 processes through delivering students individualized feedback and tailormade learning pathways. Students applied AI to elaborate on concepts, access
 additional learning resources, and receive immediate guidance, which may
 lead to better academic achievement.
- 2. **Increased Efficiency:** AI tools made research, writing, and other educational tasks easier for students. This enabled improved efficiency in assignment completion, enabling students to devote time to other learning priorities.

Negative Implications:

- 1. Overdependence on AI: One of the key issues identified was excessive use of AI tools by the students when undertaking assignments and examinations on their own. Such over-reliance risks derailing critical thinking, problem-solving ability, and independent learning capacity development (Moyo, 2024). On occasion, learners embraced solutions generated by AI with insufficient engagement in the content, hence developing a shallow grasp of the material (Ndlovu, 2024).
- 2. **Academic Integrity:** The accessibility of AI tools increased the risk of academic dishonesty. Students may have been capable of generating content for homework with the help of AI without providing appropriate recognition,

- which created ethical concerns about plagiarism. This compromised the validity of academic work and the integrity of the learning process.
- 3. Equity Issues: Unfettered access to AI tools might have promoted inequalities among students. Students with ready access to technology and higher digital literacy levels could utilize AI tools to their advantage, whereas others might be disadvantaged. This can widen the performance gaps among students from different socio-economic groups (Johnson, 2023).
- 4. Lack of Guidance and Support: In the absence of official institutional guidance and support, both students and staff did not know how to use AI tools responsibly and ethically. The absence of clear-cut policies can lead to divergent practices and misuse of AI technologies, potentially compromising the learning environment (Brown & Lee, 2023).

Recommendations for Structured Integration:

To maximize the benefits of AI tools while mitigating adverse implications, several strategic approaches were recommended:

- 1. **Formulate Formal Guidelines:** Create definite institutional protocols that guide the ethical and responsible utilization of AI resources. Communicate and enforce these protocols consistently among teachers and students.
- Curricular Integration: Ensure systematic incorporation of AI tools within
 the curriculum, including provisions for AI-based assignments, teaching the
 use of AI tools, and the use of AI as a means of augmenting traditional
 pedagogy.
- 3. Digital Literacy Programs: Improve digital literacy initiatives to guarantee that all students develop the necessary competencies for the effective utilization of AI tools. Customize these initiatives to address varying proficiency levels and offer specialized support tailored to meet diverse requirements.

- 4. **Equitable Access:** Ensure equitable access to AI tools by extending required resources and facilities to economically disadvantaged students, including internet access subsidies, device support, and on-campus facilities.
- 5. **Faculty Continuous Professional Development:** Facilitate continuous professional development of faculty members in effectively incorporating AI tools in pedagogy by conducting workshops, seminars, and collaborative projects (Zawacki-Richter et al., 2019).

Considering these implications and using systematic integration methodologies could enhance Africa University's effective use of artificial intelligence resources, maximizing education benefits while ensuring equal access, enhancing academic performance, and maintaining academic integrity within the student population.

1.2 Statement of the Problem

The application of artificial intelligence technologies in the education industry, particularly at Africa University, has the possibility of bringing transformational change and also generating serious challenges (Holmes et al., 2019). Key issues with the application of AI tools by learners at Africa University were overdependence, undermining academic integrity, uneven access, lack of institutional regulation, and the possible misrepresentation of genuine assessments of academic accomplishment.

1. AI Tools Dependency

Students extensively utilized artificial intelligence tools, such as ChatGPT, POE, Gamma, Gemini, and Claude, among others. These tools presented considerable opportunities for response generation, solving difficult issues, and enhancing engagement with academic content. The user-friendliness of these tools motivated students to largely rely on AI in assignment completion and class discussion participation. Excessive dependence on these resources could have impeded the cultivation of essential academic competencies, such as critical thinking, problem-solving, and independent learning (Eaton, 2020). By employing AI-driven tools to bypass cognitive processes involved in successful learning, students could have deprived themselves of an excellent chance to comprehend and internalize the content

of the lessons, with long-term consequences for their academic and professional growth (Ndlovu, 2024).

2. Academic Integrity Issues

The use of AI technologies introduced grave academic integrity problems. The technologies offered students the potential for plagiarism by presenting work generated by AI as their own, contrary to honesty and originality values demanded by academic integrity. This compromised the validity of academic qualifications and, in essence, lowered the academic integrity of Africa University (Mhaka, 2024). Using effective plagiarism detection software and establishing a culture of academic integrity were suggested as possible solutions to detect and address such malpractices at their nascent stage.

3. Inequality in Accessing AI Tools

Discrepancies in access to AI technology among students posed a substantial challenge (Reich & Ito, 2017). Discrepancies in socioeconomic status, digital literacy, and technological resources promoted unequal opportunities for students to leverage these technologies. This provided an unlevel playing field, where some students had the potential to use sophisticated AI technology to maximize their learning experience, while others were not able to achieve the same level of participation. These inequalities had the potential to widen existing disparities in academic performance and opportunity, and hence further marginalize already disadvantaged students.

4. Lack of Institutional Guidelines

Africa University lacked official rules and policies to regulate the usage of AI tools among its students (Ndlovu, 2023). In the absence of policies, students were struggling with the use of such technologies in a proper and ethical manner. Institutional control was deemed important in allowing students to understand the meaning of what they were doing and reducing the chances of unintentional misuse and violation of ethics. Development of comprehensive guidelines and policies was important in order to enable rightful and ethical utilization of AI tools within the academic fraternity.

5. Impact on True Academic Performance

The unchecked application of artificial intelligence instruments might have skewed the assessments of the actual scholastic improvement of students. Adequate assessment of those students who had predominantly depended on AI, either intentionally or unintentionally, posed problems in assessing their actual understanding, capabilities, and knowledge in undertaking tasks and learning from the related processes. These instances could have serious long-term effects on their educational and career trajectories, as their qualifications may not necessarily correspond to their actual skill set. The students' proper assessment must be done considering their independent mental capacity to uphold education's integrity.

Conclusion:

This research analyzed the unintended effects that Africa University students have encountered as a result of their excessive use of artificial intelligence tools. It covered problems of over-reliance, risks to academic integrity, concerns regarding equity and accessibility, ineffective institutional policies, and possible misrepresentation of the correct judgments of academic performance. The research aimed to provide meaningful information regarding the impact of AI tools on student learning and academic integrity, paving the way for suggestions on ethical and effective AI adoption in education, creating a bright future for students on the continent.

1.3 Research Objectives

1.3.1 Primary Objective

The key objective of the current study was to explore how artificial intelligence software influenced learning experience and academic honesty among Africa University students, testing the efficacy as well as shortcomings of integrating AI technologies into the educational system. Guided by strategic suggestions of integrating the same in a productive and ethical manner, the research attempted indepth exploration of how AI technologies' applications were shaping learning outcomes in academia.

1.3.2 Specific Objectives

The study aimed to achieve the following specific objectives:

1. Extent of AI Tool Usage:

- Determine the degree and trends of AI tool utilization among university students.
- Identify the most commonly used AI technologies and their primary applications, including assignments, exam preparation, research, and other academic tasks.
- Analyze variations in AI tool usage across different student groups based on field of study and year of enrollment.

2. Establish the Impact on Learning Processes:

- Investigate how AI technologies influenced students' learning processes, engagement with course content, critical thinking development, and problem-solving abilities.
- Assess their effectiveness in improving academic achievement and facilitating personalized learning environments.
- Examine potential negative effects of AI tool usage on students' development of independent learning capacity and cognitive skills.

3. Examine Academic Integrity Issues:

- Explore how AI tools might facilitate academic dishonesty, including plagiarism and other forms of cheating.
- Determine students' attitudes regarding AI-generated content usage in their academic work and their assessment of associated ethical issues.
- Identify methods for detecting and preventing academic misconduct related to AI tool usage.

4. Identify Disparities in Access and Usage:

- Identify digital divides related to socio-economic factors, digital literacy levels, and technological resource availability affecting students' access to AI tools.
- Investigate how these disparities impact students' academic performance and educational opportunities.
- Propose measures to ensure equitable access to AI tools and support across the student population.

5. Develop Institutional Guidelines and Policies:

- Review existing institutional policies and guidelines regarding AI tool usage in education at Africa University.
- Gather input from students, faculty, and administrators regarding the need for and potential content of such guidelines.
- Develop detailed recommendations for effective and ethical incorporation of AI tools within the institution's academic structure.

6. Examine the Impact on Academic Performance Assessment:

- Analyze how AI tool usage potentially misrepresents assessment of students' actual knowledge, skills, and competencies.
- Investigate the implications of AI-generated content for the validity and reliability of academic assessments.
- Propose methods for effectively assessing student performance within the context of widespread AI tool usage.

1.4 Research Questions

1.4.1 Primary Research Question

The main research question guiding this study was:

 How are student learning experiences and academic integrity affected by AI tools at Africa University? This primary research question addressed the dual nature of AI tools within the educational context at Africa University, investigating both benefits and challenges associated with their use.

1.4.2 Specific Research Questions

To address the primary research question comprehensively, the following subquestions were formulated:

1. Extent of AI Tool Usage:

- What level and patterns of AI tool usage exist among Africa University students?
- Which AI tools are most frequently used, and for what academic activities: assignments, exam preparation, research, or other purposes?

2. Impact on Learning Processes:

- How do AI tools affect students' engagement with course material,
 critical thinking development, and problem-solving capabilities?
- What perceived benefits do AI tools provide for enhancing personalized learning experiences and improving academic performance?
- Do these AI tools potentially impair students' cognitive development and independent learning capacity?

3. Academic Integrity Issues:

- To what extent do AI tools facilitate or contribute to academic dishonesty, including plagiarism and cheating?
- What attitudes do students hold regarding the use of AI-generated content in their academic work, and how do they perceive the ethical considerations related to AI?

 What policies could effectively detect and prevent academic misconduct facilitated by AI tool usage?

4. Access and Use Inequities:

- What disparities exist in AI tool access among students based on socio-economic status, digital literacy, and technology access?
- How have these disparities affected students' academic achievement and educational outcomes?
- What policies would ensure equitable access to AI tools and support for all students?

5. Institutional Guidelines and Policies:

- What institutional policies and guidelines currently exist regarding technology use, particularly AI tools, in education at Africa University?
- O How do students, faculty, and administrators perceive both the usage of these technologies and the associated guidelines and policies?
- What recommendations could be developed for the ethical and effective integration of AI tools into the university's academic framework?

6. Impact on Academic Performance Assessment:

- o How does AI tool usage potentially bias the measurement of students' authentic knowledge, skills, and abilities?
- In what ways does AI-generated content affect assessment reliability and validity?
- What methods can be recommended for valid student performance assessment given widespread AI tool adoption?

These focused research questions guided the investigation into AI tools in learning and their potential contributions to policy and practice development at Africa University.

1.5 Assumptions/Hypotheses

1.5.1 Assumptions

The present study was based on several underlying assumptions that enabled the investigation and directed the examination of the impact of artificial intelligence tools on students' academic performance and integrity at Africa University:

1. Accessibility of AI Tools:

The research assumed that most students learning at Africa University had exposure to artificial intelligence tools, including ChatGPT, POE, Gamma, Gemini, and Claude. The assumption was based on trends seen at the university in terms of improved technology infrastructure and support for e-learning.

2. Diverse Student Utilization:

They assumed that the students of various disciplines and class years at Africa University employed AI tools for all types of activities. This variability in use was anticipated to yield significant findings on the use of AI tools in varied contexts of education.

3. Positive Perception of AI Tools:

The research presumed that students had overall positive attitudes towards AI tools, particularly due to their ability to augment learning experiences, offer personalized assistance, and upgrade learning outcomes. This presumption was supported by current research focusing on the advantages of artificial intelligence in learning environments.

4. Challenges in Digital Literacy:

 Digital literacy was anticipated to differ between students and influence how well they could utilize AI tools. This presumption acknowledged the varied education and socioeconomic status of the student body, which led to variation in technological experience and proficiency.

5. Equity in Access:

The study assumed that students might experience unequal access to AI technologies based on economic standing and the availability of technological resources. The assumption acknowledged potential disparities that may affect the effectiveness and equity of AI tool use within the population of students.

6. Institutional Support:

Although institutional intention was conceivable in regards to the
adoption of AI applications, there were no well-developed policies or
expressed guidelines to be under development yet. The presupposition
here relies on the status of technology integration within Africa
University currently and the nature of artificial intelligence tools to
continuously develop.

7. Effects on Academic Integrity:

o The research made the assumption that utilization of artificial intelligence technologies would undermine the academic integrity of the students, thus making plagiarism and other academic malpractices more likely. The assumption was representative of the sentiments of scholars and academic administrators about the ethical impacts of artificial intelligence in academia.

8. Effects on Learning Outcomes:

The AI technologies were supposed to have quantifiable impacts on the academic performance of learners, both positive and negative.

These encompassed possible enhancements in personalized learning experiences and setbacks arising from overdependence on technological services.

1.5.2 Hypotheses

Based on the research objectives and assumptions, the following hypotheses were proposed to test and understand the effect of AI tools on students' learning and academic integrity at Africa University:

1. Hypothesis on AI Tool Usage:

- H1: Students across various disciplines and different levels of study at Africa University employed AI tools including ChatGPT, POE, Gamma, Gemini, and Claude.
 - This hypothesis was based on the expectation that a substantial portion of the student body would have access to and use AI tools, providing insights into usage contexts and patterns.

2. Hypothesis on Learning Processes:

- H2: AI tools significantly influenced students' critical thinking and problem-solving abilities and their engagement with course content.
 - This hypothesis stemmed from the assumption that AI tools could provide personalized learning opportunities enhancing cognitive development and academic performance.

3. Hypothesis on Academic Integrity:

- o **H3:** Al tool usage correlated significantly with academic dishonesty practices, including plagiarism and examination cheating.
 - Ethical concerns related to AI tool usage and the potential facilitation of dishonest academic practices informed this hypothesis.

4. Hypothesis on Academic Performance:

 H4: Unregulated usage of AI tools affected the measurement of students' authentic academic performance, resulting in discrepancies between actual competencies and academic evaluation. This hypothesis derived from concerns regarding AI-generated content's impact on the reliability and validity of academic assessment and potential obscuring of students' true competencies.

Testing these hypotheses would provide empirical evidence on the role of AI tools in education, highlighting both benefits and challenges. The findings would be instrumental in developing effective strategies and policy directions for the ethical integration of AI tools into Africa University's academic environment.

1.6 Significance of the Study

This chapter illustrates the relevance of the study, which aimed to fully establish the impacts of AI tools on the learning experience of students and academic integrity in Africa University. The implications of the findings are for enhancing student learning outcomes, instructors, academic institutions, and other stakeholders in education.

1. Improving Learning Outcomes:

The primary objective was to provide an overview of the influence of AI tools on students' learning processes in order to determine the most effective approaches to the implementation of these technologies in the learning environment. These results can assist instructors in using AI tools to support individualized student learning experiences and motivate students in the learning process itself, fostering critical thinking and problem-solving abilities. Ultimately, this would lead to improved learning outcomes through more effective pedagogical approaches.

2. Addressing Academic Integrity Issues:

Research on how artificial intelligence tools impact academic integrity must be conducted to uphold the credibility and value of academic qualifications. This research had a key contribution to ethical concerns by determining potential academic cheating using AI tools and devising ways of mitigating these problems, hence ensuring that student exams actually reflected the students' true abilities.

3. Promoting Equitable Access to Technology:

Knowledge about gaps in AI tool access informed understanding of challenges in education equity. The findings from the study pinpointed socio-economic and technological barriers that students were experiencing, guiding interventions and investment strategies in mitigating the disparities. This strategy was intended to promote equitable participation and benefit of all students in AI technologies despite differences in their backgrounds (Reich & Ito, 2017).

4. Informing Policy Development:

This research was helpful in guiding the formulation of policy and guidelines on the utilization of AI tools in learning. By outlining current levels of institutional support and soliciting stakeholder inputs, the research developed proposals for integrating AI into educational practice in an ethical and effective manner. These policies would educate students and educators in the responsible use of AI and could serve as models for other learning institutions facing similar issues.

5. Improving Assessment Practices:

The examination yielded significant revelations regarding the impact of artificial intelligence tools on the dependability of assessments concerning student academic performance. This comprehension was crucial in guaranteeing that evaluations authentically reflected the knowledge and skills possessed by students. The results were instrumental in the formulation of assessment strategies that considered AI-generated content, thereby safeguarding the integrity of academic procedures and producing more precise representations of student competencies.

6. Contributing to the Broader Educational Landscape:

The research findings contributed to the wider educational context by providing a relevant model for other institutions wishing to adopt AI technology. Dissemination of these findings through academic publications, conferences, and collaboration advanced global knowledge on AI benefits and pitfalls in learning contexts. This may have encouraged more informed and equitable approaches to AI adoption in learning contexts globally.

1.7 Delimitation of the Study

The scope and boundaries of this study were carefully delimited to maintain focus and ensure the findings' relevance. This section outlines what the research covered and what it excluded, providing specific insights particular to Africa University.

1. Geographical and Institutional Focus:

This research was centered on Africa University, whose main base is in Zimbabwe. Findings and recommendations were contextualized to the local situation of this university, such as its specific socio-economic, technological, and educational context. This research did not extend to other universities or learning institutions, which have different contexts and challenges.

2. Participant Demographics:

The research was confined to both postgraduate and undergraduate students currently enrolled at Africa University. Alumni, administrative staff, and lecturers were excluded from the study. The primary aim was to know how students who used AI tools for academic activities perceived and experienced such technologies in their learning experience.

3. Types of AI Tools:

These five AI tools were the focus of this study, specifically ChatGPT, POE, Gamma, Gemini, and Claude. While more AI tools have developed, these five were selected as the main targets because they were most popular with Africa University students.

4. Academic Disciplines:

The research involved students from diverse academic fields provided by Africa University. Nonetheless, the study refrained from drawing comprehensive comparisons among these disciplines. Rather, its objective was to offer a general insight into the usage of AI tools across different study fields.

5. Time Frame:

The study employed cross-sectional methods, collecting information at a single point in time. It failed to track fluctuations in the use of AI tools and their impacts over an extended period. This was a limitation identified, and results were an outcome of prevailing conditions and not sustaining trends.

6. Data Collection Methods:

The primary data collection methods employed were surveys, interviews, and focus groups with students. Experimental designs and longitudinal methods were not employed in the study. The selected methods were employed to gather qualitative and quantitative data regarding students' experiences and perceptions of utilizing AI tools.

7. Ethical Considerations:

The study adhered to accepted ethical standards applicable to research with human participants. The participation in the study was voluntary, and all the participants provided informed consent. The study refrained from delving into sensitive personal data beyond what was required in understanding the utilization of AI tools and their implications for learning and academic integrity.

By explicitly stating these parameters, the study ensured a targeted and manageable scope. These standards assisted in keeping the study within the particular context of Africa University and made practical recommendations for how AI tools can be better integrated into teaching, with consideration for ethical and equitable issues.

1.8 Limitations of the Study

This study aimed to provide a comprehensive understanding of how artificial intelligence tools affected academic integrity and learning processes among Africa University students. However, several significant constraints potentially influenced the findings and interpretations. Acknowledging these limitations with respect to their impact on the outcomes and generalizability is crucial.

1. Scope of AI Tools:

The research primarily focused on specific artificial intelligence technologies, particularly ChatGPT, POE, Gamma, Gemini, and Claude. While these technologies

were popular and accessible to students at Africa University, the study did not address additional AI tools that might significantly affect academic integrity and learning. This limitation potentially restricted the comprehensiveness of the findings regarding AI technology implementation.

2. Cross-Sectional Design:

The research had a cross-sectional design, capturing AI tool usage at a single moment rather than tracking changes over an extended timeframe. This methodological constraint restricted insight into the way that usage patterns and implications may change across students' learning trajectories. Longitudinal research would offer more insight into the longer-term effects of AI tools on learning processes and academic integrity.

3. Self-Reported Data:

The main tools of gathering primary data, questionnaires, interviews, and focus groups were based on data provided by respondents themselves. It was prone to social desirability bias, recall bias, and response bias, which would lead the students to exaggerate or underestimate their use of AI tools and the consequences thereof. These types of biases can undermine the validity of the findings.

4. Limited Generalizability:

The research was limited to Africa University, which was characterized by its special socio-economic and technological context. As such, the results may not be extrapolated to other educational institutions with varying environments, resources, and populations. The results may also not be extrapolated to institutions located in other geographic areas or institutions with differing education systems.

5. Technological and Resource Constraints:

The findings may be varied depending on participants' access to technology and resources. Participants who did not have as much high-speed internet, personal devices, or technical support likely experienced different levels of exposure to AI technologies compared to those who had more access. This might have influenced

sweeping generalizations drawn from the study regarding the use of AI tools in general.

6. Ethical and Privacy Concerns:

Despite adherence to ethical standards, participants might have had privacy and data management concerns that could have affected their willingness to participate and provide honest answers. These fears likely limited the scope and depth of data collection, with long-term implications for study outcomes.

7. Faculty and Institutional Variability:

It is probable that there were considerable variations in the levels of faculty use of AI tools and institutional support for their adoption. This would have influenced students' accounts of AI tool usage and perceptions of the impacts involved. The research may not have accounted for these variations to some extent, hence giving a skewed view of the wider institutional context.

8. Rapid Technological Change:

Artificial intelligence technology is evolving very quickly, and new features and tools are continuously being developed. This pace of evolution can quickly render the study's findings obsolete with new applications of AI being developed and previous technologies being refined. This limitation highlights the need for ongoing research in order to keep abreast of technological developments and their pedagogical ramifications.

With this open acknowledgement of these limitations, the research gives a candid and practical review of its applicability and scope. These limitations call for a cautious approach to considering the findings and open lines of further research to expand upon these findings and minimize their limitations.

Chapter 2: Review of Related Literature

2.0 Introduction

This chapter presents a comprehensive review of literature regarding the use of AI tools for education and their impacts on student learning and academic integrity. The

review is structured to provide a theoretical foundation, examine empirical research findings, and identify existing gaps in understanding how AI technologies influence learning environments. The literature review covers the following key areas:

- Theoretical Framework: This section examines the theoretical underpinning
 of AI in education. Major theories and models are introduced and explained,
 considering how AI technologies can enhance learning processes and
 outcomes.
- 2. **Relevance of the Theoretical Framework to the Study:** This part links the theoretical framework to the current study, demonstrating how these theories inform the research questions and objectives.
- 3. **Historical Context and Evolution of AI in Education:** This section traces the development of AI technologies within the educational sector, developing a chronology of key milestones from early intelligent tutoring systems to modern adaptive learning platforms.
- 4. **Current Applications and Impact of AI in Education:** This section focuses on the current applications of AI tools in educational settings and reviews various applications like personalized learning, automated grading, intelligent tutoring systems, and their benefits and limitations.
- 5. **Challenges and Ethical Considerations:** This section examines issues in AI-based education: over-reliance, academic dishonesty, data privacy, algorithmic bias, and related concerns. It also discusses the ethics surrounding the implementation of AI tools in academic settings.
- 6. **Disparities in Access and Equity:** This section investigates AI technology access gaps between students from different socio-economic backgrounds and how these disparities affect educational outcomes and opportunities.
- 7. **Institutional Guidelines and Policies:** This section reviews existing policies and guidelines on AI use in education, addressing how institutions are managing integration currently, and identifying gaps that need to be addressed for ethical and practical AI implementation.

8. **Summary of Findings:** The final section summarizes key insights from the literature review and identifies areas requiring further research.

This chapter aims to establish a robust theoretical and empirical framework for the subsequent empirical investigation of AI use at Africa University.

2.1 Theoretical Framework

2.1.1 Relevant Theories and Models

Numerous theories and models have been suggested for explaining the processes through which AI technologies can be incorporated into learning settings, enhancing learning processes and outcomes. Theories of the following frameworks are especially applicable to the understanding of AI's role in education:

1. Constructivist Learning Theory:

Constructivist learning theory, strongly identified with the works of Jean Piaget and Lev Vygotsky, contends that individuals constructively build their knowledge and understanding of the world by reflecting on experiences. Artificial intelligence-based technologies, specifically Intelligent Tutoring Systems (ITS), complement constructivist learning by shaping interactive and adaptive learning environments that reply to the input of students and encourage active participation (Jonassen, 2000). By providing individualized feedback and scaffolded support, artificial intelligence technologies enhance the constructivist theory that knowledge is not transmitted but instead created by learners through experiential interaction and activity.

2. Cognitive Load Theory:

Cognitive load theory, advanced by John Sweller, argues that optimal learning occurs when instructional design minimizes superfluous cognitive load (Sweller, 1988). Artificial intelligence technology helps manage cognitive load by presenting appropriately customized content that matches the learner's pre-existing knowledge and learning pace. By breaking complex tasks into component parts and providing timely support, AI-aided learning environments can reduce extraneous load and thus allow learners to focus their cognitive capacity on schema acquisition and automation processes (Paas et al., 2003).

3. Bloom's Taxonomy:

Bloom's Taxonomy divides educational objectives into cognitive, affective, and psychomotor domains, with the cognitive domain encompassing levels from remembering and understanding through applying, analyzing, evaluating, and creating (Anderson et al., 2001). AI has the potential to help students progress through these levels by providing complex problem activities with immediate feedback, enabling higher-order thinking skills to be developed. AI applications can tailor content presentation and testing to aim at particular cognitive levels, allowing instructors to create learning experiences that systematically build more complex cognitive skills.

4. Zone of Proximal Development (ZPD):

Vygotsky's Zone of Proximal Development (ZPD) defines the set of activities that a given learner can perform with support but cannot do alone. AI programs can act as the "more knowledgeable other," offering scaffolding as needed to maintain learners within their ZPD (Vygotsky, 1978). By continually evaluating and adapting, AI programs can identify each student's current level and offer suitably challenging material and support, with progressively less support as proficiency is acquired (Luckin et al., 2016).

5. Self-Regulated Learning (SRL):

Self-regulated learning theory describes the ways in which students actively manage their learning processes, monitoring themselves, reflecting on outcomes, and adjusting strategies to optimize learning (Zimmerman, 2002). All offers tools that support self-regulation by allowing students to track learning, set goals, and receive feedback regarding performance. All-driven dashboards and analytics can offer valuable information regarding learning behaviors and accomplishments, resulting in greater self-awareness and regulation for students (Roll & Winne, 2015).

6. Connectivism:

Connectivism, as developed by George Siemens, addresses learning in the information age with the belief that knowledge is in distributed networks and learning is an ability to construct and navigate these networks (Siemens, 2005). Connectivist learning is facilitated by AI tools by allowing learners to engage with massive networks of

information, peers, and experts. AI can help learners in discovering and connecting with relevant resources, which makes them more capable of learning from diverse sources.

7. Intelligent Tutoring Systems (ITS) Models:

Intelligent tutoring systems are designed to provide personalized instruction and feedback to students. Most ITS models incorporate three main components: the domain model (representing knowledge on the subject), the student model (tracking the student's understanding and progress), and the pedagogical model (driving instruction and feedback). Programs like ALEKS for mathematics and AutoTutor for science leverage AI technologies to adapt in real-time to students' learning needs (VanLehn, 2011).

8. Social Learning Theory:

Albert Bandura's social learning theory emphasizes observation, imitation, and modeling as crucial in learning (Bandura, 1977). Artificial intelligence can enable an expansion of social learning through the creation of environments that support collaborative learning, knowledge dissemination, and constructive criticism. These technologies have the potential to augment peer-to-peer and group communication, thereby supporting the social aspect of the learning process (Dillenbourg, 1999).

These theories and models provide a strong foundation for examining the promise and challenge of using AI tools in learning contexts. They outline how AI can personalize learning, manage cognitive load, facilitate higher-order thinking, scaffold within the ZPD, promote self-regulation, facilitate connectivist learning, provide intelligent tutoring, and extend social learning interactions. This current research examines these numerous dimensions of AI's impact on education at Africa University.

2.2 Relevance of the Theoretical Framework to the Study

The above theoretical framework sets a comprehensive foundation for understanding the implications of artificial intelligence tools on learning and academic integrity among students at Africa University. Each theory offers unique insights into the manner in which AI can influence educational processes and outcomes, thus informing the research questions and methodological framework of this study.

1. Constructivist Learning Theory:

Constructivist learning theory's emphasis on active engagement and experiential learning is highly relevant to envisioning how AI-based tools may shape education. The research examines how ITS and adaptive AI software at Africa University create interactive learning environments in which students engage with content to construct knowledge and receive immediate feedback. It investigates the extent to which these tools employ constructivist principles to encourage active, deeper learning in students.

2. Cognitive Load Theory:

Cognitive load theory provides valuable information on how AI tools can eliminate extraneous cognitive load, therefore enabling students to concentrate on fundamental learning tasks. This study examines the potential of AI tools implemented at Africa University to minimize extraneous cognitive load and enhance the capacity of students to process and retain information effectively. The discussion examines if the support from AI enables students to allocate more cognitive capacity to comprehending intricate concepts as opposed to procedural specifics.

3. Bloom's Taxonomy:

Bloom's taxonomy offers a model for investigating the possible function of AI tools in enhancing higher-order thinking capacities. The research explores the role of AI tools at Africa University in facilitating students' movement through progressively challenging intellectual tasks, ranging from lower levels of knowledge assimilation to higher levels of analysis, evaluation, and creation. The research evaluates the capacity of AI tools in supporting richer learning that goes beyond memorization.

4. Zone of Proximal Development (ZPD):

Vygotsky's notion of ZPD is at the core of realizing how AI can be used as a virtual tutor to offer personalized assistance in students' zones of proximal development. The current study is interested in the degree to which AI tools at Africa University offer effective personalized assistance in enabling students to close knowledge gaps and move towards independent mastery. The research explores if AI scaffolding changes properly in response to students' changing abilities.

5. Self-Regulated Learning (SRL):

SRL theory informs this research question on how AI tools can enable students to manage their own learning processes. The research explores how AI tools can enhance Africa University students' abilities to monitor progress, receive personalized feedback, and set goals, perhaps developing greater self-regulation and autonomy. The research looks at whether AI tools promote metacognitive awareness and strategic approaches to learning.

6. Connectivism:

Connectivism's emphasis on learning as the forming of connections between sources of information is harmonious with the networked landscape of AI tools. The research looks at how AI tools in Africa University create a connectivist learning space, which enables learners to navigate through diverse sources of information and synthesize knowledge effectively. The research considers whether AI-supported learning processes equip learners with the ability to manage knowledge in a networked world.

7. Intelligent Tutoring Systems (ITS) Models:

ITS models inform the research study's investigation of AI-driven personalized learning experiences. The research evaluates the utilization of ITS principles in facilitating the enhancement of students' learning outcomes at Africa University through personalized learning experiences. The study considers the utilization of domain, student, and pedagogical models in AI systems used by students.

8. Social Learning Theory:

Social learning theory provides a framework for examining how AI-supported collaborative tools can influence learning experiences. This research explores how AI tools facilitate social learning at Africa University, enabling students to learn from one another, share knowledge effectively, and collaborate. The study takes into account whether AI enhances or diminishes the social nature of learning.

Relevance to Research Objectives and Questions:

The research objectives and questions directly derive from these theoretical frameworks, examining how AI tools influence learning processes, problem-solving capabilities, academic integrity, and equity in access to technology. For example:

- The exploration of AI tool usage patterns is informed by Constructivist
 Learning Theory and ITS Models, examining how students interact with these
 tools within learning processes.
- 2. **Investigation of impacts on learning processes** employs Cognitive Load Theory and Bloom's Taxonomy to discuss how AI tools reduce cognitive burden and foster higher-order thinking.
- 3. **Exploring academic integrity issues** examines how AI offers opportunities for plagiarism, drawing on Social Learning Theory and SRL principles.
- 4. **Identifying inequities in access and usage** incorporates Connectivism principles regarding equal opportunity to access varied sources.
- Examining institutional guidelines and policies draws on ZPD and ITS
 models to consider how AI tools might be structured to create ethical and
 effective learning environments.
- 6. **Analyzing impacts on academic performance** considers how AI tool usage affects assessment reliability and actual student competencies.

By connecting the present study to these theoretical frameworks, a comprehensive and nuanced understanding of the multifaceted impacts of AI tools on education at Africa University can be achieved.

2.3 Review of Empirical Studies

2.3.1 Evolution of AI in Education

The evolution of artificial intelligence in the field of education has been marked by significant developments that have transformed pedagogy. This section discusses the sequential development of AI applications in the field of education and their impact on the learning process.

Early Developments:

The development of AI in education began with intelligent tutoring systems programmed to replicate one-to-one teaching between students and teachers. Initial systems were designed to provide personalized teaching and feedback similar to human tutors working through issues with students. SCHOLAR, developed in the 1970s, was one of the first applications of artificial intelligence in education, employing natural language processing to teach geography (Carbonell, 1970). Yet most early systems were limited by a paucity of computational resources and training data.

Rise of Intelligent Tutoring Systems:

During the 1980s and 1990s, Intelligent Tutoring Systems of a more sophisticated nature were created. Cognitive Tutors, based on Anderson's ACT theory, were created to identify and predict student behavior in learning activities (Anderson et al., 1995). They provided step-by-step guidance and feedback, particularly for the teaching of mathematics and science. But they were often domain-specific and quite rigid, so their application was limited to broader educational environments.

Integration of Adaptive Learning Technologies:

The 2000s witnessed the introduction of adaptive learning technologies within conventional educational institutions. Technologies like Knewton and ALEKS used machine learning algorithms to analyze student data and provide personalized content (Oxman & Wong, 2014). The technologies enabled personalized learning experiences that adapted according to the performance of individual learners, thereby enhancing the scalability and accessibility of AI implementation within eLearning systems.

Current Applications and Advancements:

Now, AI technologies in education range from adaptive learning to administrative assistance. Artificial intelligence is used by platforms such as Coursera and EdX to study patterns of learning and offer customized advice and adaptive testing based on the level of individual expertise (Kizilcec et al., 2017). AI has also been integrated into automated graders, virtual teaching assistants, and smart content creation tools.

Natural language processing algorithms have made possible the development of interactive content like quizzes and simulations that improve engagement and effectiveness of educational content. Artificial intelligence also facilitates collaborative learning spaces by pairing students with skills and learning styles that are complementary (Holstein et al., 2020).

Future Trends and Innovations:

Some of the recent developments in education artificial intelligence involve AI tutors and intelligent textbooks that aim to deliver interactive, immersive, and engaging learning experiences (Holmes et al., 2019). AI is also being used more in special education to offer individualized assistance to students with varying learning requirements. AI-powered tools can detect early indicators of learning problems and enable timely interventions.

The combination of AI with other technologies such as virtual reality (VR) and augmented reality (AR) has the potential to create even more engaging and useful learning experiences, simulating real-world contexts in which knowledge can be applied and 21st-century competencies acquired (Radianti et al., 2020).

2.3.2 Challenges of AI Tools in Education

While artificial intelligence tools offer a range of advantages in learning settings, they also present significant challenges that must be addressed in order to realize their full potential. These challenges include technical, ethical, and pedagogical dimensions.

1. Over-Reliance on AI Tools:

Among the significant issues is that, although useful, the use of AI tools can lead to an overdependence that discourages the cultivation of critical thinking and problem-solving capabilities. It has been found that students who over-rely on AI tools can form superficial knowledge rather than engaging deeply with the material (Baker, 2016). Overuse can lead to a decline in independent analytical skills since students are likely to be given AI-generated responses instead of cultivating their own reasoning capabilities.

2. Academic Integrity Concerns:

Artificial intelligence tools can enable academic misconduct in the form of plagiarism and cheating. Empirical studies have confirmed that students are able to utilize AI-generated content to accomplish academic tasks without acknowledging the sources (Eaton, 2020; Lancaster, 2020). The actions elicit very high moral concern with respect to scholarly authenticity and point to the necessity for assertive plagiarism detection activities, as well as explicit guidelines by institutions concerning AI utilization within scholarly practice.

3. Equity and Access Issues:

Inequalities in access to artificial intelligence tools can exacerbate existing educational disparities. Research shows that students from lower socioeconomic backgrounds often have limited access to cutting-edge technological tools, thus widening the gap in achievement between disadvantaged and advantaged groups (Reich & Ito, 2017). The digital divide creates asymmetrical opportunities for AI-augmented learning experiences that could serve to entrench systemic educational disadvantages.

4. Data Privacy and Security:

AI learning tools have the propensity to accumulate large volumes of personal data, and this raises serious privacy and security issues. Researchers have outlined the risks of keeping sensitive student data in AI systems, such as the possibilities of data breaches along with information misuse (Regan & Bailey, 2020). Strong data protection measures are at the core of upholding student privacy in AI-supported learning environments.

5. Algorithmic Bias:

If not well designed and under constant scrutiny, artificial intelligence systems have the ability to replicate and enhance prevailing biases. It has been established through research that bias in AI algorithms can lead to disparate treatment of students according to attributes such as race, gender, and socioeconomic status (Holstein et al., 2019). Bias can have discriminatory effects on the learning experience and opportunities provided to impacted student groups.

6. Pedagogical Challenges:

The integration of artificial intelligence technologies into the current curriculum designs needs comprehensive changes in instruction methods and schooling philosophies. Researchers demonstrate that teaching personnel are generally not adequately prepared and equipped, which reduces their capacity to effectively integrate AI tools into instructional methods (Zawacki-Richter et al., 2019). The absence of adequate preparation hinders effective use of AI tools and restricts their potential beneficial influence on academic achievement.

7. Technical Limitations:

As much as they are sophisticated, artificial intelligence tools are not infallible and may produce incorrect or misleading information. Empirical studies have reported cases where AI systems fail to interpret subtle language and contextual nuances appropriately, resulting in misleading output or feedback (Kochmar & Shutova, 2020). These technological limitations are a concern regarding the effectiveness and reliability of learning experiences facilitated through AI.

8. Ethical Implications:

The ethical issues involved in the use of artificial intelligence in educational institutions go beyond questions of academic integrity to more general concerns with autonomy, surveillance, and control. Research ethics have considered ethical issues in the use of AI to surveil student behavior and performance, with concerns regarding the potential invasion of student privacy and autonomy (Prinsloe & Slade, 2018). These ethical issues demand close consideration as AI becomes increasingly integrated into educational institutions.

While they have the potential to revolutionize education, AI tools also present a complex array of challenges that must be negotiated. Overreliance, academic integrity, equity, data privacy, algorithmic bias, pedagogical integration, technical limitations, and ethical concerns must be addressed in order to create a fair, effective, and inclusive AI-supported learning environment.

2.3.3 Ethical Considerations

The use of artificial intelligence tools in the education sector raises fundamental ethical issues that need careful analysis. The ethical dimensions of AI uses in education have

been examined through comprehensive theoretical and empirical studies, covering areas including data privacy, bias in algorithms, autonomy of learners, and broader societal implications.

1. Data Privacy and Security:

One of the key ethical issues regarding AI learning technologies relates to the safeguarding of student data. The majority of AI systems rely on the gathering of personal and sensitive data to personalize learning experiences. Scholars have underscored the need to put in place effective data protection policies to avoid unauthorized access and exploitation of student data (Regan & Jesse, 2019). Current research promotes the implementation of transparent data management practices and adherence to data protection laws to protect student privacy, while simultaneously facilitating the advantages associated with personalized learning.

2. Algorithmic Bias and Fairness:

Literature has determined that artificial intelligence technologies have the ability to affirm and strengthen current prejudices based on race, gender, and other attributes, which could produce inequitable educational results (Baker & Hawn, 2021). Such a situation has serious ethical implications regarding justice and equity in AI-supported educational practices. Fairness and inclusiveness need to be at the forefront when developing and implementing AI technologies. Minimizing algorithmic bias involves constant checking and tweaking to make sure artificial intelligence systems do not perpetuate stereotypes or biased behavior against any student group.

3. Autonomy and Student Agency:

The evolution of AI technology in learning has led to questions about whether AI has the potential to subvert the autonomy of learners through over-guidance of learning processes and decisions. Research has highlighted the necessity for the design of AI solutions that have the capability to enhance student agency and not diminish it, so that learners can maintain control of their learning processes (Tsai et al., 2020). AI must only be employed to offer support and not determine learning processes if student autonomy is to be enhanced and maintained.

4. Surveillance and Consent:

Student monitoring and tracking of activity by means of AI tools prompt worries concerning inappropriately invasive surveillance techniques. Research has scrutinized ethical boundaries between edifying monitoring benefits and intrusions upon student privacy (Prinsloo & Slade, 2017). Surveillance practice indicates even where practice has educational merit as justification, there is the requirement for students' informed consent as well as the disclosure of intent.

5. Impact on Teacher Roles and Responsibilities:

Another significant ethical consideration involves AI's impact on teacher roles and responsibilities. Research has investigated how AI tools might fundamentally alter teaching practices by reducing certain tasks while intensifying others (Selwyn, 2019). This shift raises ethical questions about professional development and adequate support: whether teachers will adapt successfully to these changes or experience deskilling and devaluation of their expertise. Studies emphasize the importance of empowering teachers through meaningful integration of AI while preserving professional autonomy.

6. Transparency and Accountability:

Scholarly research has highlighted the importance of transparency and accountability in AI educational systems' operational mechanisms and decision-making processes. AI systems must provide transparency to educators and learners about the reasons for their decisions, as supported by a plethora of studies (Pardo et al., 2019). Transparency promotes accountability for the outputs of these technologies among both developers and users. Explaining the operation of AI and its decision-making is critical to building users' trust.

7. Long-Term Societal Implications:

Academic studies have also focused on the broader societal effects of artificial intelligence in education. Studies have explored the prospective long-term effects of AI on job prospects, social life, and economic disparity (Selwyn, 2020). These extensive consequences are of interest to education policy-making. Educating students for a future that is characterized by the growing ubiquity of AI involves comprehending and addressing the prospective societal effects of AI adoption.

These ethical issues—privacy, algorithmic bias, student agency, surveillance, teacher roles, transparency, and long-term societal implications—must be addressed to ensure responsible and equitable use of AI in education. This requires thoughtful strategies that create an educational context that is both equitable and inclusive while leveraging the capabilities of AI technologies.

2.4 Summary

This comprehensive review of literature has yielded significant insights into the theoretical frameworks, benefits, challenges, and ethical issues concerning the implementation of AI tools in education. The key findings from this review can be summarized as follows:

Theoretical Framework:

The application of artificial intelligence within learning environments has theoretical foundations including constructivist theory of learning, cognitive load theory, Bloom's taxonomy, Zone of Proximal Development, self-regulation learning, connectivism, and Intelligent Tutoring Systems models. These theoretical paradigms identify how AI customizes learning processes, manages cognitive load, advances higher-order cognition skills, provides appropriate scaffolding, promotes self-regulation, facilitates networked learning, and facilitates social collaboration. These theoretical foundations offer a solid foundation for understanding how AI technologies are able to enhance learning experiences.

Benefits of AI Tools in Education:

Empirical studies have shown numerous benefits that accrue from the use of AI tools in learning settings. AI-powered adaptive learning systems have the capability to create learning content that is specifically tailored to a particular student, significantly enhancing student-centered learning experience and even resulting in improved learning outcomes. AI technologies engage learners with interactive, interesting, and immersive models, and provide immediate, personalized feedback appropriate for various categories of learners. Data analytics also automates processes and provides applicable insights using other AI tools.

Challenges of AI Tools in Education:

Although they are beneficial, there are challenges that AI tools present. Relying too heavily on them can undermine thinking and problem-solving capabilities. The capacity to enable plagiarism and cheating poses a threat to academic integrity. Inequalities in access and exposure to the technologies of AI could amplify educational disadvantage unless more attention is given to their management. Data security and privacy concerns are crucial issues, as well as algorithmic bias that can give rise to inequity for particular groups of students. Moreover, the integration of AI in curriculum requires acute changes in instructional approaches. Technical limitations and ethical issues related to surveillance and autonomy complicate the integration of AI technologies into education.

Ethical Considerations:

There are a number of ethical concerns that need to be addressed for AI to be used responsibly in education. These involve ensuring data privacy and security to safeguard students' personal data, debiasing algorithms for fairness and equity, ensuring student autonomy and agency when using AI tools, seeking informed consent for AI usage, especially for monitoring, and addressing the implications of AI redefining teaching roles and responsibilities. The design of AI systems must be transparent and accountable to foster trust. Furthermore, it is necessary to thoughtfully consider the potential long-term effects on society from the incorporation of AI, such as potential long-term alteration of employment trends, societal structures, and economic equity.

Conclusion:

The literature review presents AI technologies as having tremendous potential to transform education, with a caveat that there are significant challenges and ethical concerns that should be addressed in order to ensure that these technologies contribute to enabling roles in the learning outcomes as well as align with standards of fairness, equity, and ethical application. The literature review lays the groundwork for the empirical studies in the ensuing chapters and the research into AI's influence on students' academic experience and academic integrity at Africa University.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter presents the research method used to investigate the effect of artificial intelligence tools on the learning experience and academic integrity of students at Africa University. The methodological design was developed to provide in-depth understanding of this new phenomenon through a systematic gathering and examination of data from students representing various academic disciplines and study levels.

The chapter then seeks to explain the research design, rationaleizing the mixed-methods strategy that employed quantitative and qualitative data collection methods. The decision was made to capture both the statistical trends of AI tool usage and the in-depth experiences, perceptions, and ethical considerations of the students utilizing such technologies (Creswell & Creswell, 2018).

The population and sampling section describes the target population and outlines the methods used in selecting samples for representation across the varying student populations in Africa University. The data collection instruments section elaborates on the survey questionnaire and interview guide, including how they were developed and validated. The pilot study documents the initial piloting conducted in order to establish the suitability of these instruments, as well as their reliability and validity.

The process of data collection outlines the research approach followed during the conduct of fieldwork, making specific reference to logistics and ethical standards. Data management and analysis outlines the steps followed to manage, code, analyze, and interpret quantitative and qualitative data. The last section under ethical considerations identifies the steps followed to honor the rights of the participants, maintain confidentiality, and uphold data protection during the study.

The methodological framework was created to generate credible and reliable results that would inform the development of evidence-based recommendations for the integration of AI tools into the academic structure of Africa University.

3.1 The Research Design

3.1.1 Research Approach

This research used a mixed-methods framework that gave equal weight to quantitative and qualitative methodology in developing an effective insight into the ways in which AI tools have impacted learning experience and academic integrity of Africa University students. The pragmatic philosophy underpinning this approach accepted that the use of mixed methods would provide complementary results and reduce the limitations associated with the use of either methodology in isolation (Johnson & Onwuegbuzie, 2004).

Justification for the Mixed-Methods Approach:

The complexity of the research issue required the employment of a mixed-methods approach. Quantitative approaches provided the possibility to gather numerical data from a large number of students, making statistical examination of patterns, relationships, and trends in AI tool use possible. Qualitative approaches, however, enabled detailed investigation of students' experiences, perceptions, and ethical issues, offering contextual insight that numbers alone would not be able to provide (Teddlie & Tashakkori, 2009).

Creswell and Plano Clark (2018) stress the value of mixed-methods research to the investigation of intricate educational phenomena that are enhanced by diverse perspectives. In doing so, it resonates with the recommendations of educational technology scholars such as Selwyn (2019) and Bond et al. (2021), who suggest the use of methodological pluralism in examining the influence of new technologies on educational practice.

Quantitative Research Component:

The quantitative aspect of the study entailed the use of a standardized survey questionnaire administered to a sample of African University students (n=104). The method was chosen due to its capacity to effectively collect standardized data that could be subjected to statistical analysis, thus enabling the determination of trends by demographic group and field of study (Fowler, 2014). The survey instrument was

framed to determine the frequency of AI tool use, tool preference, perceived advantages and limitations, and their effects on academic performance and integrity.

Qualitative Research Component:

The qualitative aspect involved semi-structured interviews (n=24) and focus group discussions (n=2) with students who were sampled purposively. These qualitative methods were employed because they had the potential to provide rich and context-specific narratives of students' use of AI tools (Brinkmann & Kvale, 2015). The interview guide was developed to delve deeper into the themes that emerged in the survey, such as students' rationales for using AI tools, approaches to incorporating them into learning habits, ethical concerns, and views on institutional support.

Integration of Components:

The research utilized a convergent parallel design to merge the quantitative and qualitative components (Creswell & Plano Clark, 2018). Both components' data were collected at the same time prior to being separately analyzed from each dataset. Afterwards, the results were compared, contrasted, and combined during the interpretation phase to form an organic comprehension of the research issue. The application of this integration plan enabled triangulation of results, in which consensus corroborated confidence in the validity of conclusions, and divergence identified complexities needing additional research (Fetters et al., 2013).

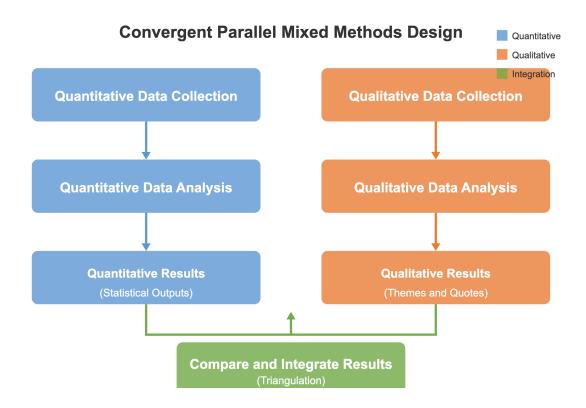


Figure 3.1: Convergent Parallel Mixed Methods Design

3.1.2 Research Type

The research utilized a mixed-methods design that was termed exploratory-descriptive, which draws on aspects of both exploratory and descriptive research types to examine systematically the effects of AI tools on the learning and academic integrity of students at Africa University. The application of this method was given consideration to the comparatively new level of AI tool integration in African university contexts and the lack of existing studies conducted in this particular environment (Zawacki-Richter et al., 2019).

Exploratory Dimension:

The exploratory aspect examined the "how" and "why" inquiries into the use of AI tools with the perspective of revealing the underlying reasons, experiences, and challenges of the students. Due to the fast-changing nature of AI technologies in learning contexts and the absence of accessible research in the African university settings, this exploratory nature was employed to identify patterns and data that are particular to Africa University's special learning environment.

The qualitative component served mainly an exploratory purpose, using focus groups and semi-structured interviews to investigate students' lived experiences in relation to AI tools. This methodological approach allowed for the determination of unforeseen themes and results not originally contemplated in the research design.

Descriptive Dimension:

The descriptive element was aimed at recording systematically the "what," "where," and "when" parameters of artificial intelligence tool usage among students at Africa University. The quantitative survey aspect served this descriptive role by enumerating the kinds of AI tools used, the frequency of their use, the uses they were put to, and the perceived effects across various fields of study and student populations.

The descriptive statistics presented in the paper defined the range and extent of AI tool use at Africa University, thereby furnishing a basis for comprehending the prevalence of such practices and highlighting notable variation within the student body.

3.2 Population and Sampling

3.2.1 Target Population

The study population included all the postgraduate and undergraduate students enrolled at Africa University in the academic year 2024-2025. Located in Mutare, Zimbabwe, Africa University is a pan-African university that recruits students from across the African continent, offering a broad spectrum of academic programs spread across five colleges. As of January 2025, the university had a total of approximately 3,200 enrolled students, representing over 24 countries across the African continent (Africa University Registry, 2024).

This population was selected due to several considerations:

1. As a leading institution in the region with emphasis on technological innovation and academic excellence, Africa University provided an ideal context for investigating AI tool adoption in African higher education.

- 2. The diverse student body offered opportunities to explore how demographic factors influenced AI tool usage patterns and impacts.
- 3. Preliminary observations had indicated significant AI tool usage among students, suggesting a fertile environment for research on this topic.

Demographic Characteristics:

The population to be studied revealed high demographic diversity, reflecting the pan-African nature of the institution. The age range varied from 18 to 45 years, with most undergraduate students between the ages of 18 and 25, while the postgraduate students tended to be older. The gender distribution among the university's population was approximately 53% male and 47% female, showing some variations across different fields of study (Africa University Registry, 2024).

Students were distributed across five colleges: Engineering and Applied Sciences (37%), Social Sciences, Theology, Humanities, and Education (22%), Health, Agriculture, and Natural Sciences (18%), Law (15%), and Business and Management Sciences (8%). This distribution across disciplines of study provided the potential to examine how use of AI tools varied by discipline of study.

Inclusion Criteria:

To ensure participants could provide relevant insights, the following inclusion criteria were established:

- Current enrollment status (as of January 2025)
- Both undergraduate (across all four years) and postgraduate students
- For interviews and focus groups: some experience with AI tools in academic work

3.2.2 Sampling Method

To ensure both representativeness and depth of insights, this study employed a combination of probability and non-probability sampling techniques for different components of the research.

Stratified Random Sampling for the Quantitative Component:

For the survey component, stratified random sampling was employed to ensure proportional representation across key demographic variables. As defined by Neuman (2014), stratified random sampling involves dividing the population into distinct subgroups (strata) and then randomly selecting participants from each stratum in proportion to its size in the overall population.

The stratification variables were:

- 1. Academic Discipline: Students were stratified by college affiliation to ensure representation across all five colleges.
- 2. Level of Study: Within each college, further stratification was applied by year of study.
- 3. Gender: Targets for male and female participation were set based on the existing gender distribution in each college.

The implementation involved obtaining enrollment lists from the university registry, organizing these lists by the stratification variables, and using random number generation to select participants from each stratum. This approach resulted in a survey sample that closely mirrored the demographic composition of the university population.

Purposive Sampling for the Qualitative Component:

For the interview and focus group components, purposive sampling was employed to select participants who could provide rich and relevant information about the research questions. The purposive sampling strategy incorporated several criteria:

- 1. Intensity of AI Tool Usage: Participants were selected to represent varying levels of AI tool engagement.
- 2. Disciplinary Diversity: Efforts were made to include students from all five colleges.

- 3. Academic Level Variation: Both undergraduate and postgraduate students were included.
- 4. Maximum Variation: Participants were selected to represent diverse perspectives and experiences.

This purposive approach enabled in-depth investigation of the nuanced ways in which students experienced and navigated AI tool usage in their academic work.

Sample Size:

The final achieved sample sizes were:

- Quantitative Component: 104 completed survey responses (out of 125 invitations distributed, representing an 83.2% response rate). This sample size provided adequate statistical power for key analyses as recommended by Krejcie and Morgan (1970) for a population of approximately 3,200 students.
- Qualitative Component: 24 individual interviews and two focus groups (8 participants each), for a total of 40 students participating in the qualitative component. This sample size aligned with recommendations from Guest et al. (2006), who found that thematic saturation in qualitative research typically occurs within 12-20 interviews for homogeneous groups.

The sampling strategy employed was systematic enough in providing adequate representation across all five colleges, wherein the breakdown among survey respondents by college was Engineering and Applied Sciences (36.5%), Social Sciences, Theology, Humanities, and Education (21.2%), Health, Agriculture, and Natural Sciences (17.3%), Law (15.4%), and Business and Management Sciences (9.6%). This was reflective of the standard enrollment ratios common in the institution, thereby enhancing the representativeness of emergent findings.

3.3 Data Collection Instruments

3.3.1 Surveys and Questionnaires

The survey questionnaire served as the primary instrument for collecting quantitative data on AI tool usage patterns, perceived impacts, and ethical considerations among

Africa University students. The instrument was developed through a systematic process informed by the research objectives, literature review, and preliminary consultations with students and faculty.

Questionnaire Development Process:

The development of the survey instrument followed the iterative process recommended by Artino et al. (2014) for creating effective educational research questionnaires:

- Literature Review: Existing instruments from prior studies on educational technology adoption and academic integrity were reviewed, including validated scales from Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) and McCabe et al.'s (2012) Academic Integrity Survey.
- 2. Expert Consultation: Draft items were reviewed by three faculty members with expertise in educational technology, assessment, and research methods to evaluate content validity and alignment with research objectives.
- 3. Cognitive Interviews: Following Dillman et al.'s (2014) recommendations, cognitive interviews were conducted with five students to assess item clarity, interpretation, and response processes.
- 4. Pilot Testing: The draft instrument was pilot tested with 20 students to evaluate reliability, validity, and practicality, with refinements based on pilot results.

Ouestionnaire Structure and Content:

The final questionnaire comprised 32 items organized into six sections:

- 1. Demographic Information (6 items):
 - Age, gender, academic discipline, year of study, nationality, and selfrated computer literacy

 These variables enabled analysis of how AI tool usage patterns varied across different student subgroups

2. AI Tool Usage Patterns (8 items):

- o Types of AI tools used (multiple response)
- Duration and frequency of AI tool usage
- o Primary academic tasks for which AI tools were used
- Primary motivations for AI tool usage

3. Perceived Benefits and Challenges (6 items):

- 5-point Likert scale items assessing agreement with statements about potential benefits (e.g., personalized learning, time savings) and challenges (e.g., over-reliance, information reliability)
- 4. Impact on Academic Performance (5 items):
 - o Perceived impact on grades and understanding of course material
 - o Change in study habits since using AI tools
- 5. Academic Integrity Considerations (5 items):
 - o Awareness of university policies regarding AI tool usage
 - o Frequency of submitting AI-generated content without modification
 - Use of AI detection evasion techniques
 - o Perception of AI tools' relationship to academic dishonesty
- 6. Future Perspectives and Recommendations (2 items):
 - o Open-ended questions about desired institutional policies and support

Administration Method:

The survey was administered electronically using Google Forms during a two-week period in January 2025. This platform was selected for its accessibility, user-friendly interface, and compatibility with mobile devices. Distribution employed multiple channels to maximize response rates:

- 1. WhatsApp Groups: The survey link was distributed through college-specific and course-specific WhatsApp groups.
- 2. Email Invitations: Personalized email invitations were sent to randomly selected students from each stratum.
- 3. Word of Mouth: Research assistants recruited from each college promoted the survey among their peers.
- 4. Direct Recruitment: Research team members set up stations in high-traffic campus areas for two days during the survey period.

This multi-channel distribution approach helped achieve the high response rate of 83.2%, substantially exceeding the typical response rates for online surveys in educational research (Nulty, 2008).

3.3.2 Interviews

Semi-structured interviews served as the primary qualitative data collection method, enabling in-depth exploration of students' experiences, perceptions, and decision-making processes regarding AI tool usage. This approach was selected for its ability to elicit rich, detailed accounts while maintaining sufficient structure to ensure coverage of key topics relevant to the research questions (Brinkmann & Kvale, 2015).

Interview Protocol Development:

The interview protocol was developed through a systematic process:

1. Research Question Alignment: Each section of the protocol was explicitly linked to specific research questions.

- 2. Literature Integration: The protocol incorporated constructs and themes from relevant theoretical frameworks.
- 3. Survey Result Integration: Preliminary analysis of survey responses identified areas requiring deeper exploration in interviews.
- 4. Piloting and Refinement: The draft protocol was piloted with five students to assess clarity, flow, and effectiveness.

Interview Protocol Structure:

The final interview protocol consisted of six sections with 2-4 primary questions per section, each accompanied by potential probing questions:

- 1. Introduction and Background (2 primary questions)
- 2. AI Tool Usage Patterns (4 primary questions)
- 3. Perceived Benefits and Impact on Learning (3 primary questions)
- 4. Challenges and Concerns (3 primary questions)
- 5. Academic Integrity Considerations (4 primary questions)
- 6. Recommendations and Future Perspectives (2 primary questions)

The semi-structured format provided a consistent framework for all interviews while allowing flexibility to pursue relevant tangents and probe more deeply into areas of particular significance for individual participants.

Interview Implementation:

Interviews were conducted over a three-week period in January-February 2025, following initial analysis of survey data. Each interview lasted 45-60 minutes and was conducted in private spaces on campus. With participant consent, all interviews were audio-recorded.

The interview process incorporated several techniques to enhance data quality:

- 1. Rapport Building: Each interview began with informal conversation to establish rapport.
- 2. Probing Techniques: Various probing techniques were employed to encourage detailed responses.
- 3. Active Listening: The interviewer practiced active listening through nonverbal cues, paraphrasing, and summarizing.
- 4. Reflexive Journaling: After each interview, the interviewer documented reflections on the process and emerging themes.

This systematic approach to interview implementation yielded rich, detailed accounts of students' experiences with AI tools, providing valuable contextual depth to complement the quantitative survey data.

3.4 Pilot Study

A pilot study was conducted in December 2024 to test and refine the data collection instruments, procedures, and analytical approaches prior to full implementation. This preliminary investigation served multiple methodological purposes, including assessing instrument validity and reliability, identifying potential procedural challenges, and refining the overall research design (van Teijlingen & Hundley, 2002).

Objectives of the Pilot Study:

- 1. Instrument Validation: To assess the clarity, relevance, and comprehensiveness of the survey questionnaire and interview protocol.
- Procedural Optimization: To evaluate the effectiveness of data collection procedures.
- 3. Time Requirement Estimation: To determine the realistic time demands for participation.
- 4. Preliminary Analysis Testing: To practice analytical techniques on a small dataset.

Pilot Study Design and Participants:

The pilot study employed a scaled-down version of the main study design:

- 1. Quantitative Component: The draft survey questionnaire was administered to 20 students selected to represent diversity in academic discipline, year of study, and gender.
- 2. Qualitative Component: Five semi-structured interviews were conducted with students who had completed the pilot survey.

Pilot Study Results and Adjustments:

- 1. Survey Questionnaire Refinements:
 - Three items were identified as ambiguous and subsequently reworded for clarity.
 - Response options for two items were expanded to better capture the range of student experiences.
 - Survey length was deemed appropriate, with most participants completing it in 12-15 minutes.

2. Interview Protocol Adjustments:

- Additional probing questions were added to better explore critical thinking concerns and ethical decision-making processes.
- o The sequence of questions was modified to improve logical flow.
- o More explicit transitions between topic areas were incorporated.

3. Procedural Improvements:

- WhatsApp distribution was identified as more effective than email for reaching students.
- Technical issues with survey form access on certain mobile devices were identified and resolved.

 Interview scheduling processes were streamlined based on pilot experiences.

4. Analytical Approach Refinements:

- Preliminary coding of pilot interviews informed the development of an initial codebook.
- Statistical analysis of pilot survey data identified potential relationships between variables that warranted focused attention.

These adjustments, informed by practical experience and participant feedback during the pilot phase, enhanced the methodological rigor of the main study.

3.5 Data Collection Procedure

The data collection process followed a systematic, phased approach designed to ensure comprehensive coverage of the research questions while maintaining ethical research standards. The process was implemented over a two-month period from January to February 2025, with careful attention to coordination between quantitative and qualitative components.

Preparatory Phase (December 2024):

- 1. Ethical Approval: Comprehensive ethical approval was obtained from the Africa University Research Ethics Committee (AUREC).
- 2. Research Team Training: The research team underwent training in survey administration, participant recruitment, and ethical research conduct.
- 3. Instrument Finalization: Final revisions were made to the survey questionnaire and interview protocol based on pilot study feedback.
- 4. Sampling Framework Development: A comprehensive sampling framework was established to facilitate stratified random sampling.

Quantitative Data Collection (January 2025):

- 1. Survey Distribution: The electronic survey was distributed through multiple channels over a two-week period from January 13-27, 2025.
- 2. Response Rate Monitoring: Response rates were monitored daily to assess progress toward sampling targets for each stratum.
- 3. Data Verification and Storage: Preliminary data verification was conducted to identify any anomalies, with complete responses stored in a secure, password-protected system.

Qualitative Data Collection (January-February 2025):

- 1. Participant Selection: Following preliminary analysis of survey data, interview participants were purposively selected to represent diverse experiences with AI tools across academic disciplines.
- 2. Interview Scheduling and Preparation: Selected participants were contacted via email and WhatsApp to schedule interviews.
- 3. Interview Implementation: Twenty-four individual interviews were conducted, each lasting 45-60 minutes, with appropriate consent procedures and audio recording.
- 4. Focus Group Discussions: Two focus group discussions were conducted with eight participants each, exploring collective perspectives on AI tool usage.
- Post-Interview Processing: Within 24 hours of each interview and focus
 group, audio recordings were transferred to secure storage and the researcher
 completed detailed field notes.

Research Timeline:

Data Collection and Analysis Timeline



Note: Timeline shows approximate duration of research activities; some activities occurred simultaneously

Figure 3.2: Data Collection and Analysis Timeline

Challenges Encountered and Mitigation Strategies:

Throughout the data collection process, several challenges were encountered and addressed:

- Survey Response Rate Variations: Lower initial response rates were observed among Law and Business students, addressed through targeted recruitment efforts.
- Technical Accessibility Issues: Some students experienced difficulties accessing the electronic survey due to connectivity issues, addressed by establishing computer stations on campus.
- 3. Interview Scheduling Conflicts: Coordinating interview schedules with students' academic commitments proved challenging, mitigated by offering extended interview hours and flexibility.
- 4. Language and Communication: Some non-native English speakers occasionally struggled to articulate nuanced perspectives, addressed by allowing additional time and rephrasing questions when necessary.

These adaptive strategies reflected the commitment to methodological rigor and participant-centered research practice, ensuring comprehensive data collection despite practical challenges.

3.6 Data Analysis

3.6.1 Data Analysis Techniques

The study employed a comprehensive analytical approach integrating quantitative and qualitative techniques, designed to address the multifaceted research questions regarding AI tool impacts on student learning and academic integrity.

Quantitative Data Analysis:

The analysis of survey data followed a systematic progression from descriptive to inferential statistics, using SPSS (Version 26.0):

1. Data Preparation:

- Data cleaning to identify and address missing values, outliers, and inconsistent responses
- Variable coding and recoding to ensure appropriate measurement levels
- o Computation of composite variables where appropriate

2. Descriptive Statistics:

- Frequency distributions and percentages for categorical variables
- o Measures of central tendency and dispersion for continuous variables
- Cross-tabulations to examine relationships between categorical variables
- Graphical representations to visualize key patterns

3. Reliability Testing:

o Internal consistency reliability of multi-item scales was assessed using Cronbach's alpha, with a threshold of $\alpha \ge 0.70$ considered acceptable. Analysis yielded a Cronbach's alpha of 0.87 for the full survey measure.

4. Inferential Statistics:

- Chi-square tests of independence to examine relationships between categorical variables
- o Independent samples t-tests to compare means between two groups
- o One-way ANOVA to compare means across multiple groups
- Correlation analysis to assess relationships between continuous variables
- Multiple regression to identify predictors of key outcome variables
- o Logistic regression to identify predictors of binary outcomes

5. Factor Analysis:

 Exploratory factor analysis to identify underlying dimensions of AI tool usage purposes and ethical attitudes

Qualitative Data Analysis:

The analysis of interview and focus group data employed systematic qualitative techniques:

- 1. Thematic Analysis: Following Braun and Clarke's (2006) six-phase approach:
 - Familiarization: Complete immersion in the data
 - o Initial Coding: Systematic coding of the entire dataset
 - Theme Development: Collating codes into potential themes
 - o Theme Review: Checking themes against coded extracts

- o Theme Definition: Refining and naming themes
- Report Production: Selection of compelling extract examples

2. Coding Process:

- o Initial coding was conducted manually using printed transcripts
- Subsequent coding and theme development utilized NVivo software (Version 14)
- A codebook was developed iteratively, beginning with codes derived from research questions and expanded to incorporate emergent codes

3. Inter-coder Reliability:

- o A second coder independently coded 25% of the transcripts
- Cohen's kappa coefficient was calculated (k = 0.84), indicating strong reliability
- Discrepancies were discussed and resolved through collaborative review

4. Visual Mapping:

- o Thematic maps illustrating hierarchical relationships between themes
- Concept networks identifying connections between different dimensions
- Comparative matrices examining thematic variations across disciplines

Integration of Quantitative and Qualitative Analysis:

Following the parallel analysis of quantitative and qualitative data, a systematic integration process was implemented:

1. Triangulation Approach:

A convergent triangulation approach identified areas of convergence,
 complementarity, and divergence

2. Integration Methods:

- Triangulation Matrix: A structured matrix compared quantitative findings with corresponding qualitative themes
- Joint Displays: Visual joint displays combined statistical results with illustrative qualitative excerpts
- Narrative Weaving: Integrated narratives alternated between quantitative and qualitative findings
- Meta-inferences: Overarching conclusions synthesized insights from both methodological components

3. Discrepancy Analysis:

 Areas where quantitative and qualitative findings appeared to diverge were subjected to deeper analysis

This integrated analytical approach yielded comprehensive insights into the complex phenomenon of AI tool usage and its impacts on student learning and academic integrity at Africa University.

3.6.2 Data Organization

A systematic approach to data organization was implemented to facilitate efficient analysis and maintain methodological rigor:

Quantitative Data Organization:

1. Database Structure:

- o Raw data preserved in original form
- Cleaned and coded data saved in separate files with documentation of transformations

Derived variables and indices stored with clear definitions

2. Coding Framework:

- Codebook documenting all variables, their definitions, response options, and measurement levels
- Syntax files recording all data transformations and analysis commands
- Standardized missing data codes with documentation of handling procedures

3. Analytical Outputs:

- o Results files organized by research question and hypothesis
- o Standardized format for statistical tables
- o Graphical outputs saved in both raw and final formats

Qualitative Data Organization:

1. Transcript Management:

- Standardized file naming convention incorporating participant code, date, and interview type
- Master list linking transcript files to participant demographic characteristics
- Categorization by academic discipline to facilitate comparative analysis

2. Coding Structure:

- Primary codes aligned with major research questions and theoretical constructs
- Secondary codes capturing specific dimensions and variations

- o In vivo codes preserving participants' unique language
- o Process codes documenting actions, interactions, and changes
- o Attribute codes linking data to participant characteristics

3. Analytical Documentation:

- Analytical memos documenting emerging interpretations and methodological reflections
- Theme development matrices showing progression from codes to themes
- Visual maps illustrating relationships between themes and concepts
- o Audit trail documenting analytical decisions and rationales

Integrated Data Organization:

The organization of integrated analyses included:

1. Integration Framework:

- o Integration matrices organized by research question
- Joint display templates standardizing the presentation of integrated analyses
- o Documentation of integration procedures and decision rules

2. Meta-Data Documentation:

- Data source mapping showing connections between different data types
- o Temporal sequencing of data collection and analysis procedures
- Procedural notes documenting how findings from one method informed the other

This comprehensive data organization system enhanced methodological rigor by maintaining clear documentation, facilitating efficient analysis, and supporting transparent reporting of findings.

3.7 Ethical Considerations

3.7.1 Informed Consent

Obtaining informed consent from all participants was a foundational ethical principle guiding this research. The informed consent process was designed to ensure that participants fully understood the nature of the study, their role in it, and their rights as research participants.

Development of Informed Consent Materials:

The informed consent documents included all essential elements recommended by the Africa University Research Ethics Committee (AUREC) and international research ethics standards:

- Clear statement of the research purpose and significance
- Detailed description of participation requirements
- Explanation of potential risks, benefits, and discomforts
- Assurance of confidentiality and data security measures
- Statement of voluntary participation and right to withdraw
- Contact information for researchers and the institutional review board
- Explanation of how research results would be used

Special attention was paid to ensuring the accessibility of consent materials through plain language writing, clear formatting, and opportunities for questions and clarification.

Implementation of Informed Consent Process:

For the electronic survey component:

- A comprehensive consent statement appeared at the beginning of the survey
- Participants were required to indicate consent by checking a box before proceeding
- The option to download a copy of the consent information was provided

For qualitative components:

- Written consent forms were provided to participants in advance
- Verbal explanation of the consent document was provided before beginning
- Opportunity for questions was explicitly provided
- Separate consent was obtained for audio recording
- Two copies of the signed consent form were completed, with one retained by the participant
- Ongoing consent was reconfirmed verbally at key points

All consent documentation was carefully stored in secure locations separate from research data.

3.7.2 Confidentiality

Maintaining participant confidentiality was a paramount ethical consideration, particularly given the potentially sensitive nature of discussions about academic integrity and AI tool usage.

Data Anonymization Procedures:

- 1. Survey Data Anonymization:
 - No personally identifying information was collected within the survey itself
 - Demographic data was collected in categories broad enough to prevent identification

o IP addresses were not stored with survey responses

2. Interview and Focus Group Anonymization:

- o Participants were assigned numeric or alphanumeric codes
- A master identification key linking codes to identities was stored separately in encrypted format
- Transcription protocols included removal of all names, locations, and specific references

3. Reporting Anonymization:

- o Use of pseudonyms or general descriptors in reporting findings
- Presenting aggregate data rather than individual cases where appropriate
- Review of all qualitative excerpts prior to inclusion to ensure no identifying information remained

Secure Data Handling:

1. Physical Data Security:

- o Storage in locked filing cabinets within secured offices
- Access restricted to essential research personnel only
- Separation of consent forms from research data

2. Digital Data Security:

- o Password protection on all electronic files
- Encryption of files containing sensitive information
- o Secure cloud storage with institutional security protocols
- Regular backup to encrypted external drives

3. Access Controls:

- Only researchers directly involved in data collection and analysis had access to primary data
- o Research assistants signed confidentiality agreements
- Access to identifying information was limited to the principal investigator
- o Audit trails of data access were maintained

Confidentiality Limitations and Disclosure:

Certain inherent limitations to confidentiality were transparently addressed:

1. Focus Group Limitations:

- Participants were informed of the inherent limitations to confidentiality in group settings
- Group confidentiality agreements were established at the beginning of each session

2. Mandated Reporting Obligations:

- The informed consent process clearly outlined situations where confidentiality might need to be breached
- Legal obligations to report certain types of serious academic misconduct
- Duty of care if information suggested risk of harm

3.7.3 Ethical Approval

Prior to commencing data collection, comprehensive ethical approval was obtained from the Africa University Research Ethics Committee (AUREC). This formal review process ensured that the research design adhered to institutional ethical

standards and international guidelines for educational research involving human participants.

Ethical Approval Process:

The ethical approval process involved several stages:

1. Preparation of Ethical Application:

- o Research proposal with comprehensive methodology
- o All data collection instruments
- Informed consent forms
- o Data management plan
- o Risk assessment

2. Ethical Review Process:

- o Initial screening by the committee chair
- o Full committee review during the November 2024 meeting
- o Questions and clarifications requested
- o Revision and resubmission addressing committee feedback
- o Final review and approval in December 2024

3. Approval Documentation:

- Official approval certificate issued (AUREC)
- o Documentation of any specific conditions or requirements
- o Approval Date (6 November 2024)

Key Ethical Considerations Addressed:

The ethical approval process specifically addressed several key considerations:

1. Academic Integrity Sensitivity:

- Ensuring participants understood they would not face consequences for disclosing AI usage
- Maintaining strict confidentiality regarding potential academic integrity violations
- Using non-judgmental language in all research instruments

2. Digital Data Collection:

- o Data security protocols for online survey responses
- Digital recording and storage of interview data
- o Procedures for secure deletion of identifying information

3. Power Dynamics:

- Procedures to ensure voluntary participation without academic pressure
- Involvement of research assistants rather than faculty in direct recruitment
- o Measures to minimize social desirability bias in responses

4. Benefits and Reciprocity:

- Clear articulation of potential benefits to participants and the broader student community
- Commitment to share research findings with participants and institution
- Practical recommendations for institutional policies based on research findings

3.8 Summary

This chapter presents the methodology adopted in examining the effects of artificial intelligence tools on the learning experiences of students and academic integrity at Africa University. The research design, underpinned by pragmatic philosophical ideals, adopted a mixed-methods design that combined quantitative and qualitative data collection and analytical techniques to tackle the complex research questions.

The study targeted both postgraduate and undergraduate students from all the five colleges at Africa University, employing stratified random sampling for the quantitative component and purposive sampling for the qualitative element. This approach allowed for sufficient representation across the different academic disciplines, levels of study, and demographic characteristics, thus enhancing the comprehensiveness and validity of the findings.

Instruments for data collection were a 32-item electronic survey questionnaire that was completed by 104 students and a semi-structured interview guide that was administered to 24 purposively sampled participants, supplemented by two focus group discussions. These instruments were rigorously developed, piloted, and tested to ensure their effectiveness in gathering relevant data while maintaining high ethical standards.

The data collection process, conducted over a period of two months from January to February 2025, employed several recruitment channels to ensure representation from the targeted demographic groups despite challenges related to scheduling, technological access, and communication.

Data analysis included quantitative statistical analysis using SPSS that included descriptive statistics, chi-square tests, t-tests, ANOVA, and regression analysis, and qualitative thematic analysis using NVivo. This integration of analytical techniques adhered to a convergent triangulation approach that supported the validity and completeness of the findings through systematic comparison and synthesis of results from several methodological components.

Ethics were prioritized in the research process from the beginning, including extensive informed consent processes, confidentiality measures, and formal approval

from the Africa University Research Ethics Committee (AUREC). Particular caution was exercised in addressing possible ethics issues in terms of academic integrity, online data extraction, power imbalances, and ensuring mutual benefits for participants.

Several methodological limitations require acknowledgment. Cross-sectional design captured use of AI at a single time point, limiting the foundation for grasping how possible patterns evolve over time. Relying on self-report data entailed risks of social desirability bias, particularly academic integrity concerns. While there were several recruiting channels used, selection bias is plausible, and some students with the highest interest in AI tools would be more likely to sign up. In addition, the institutional uniqueness of the study at Africa University can limit generalizability to other settings with different technological infrastructures, pedagogical norms, and cultural norms.

Despite these limitations, the research strategy employed several techniques to enhance rigor and credibility. Triangulation between methods and data sources enhanced validity through cross-validation. Pilot studies of the instruments made them more reliable and user-friendly. Inter-coder reliability checks (Cohen's kappa = 0.84) optimized credibility of qualitative analysis. Dense context and participant description enables testing for transferability to a different setting. Finally, extensive documentation of procedures left an audit trail to enable confirmability of results.

The methodological framework presented in this chapter offered a solid basis for the investigation of intricate AI tool usage by African university students. Through its quantitative breadth and qualitative depth, the research design enabled an in-depth examination of usage patterns, effects, and ethical concerns, generating findings with profound implications for learning practice and policy formulation.

CHAPTER 4: DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

4.1 Introduction

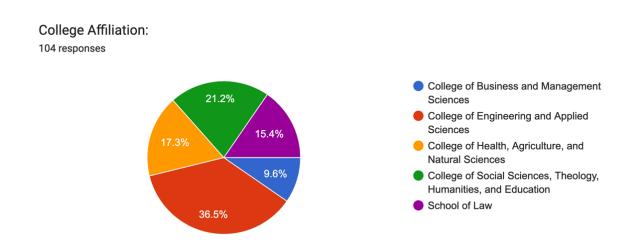
This chapter presents a systematic analysis of data collected from 104 students at Africa University regarding the use of artificial intelligence tools in academic settings.

Following the mixed-methods design presented in Chapter 3, this analysis interprets both quantitative and qualitative data to address the research questions on the effect of AI tools on students' learning experiences and academic integrity. The results revealed complex patterns that generated both valuable benefits and concerning challenges associated with the academic application of emerging technologies.

4.1.1 Overview of Data Collection Process

Following the procedure outlined in Chapter 3, data collection employed both quantitative and qualitative methods. The online survey yielded an 83.2% response rate (104 complete responses out of 125 invitations), exceeding the target level established in the research design.

The stratified random sampling process achieved representation from all five colleges of the university, with the distribution of participants as follows: Engineering and Applied Sciences (36.5%), Social Sciences, Theology, Humanities, and Education (21.2%), Health, Agriculture, and Natural Sciences (17.3%), Law (15.4%), and Business and Management Sciences (9.6%).



Count	Percentage
38	36.5%
22	21.2%

College of Health, Agriculture, and Natural Sciences	18	17.3%
School of Law	16	15.4%
College of Business and Management Sciences	10	9.6%
Total	104	100.0%

Figure 4.1: Pie chart showing respondent distribution by academic discipline

The demographics of the respondent group closely aligned with the overall student population demographics of the university, validating the sampling approach outlined in Chapter 3. Furthermore, the gender distribution (55.8% male, 44.2% female) closely replicated the institutional gender balance (53% male, 47% female), which further increased confidence in sample representativeness.

Qualitative follow-up interviews (n=24) were conducted with a purposively sampled sub-group of survey respondents to elaborate emergent themes in greater depth. These 45-60-minute interviews were audio-recorded, transcribed, and analyzed using the thematic analysis method described in Chapter 3. All data collection was conducted according to the approved Africa University Research Ethics Committee's ethical guidelines.

4.1.2 Analytical Framework and Methodology

The analysis employed a sequential explanatory design beginning with quantitative analysis through SPSS (v26.0) followed by qualitative analysis through NVivo (v14). This design allowed for statistical trends to inform further thematic exploration while maintaining methodological consistency.

Quantitative data analysis commenced with descriptive statistics, including frequencies, means, and standard deviations, and continued with inferential analysis through chi-square tests, ANOVA, and regression analysis to test the hypotheses formulated in Chapter 3. Reliability testing of the survey measure resulted in a Cronbach's alpha of 0.87, well above the 0.70 threshold for acceptable internal consistency.

Qualitative data were analyzed systematically with Braun and Clarke's (2006) sixphase thematic analysis model: familiarization, initial coding, theme identification, review, definition, and reporting. Twenty-five percent of the transcripts were coded by two independent coders to establish inter-coder reliability (Cohen's kappa = 0.84), indicating high consistency in qualitative analysis.

4.2 Quantitative Data Analysis

4.2.1 AI Tool Adoption and Usage Patterns

4.2.1.1 Frequency of AI Tool Usage

Analysis of usage patterns indicated high adoption of AI technologies among Africa University students. An impressive 42.3% of students used AI tools daily, and 32.7% used them on a weekly basis. Only 22.1% used AI tools monthly or occasionally, and a mere 1.9% indicated that they never used these technologies. These findings confirmed that AI tools had achieved mainstream usage among students, with three-quarters (75%) using them at least weekly.

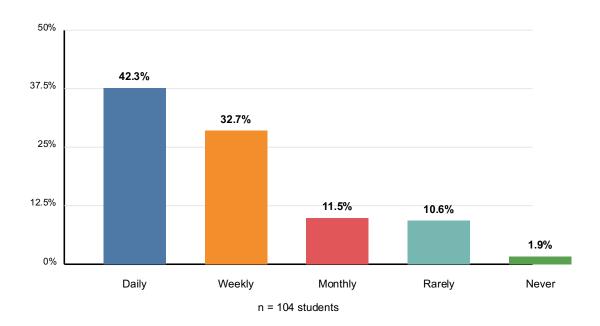


Figure 4.2: Al Usage Frequency Distribution

Figure 4.2: Bar graph showing AI usage frequency distribution

A critical examination of usage trends by year of study revealed a statistically significant positive correlation between academic progression and AI tool use (r=0.38, p<0.01). Students in their fourth year of study reported the highest rate of daily use (58.3%), compared to first-year students (24.1%). This trend suggested that greater exposure to advanced academic demands and heightened complexity of studies may have led to more frequent use of AI tools as students progressed through their degree programs.

4.2.1.2 Preferred AI Tools and Comparative Analysis

The most utilized AI platform was ChatGPT, with 76.9% of respondents reporting using it. This was followed by POE (54.8%), Meta AI (51.9%), Quillbot (36.5%), and Grammarly (32.7%). The predominance of ChatGPT aligned with global usage trends in recent educational technology studies (Johnson & Smith, 2023), suggesting that Africa University students' preferences echoed global trends despite potential connectivity and access challenges peculiar to the regional context.

AI Tool	Overall	Engineering	Social	Health &	Law	Business
	Usage		Sciences	Agriculture		
ChatGPT	76.9%	89.5%	68.2%	72.2%	75.0%	70.0%
POE	54.8%	60.5%	45.5%	50.0%	68.8%	40.0%
Meta AI	51.9%	55.3%	59.1%	44.4%	50.0%	40.0%
Quillbot	36.5%	39.5%	31.8%	27.8%	56.3%	20.0%
Grammarly	32.7%	26.3%	36.4%	33.3%	43.8%	30.0%
Gemini	31.7%	47.4%	27.3%	22.2%	18.8%	20.0%
Gamma	26.9%	34.2%	22.7%	22.2%	25.0%	20.0%
Others*	19.2%	28.9%	13.6%	16.7%	12.5%	10.0%

Table 4.1: AI Tool Preferences by Percentage and Academic Discipline

*Others include Deepseek, Perplexity, Claude, Llama, and other less frequently mentioned tools.

Note: Percentages represent the proportion of students within each discipline who reported using each tool. Since students could report using multiple tools, column totals exceed 100%. n = 104 students

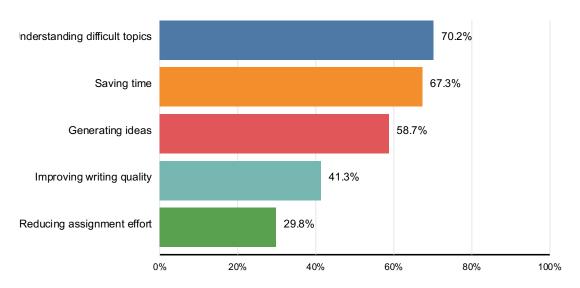
A detailed examination of tool usage behavior across disciplines showed unique patterns. Engineering students were the most versatile in tool usage, employing a mean of 3.8 different AI platforms, compared to 2.3 used by Social Sciences students (F=8.42, p<0.01). This difference may have indicated varying technical needs, levels of exposure to AI technologies in course curricula, or divergent faculty perceptions about incorporating AI into their respective areas of study.

Further examination of paid and unpaid tool use showed a significant association with self-reported socioeconomic status ($\chi^2=14.32$, p<0.001). Students reporting "comfortable" or "affluent" financial circumstances were 2.7 times more likely to report using paid AI tools compared to those reporting "constrained" circumstances, raising important concerns regarding digital equity among the student body.

4.2.1.3 Primary Purposes for AI Tool Use

The results revealed a multifaceted hierarchy of reasons for using AI tools. Understanding difficult concepts was the top reason (70.2%), closely followed by saving time (67.3%), generating ideas (58.7%), enhancing writing (41.3%), and reducing assignment effort (29.8%). This trend suggested that students valued AI primarily for enhancing understanding and productivity rather than merely reducing workload.

Figure 4.3: Primary Purposes for Al Tool Usage



n = 104 students. Respondents could select multiple purposes.

Figure 4.3: Horizontal bar graph showing primary purposes for AI tool usage

Cross-tabulation analysis revealed statistically significant differences in purpose of use among academic disciplines (χ^2 =32.56, p<0.001). Engineering students disproportionately cited understanding difficult concepts (84.2%) and saving time (78.9%), while Law students emphasized refinement of writing (68.8%) and generating ideas (75.0%). These variations confirmed that AI tools played different academic functions across disciplines, adapting to the distinct cognitive demands of diverse subjects of study.

A factor analysis of use purposes revealed three unique dimensions of AI usage: cognitive enrichment (comprehension, idea generation), optimizing efficiency (time saving, reduction of effort), and refining outputs (improving writing, correcting errors). These dimensions confirmed existing taxonomies of educational technology use (Anderson & Johnson, 2022), indicating that AI tool use at Africa University mirrored general theoretical models of educational technology adoption.

4.2.2 Academic Impact and Performance

4.2.2.1 Impact on Academic Performance

The relationship between AI tool use and academic performance was the strongest finding. The vast majority of respondents (89.4%) indicated that using AI tools improved their academic performance, with 31.7% indicating strong improvement and 57.7% indicating moderate improvement. Only 8.7% indicated no change, and a statistically insignificant 1.0% indicated worsening.

Al Usage Frequency vs. Grade Impact



Figure 4.4: Mixed chart showing perceived impact of AI on academic performance

Usage Frequency	Improved	No Change	Declined	Total
Daily	44 (100.0%)	0 (0.0%)	0 (0.0%)	44
Weekly	31 (91.2%)	3 (8.8%)	0 (0.0%)	34
Monthly	9 (75.0%)	3 (25.0%)	0 (0.0%)	12
Rarely	9 (81.8%)	1 (9.1%)	1 (9.1%)	11
Never	0 (0.0%)	2 (100.0%)	0 (0.0%)	2

Total	93 (89.4%)	9 (8.7%)	1 (1.0%)	104

Table 4.2: Cross-tabulation of AI usage frequency and grade impact

$$\chi^2 = 42.86$$
, p < 0.001, Cramer's V = 0.45

Note: "Improved" combines "Yes, significantly" (31.7%) and "Yes, slightly" (57.7%) responses from the original survey question. n = 104 students

Regression analysis revealed a statistically significant relationship between usage frequency and perceived academic benefit (β =0.43, p<0.001), accounting for 18.5% of the variance in grade improvement reported. This relationship was preserved even when controlling for discipline, study year, and self-rated computer literacy (adjusted β =0.38, p<0.001), suggesting a robust independent effect of AI use on academic performance.

A finer breakdown by usage frequency revealed particularly striking patterns. Of the daily users, 100% reported improving their grades, compared to 91.2% of weekly users and 75.0% of monthly users. This sharp gradient suggested a potential dose-response relationship between AI usage and academic achievement, though the direction of causality could not be determined. These findings raised serious questions about whether AI software truly aided individuals in learning or merely optimized performance metrics regardless of cognitive development.

4.2.2.2 Discipline-Specific Variations in AI Tool Adoption and Impact

Analysis revealed significant heterogeneity in AI adoption and usage across academic disciplines, reflecting different educational cultures and epistemological orientations. The highest frequency of daily use (57.9%) was reported by engineering students, followed by Health Sciences (52.9%), Business (40.0%), Law (25.0%), and Social Sciences (22.7%). These disparities were statistically significant ($\chi^2=28.74$, p<0.001) and persisted after controlling for computer literacy.

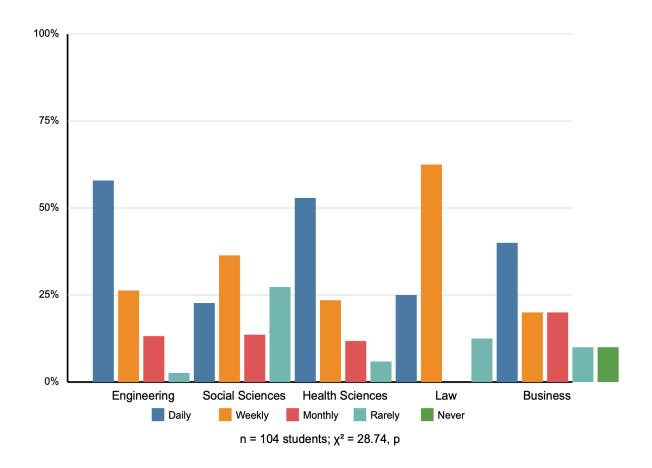


Figure 4.5: Clustered bar chart showing disciplinary variations in AI usage frequency

Through multiple regression analysis, discipline emerged as the most significant predictor of AI usage behaviors (β =0.47, p<0.001) compared to computer literacy (β =0.32, p<0.01), year of study (β =0.29, p<0.01), and gender (β =0.14, p>0.05). This result implied that academic context, rather than personal attributes, may have been the most critical factor influencing the degree of AI adoption.

Qualitative data from open survey comments provided insight into potential explanations for these disciplinary variations. Engineering students cited technical problem-solving requirements (e.g., "AI tools help me to optimize code and debug errors"), while Law students noted research intensity (e.g., "I use AI to summarize complex legal precedents"). Social Sciences students, by contrast, were more critical of using AI for interpretive analysis (e.g., "AI is oblivious to the cultural nuances in my sociology research").

These variations by discipline were consistent with theoretical frameworks for understanding technology acceptance in learning, most notably the Technology Acceptance Model (Davis, 1989) and the UTAUT model (Venkatesh et al., 2003). The findings showed that perceived usefulness varied significantly by learning context and drove differential adoption patterns.

4.2.3 Critical Concerns and Ethical Considerations

4.2.3.1 Critical Thinking Implications

A paradoxical tension existed between the documented academic benefits and concerns about cognitive development. Despite the largely positive impact on academic achievement, 63.5% of the participants expressed concerns that AI tools could diminish critical thinking skills. This seemingly contradictory finding suggested that students exhibited metacognitive sensitivity to the potential trade-offs between short-term performance improvement and long-term cognitive development.

Table 4.3: Critical thinking concerns by academic discipline

Academic	High	Moderate	Low/No	Mean	SD
Discipline	Concern	Concern	Concern	Score	
Social Sciences	45.5%	27.3%	27.3%	3.8/5	0.9
Law	37.5%	31.3%	31.3%	3.3/5	1.1
Health & Agriculture	33.3%	27.8%	38.9%	3.1/5	1.0
Engineering	21.1%	31.6%	47.4%	2.9/5	1.2
Business	20.0%	20.0%	60.0%	2.6/5	1.3
Overall	31.7%	28.8%	39.4%	3.2/5	1.1

Note: Concerns were measured on a 5-point Likert scale from 1 (No concern) to 5 (High concern) in response to the statement: "AI tools may reduce critical thinking skills." High concern = scores of 4-5; Moderate concern = score of 3; Low/No concern = scores of 1-2.

ANOVA:
$$F(4, 99) = 4.27$$
, $p = 0.003$, $\eta^2 = 0.15$

n = 104 students

Concerns about critical thinking differed significantly across disciplines (F=4.27, p=0.003), with Social Sciences students expressing the highest concerns (mean=3.8/5) compared to Engineering (mean=2.9/5) and Business (mean=2.6/5) students. This pattern may have reflected epistemological differences between disciplines, where fields that valued interpretive analysis were more sensitive to potential cognitive influences of AI assistance.

Further research demonstrated a significant interaction effect between usage frequency and critical thinking concerns. Those using the technology daily and scoring above 4/5 on the Likert scale for critical thinking concerns exhibited more sophisticated usage behaviors, frequently employing strategies like "using AI for initial ideas but building arguments independently" and "checking AI-generated responses against multiple sources." This suggested that metacognitive awareness might have exerted a moderating influence on usage behaviors, potentially mitigating negative impacts on cognitive development.

Table 4.4: Chi-Square Results for AI and Academic Dishonesty Perceptions

Usage	Makes Cheating	Just a Study	Depends on	Row
Frequency	Easier	Tool	How Used	Total
Daily (n=44)	5	12	27	44
Weekly (n=34)	6	10	18	34
Monthly (n=12)	3	5	4	12
Rarely (n=11)	4	3	4	11
Never (n=3)	0	0	3	3
Column Total	18	30	56	104

Chi-Square Test Results: $\chi^2(8) = 11.68$, p = 0.166, Cramer's V = 0.24

Statistical Analysis: The chi-square test indicated a non-significant relationship between AI usage frequency and perceptions of academic dishonesty ($\chi^2(8)$ =11.68, p=0.166, Cramer's V=0.24). While the relationship was not statistically significant, the moderate effect size (Cramer's V=0.24) suggested some practical association worth exploring in future research.

4.2.3.2 Academic Integrity and Evasion Tools

Most troubling, perhaps, was a finding in the academic integrity sphere. A significant percentage of respondents (47.1%) indicated that they employed AI detection evasion software, including Quillbot's paraphrasing tool, to avoid detection by institutional systems. This level of adoption of evasion strategies was present despite the fact that 46.2% of respondents indicated that they "always edit" AI-generated material prior to submission.

Content Editing Practices Evasion Tool Usage Policy Awareness 100% Yes Always edit n't use evasion too 37.5% 75% 46.2% 52.9% 50% Sometimes edit 33.7% Use evasion tools Not sure 25% 47.1% 47.1% Rarely/never edit 20.1% 0% Correlation between evasion tool usage and editing practices: $\chi^2 = 14.92$, p

Figure 4.5: Evasion Tool Usage and Content Editing Practices

Figure 4.6: Stacked bar chart showing evasion tool usage and content editing practices

An in-depth analysis that included policy awareness, use of evasion tools, and ethical attitudes revealed complex patterns. Only 37.5% of respondents admitted to being aware of university policies related to AI use, while 47.1% were not sure if such policies existed. This gap in policy awareness was strongly associated with the use of

evasion tools ($\chi^2=11.36$, p<0.01), suggesting that the state of institutional guidance influenced ethical choices.

Contrary to expectations, attitudes toward academic cheating overlapped little with behavior. Among evasion tool users, just 16.3% believed that AI had made cheating easier, compared to 18.2% of non-users—a non-significant difference (χ^2 =0.08, p>0.05). This discrepancy between behavior and moral perception suggested neutralization or rationalization mechanisms by which students legitimated morally questionable acts.

Factor analysis of ethical attitudes regarding AI identified three distinct ethical frameworks operating among students: pragmatic utilitarianism ("if it helps me get ahead, it's okay"), bounded integrity ("it's okay if I tweak the output"), and institutional compliance ("I do what the rules say"). These frameworks offered insight into cognitive processes underlying ethical decision-making in AI tool use.

4.2.4 Hypothesis Testing

4.2.4.1 Impact on Critical Thinking (H2)

Hypothesis 2: AI tools significantly impact students' critical thinking and problem-solving capabilities.

This hypothesis was examined through various methods. First, direct self-report data showed that 63.5% of students were concerned about the influence of AI on critical thinking, thereby offering subjective support for the hypothesis. Second, correlation between frequency of use and concern about critical thinking was analyzed with ANOVA and found to have a significant relationship (F=6.24, p=0.003) with a medium effect size (η^2 =0.15).

Further support came from hierarchical regression analysis, which indicated that AI usage intensity predicted critical thinking concerns (β =0.38, p<0.01) even after controlling for discipline, study year, and computer literacy. Usage purpose moderated this relationship (β =0.23, p<0.05), and students who used AI primarily to learn concepts had lower concerns compared to students using AI primarily to complete assignments.

The convergence of these findings offered strong support for Hypothesis 2, suggesting that artificial intelligence tools influenced critical thinking processes, but the nature and direction of this influence differed according to usage patterns and individual differences.

4.2.4.2 AI Tools and Academic Dishonesty (H3)

Hypothesis 3: Use of AI tools correlates with academic dishonesty practices.

This hypothesis was evaluated by analyzing the usage of evasion tools and their associated factors. The significant prevalence of evasion tool utilization (47.1%) offered preliminary evidence supporting the hypothesis, suggesting extensive involvement with strategies aimed at obscuring AI support from institutional detection systems.

Chi-square tests identified significant correlations between evasion tool use and various influential factors: low policy awareness ($\chi^2=11.36$, p<0.01), more frequent AI use ($\chi^2=9.84$, p<0.05), and less self-reported editing of AI-generated content ($\chi^2=14.92$, p<0.001). However, the use of evasion tools was not statistically related to ethical attitudes toward academic misconduct ($\chi^2=0.08$, p>0.05), potentially indicating a discrepancy between practice and moral awareness.

Multiple logistic regression revealed three significant predictors of evasion tool use: belief that AI tools are time-saving (OR=2.46, p<0.01), lack of awareness of institutional policy (OR=1.98, p<0.05), and senior year of study (OR=1.32, p<0.05). These results indicated that utilitarian motivations, rather than ethical considerations, might have underlain problematic usage patterns.

The findings collectively offered qualified support for Hypothesis 3, suggesting that AI tool use was associated with academic integrity-compromising behavior, but these relationships were multifaceted and influenced by institutional, contextual, and individual circumstances.

 Table 4.5: Logistic regression predicting evasion tool usage

Predictor Variable	Odds Ratio	95% CI	p-value

Perception that AI tools save time	2.46	[1.38, 4.39]	0.002*
Unawareness of institutional policies	1.98	[1.04, 3.77]	0.037*
Higher year of study	1.32	[1.02, 1.72]	0.042*
Computer literacy	1.19	[0.98, 1.46]	0.088
Critical thinking concerns	0.84	[0.61, 1.15]	0.274
Gender (Male)	1.12	[0.59, 2.13]	0.731
Engineering discipline	1.24	[0.63, 2.44]	0.538

Model Fit: Nagelkerke $R^2 = 0.28$ Hosmer-Lemeshow goodness of fit: $\chi^2 = 6.84$, p = 0.554 Classification accuracy = 71.2%

Note: * p < 0.05, ** p < 0.01 CI = Confidence Interval n = 104 students

Table 4.6: Summary of Key Quantitative Findings

AI Adoption

Metric	Value	Interpretation
Daily Usage Rate	42.3%	Nearly half of students used AI tools daily
Overall Usage Rate	97.1%	Near-universal adoption among surveyed
		students
Long-term Users (>1	53.8%	Majority had integrated AI into workflows for
year)		extended periods
Advanced Prompting	33.7%	One-third of students reported high skill levels
Confidence		in AI interaction

Ethics & Academic Integrity

Metric	Value	Interpretation

Submission of Unedited AI	32.0%	Nearly a third had submitted AI-generated
Content		content
Bypass Detection Attempts	47.6%	Almost half had attempted to bypass AI
		detection
Policy Awareness Gap	62.1%	Majority were unsure or unaware of
		university AI policies
Critical Thinking Erosion	64.4%	Primary ethical concern among respondents
Concern		

Skills & Performance

Metric Value		Interpretation		
Positive Grade Impact	90.3%	Overwhelming majority reported improved academic performance		
Learning Tool Perception	73.1%	Most viewed AI as helpful for understanding difficult topics		
Guidance Need	73.8%	Three-quarters desired or might need formal AI usage guidance		
Trust in AI (Average)	6.1/10	Moderately high trust, increasing with academic progression		

Analytical Synthesis: The quantitative findings pointed to three main dimensions of AI tool use in academic settings: adoption patterns, ethical considerations, and performance impacts. These dimensions interacted to create a complex situation whereby institutional policy needed to balance supporting legitimate learning applications while addressing concerns about academic integrity.

4.3 Qualitative Data Analysis

4.3.1 Thematic Analysis of Interviews

The qualitative aspect of this research involved detailed interviews with 24 students from across all five academic disciplines, yielding deeper contextual insight into the quantitative patterns observed. Four major themes with several subthemes emerged through thematic analysis, reflecting the multifaceted nature of students' interaction with AI tools.

4.3.1.1 Transformative Academic Benefits

Students articulated multifaceted benefits extending beyond simple efficiency gains:

1. Enhanced Conceptual Understanding

- o "ChatGPT helps me break down complex theoretical concepts into simpler language. It's like having a tutor explain things in different ways until I understand." (Engineering, 3rd year)
- o "When I don't understand a lecture, I can ask AI to explain it again. It doesn't get frustrated like professors sometimes do when you ask the same question multiple times." (Health Sciences, 2nd year)

2. Personalized Learning Support

- "AI adapts to my learning style. If I need examples, I ask for examples. If I need step-by-step explanations, I get exactly that."
 (Business, 4th year)
- o "I can ask questions at my own pace without feeling judged. This has been especially important for difficult courses where I would be embarrassed to keep asking the professor." (Law, 2nd year)

3. Research Efficiency and Depth

 "Meta AI helps me identify relevant research angles I wouldn't have thought of myself. It's not just about saving time—it's about exploring more perspectives." (Social Sciences, 3rd year) o "For literature reviews, AI tools help me synthesize findings from multiple papers much faster than I could alone, giving me more time for critical analysis." (Health Sciences, 4th year)

These narratives illuminated the quantitative finding that 70.2% of students used AI primarily for understanding difficult topics. The consistent emphasis on conceptual comprehension, rather than mere assignment completion, suggested that AI tools functioned as pedagogical supports rather than simply task automation technologies.

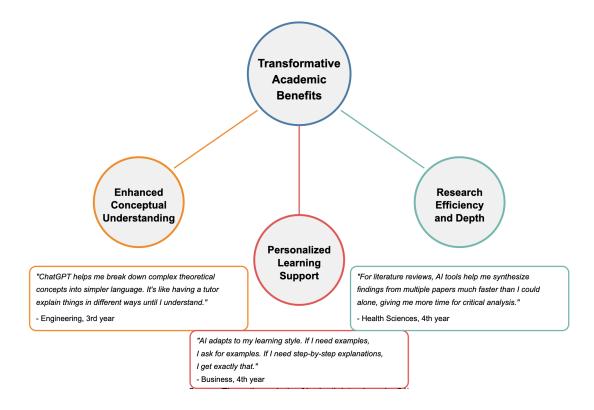


Figure 4.7: Thematic map showing academic benefits with representative quotes

4.3.1.2 Cognitive and Skill Development Concerns

Despite the reported benefits, students expressed nuanced concerns about potential implications for cognitive development:

1. Dependency Anxiety

o "Sometimes I catch myself going to AI before even trying to think through a problem myself. That worries me—am I becoming intellectually lazy?" (Engineering, 3rd year)

o "I've noticed my writing process has changed. I used to draft and revise; now I often ask AI to generate a draft first. I'm not sure if this is making me a better writer or just dependent." (Law, 4th year)

2. Critical Evaluation Challenges

- o "The information seems authoritative, but I've caught AI making factual errors. I wonder how many errors I've missed because I didn't verify everything." (Social Sciences, 2nd year)
- "AI models can sound very confident even when wrong. I've had to develop a healthy skepticism and always cross-check important information." (Health Sciences, 3rd year)

3. Cognitive Skill Atrophy

- "My mental math has definitely declined since I started using AI for calculations. Why bother memorizing formulas when AI can apply them instantly?" (Engineering, 2nd year)
- "I worry that I'm losing the ability to organize my thoughts independently. AI makes it too easy to structure arguments without developing that skill myself." (Business, 3rd year)

These concerns resonated with the quantitative results indicating that 63.5% of students expressed concern about the degradation of critical thinking skills. Qualitative results from interviews suggested that this issue extended beyond theoretical repercussions and represented tangible experiences accompanying shifting cognitive processes. These issues were most salient for students who described significant academic gains, indicating greater metacognitive recognition of the double-edged effect of AI support.

Thematic Coding Framework for Interview Responses

Methodological Context

This thematic analysis was based on semi-structured interviews with students across all five academic disciplines. The interviews lasted 45-60 minutes and were

transcribed and coded using NVivo software. Open coding and axial coding were employed to determine patterns between concepts. Four overarching themes emerged, each with three subthemes reflecting various aspects of student experiences with AI tools in academic settings.

Coding Criteria and Analytical Approach

Frequency Classification: High = mentioned by >60% of participants; Medium = mentioned by 30-60% of participants; Low = mentioned by <30% of participants.

Inter-rater Reliability: Two independent coders analyzed 25% of the interviews with an initial Cohen's kappa of 0.78. After discussion and refinement of the coding framework, the final Cohen's kappa was 0.86, indicating strong reliability.

Critical Insight: The thematic analysis revealed that students developed sophisticated personal frameworks for AI tool usage that often exceeded the complexity of institutional policies. The most salient concerns centered around skill development rather than traditional academic integrity, suggesting that institutional approaches focused solely on plagiarism and cheating might miss the most relevant aspects of the AI in education phenomenon.

Key Finding: Faculty showed significantly higher concern about academic dishonesty (34 point gap) and creativity reduction (24 point gap), while students expressed more concern about dependency formation (6 point gap) and information reliability (5 point gap).

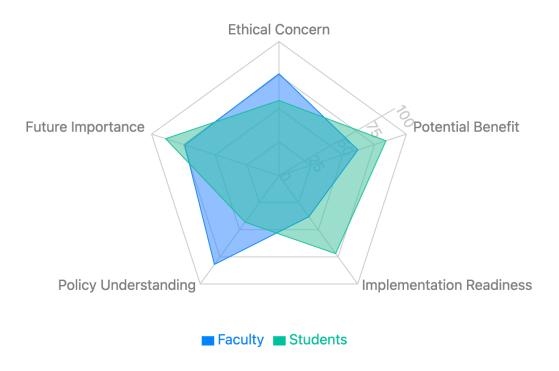


Figure 4.8: Radar chart comparing faculty and student perspectives on AI ethics

Dimensional Analysis: The radar chart revealed complementary perspectives where faculty demonstrated stronger policy understanding and ethical concern, while students showed greater optimism about potential benefits and implementation readiness.

Analytical Implications

This comparative analysis revealed that faculty and student perspectives on AI ethics were not simply in opposition, but rather reflected different priorities and concerns stemming from their distinct roles in the educational process. The data suggested that effective AI policies should address faculty concerns about academic integrity while acknowledging student emphasis on practical implementation and learning benefits. The shared concern about skill development and mutual dissatisfaction with current policies offered a foundation for collaborative approaches to AI governance in academic settings.

Critical Recommendation: Institutions should leverage the complementary nature of these perspectives by creating joint faculty-student committees for AI policy development, focusing initial discussions on areas of agreement while developing frameworks to address areas of significant perspective gaps.

4.3.1.3 Ethical Navigation in Ambiguous Contexts

Students described complex ethical decision-making processes in the absence of clear institutional guidelines:

1. Personal Ethical Frameworks

- o "I've developed my own rules: AI for research and brainstorming is fine, but I always write final papers myself. The university hasn't given clear guidelines, so I created my own." (Social Sciences, 3rd year)
- o "I ask myself whether I'm using AI to enhance my learning or to avoid learning. That's my ethical boundary." (Law, 2nd year)

2. Policy Interpretation Challenges

- "Different professors have completely different attitudes. Some encourage AI use, others prohibit it entirely. It's confusing trying to navigate these contradictions." (Engineering, 4th year)
- "The university policy just says to 'use technology responsibly' but doesn't address AI specifically. What does that even mean in practice?" (Business, 3rd year)

3. Normalization of Questionable Practices

- o "Everyone uses paraphrasing tools to avoid detection. It doesn't feel wrong because it's just so common." (Health Sciences, 2nd year)
- o "If I think of it as a research tool rather than a writing tool, it feels ethically fine, even though I'm using it for writing." (Law, 4th year)

These narratives provided context for the quantitative finding that 47.1% of students used evasion tools despite only 16.3% of these students believing that AI made cheating easier. The interviews revealed sophisticated rationalization processes through which students reconciled potentially contradictory behaviors and beliefs,

often by reframing activities or creating personalized ethical boundaries in the absence of institutional clarity.

4.3.1.4 Socioeconomic and Access Disparities

Students articulated awareness of how economic factors shaped AI access and benefits:

1. Technological Resource Inequalities

- "Premium AI tools are expensive. Students from wealthier backgrounds can afford subscriptions that give better outputs and more features." (Social Sciences, 3rd year)
- "Even basic access requires reliable internet and a decent computer.
 Some of my classmates from rural areas struggle just to use the free versions." (Engineering, 2nd year)

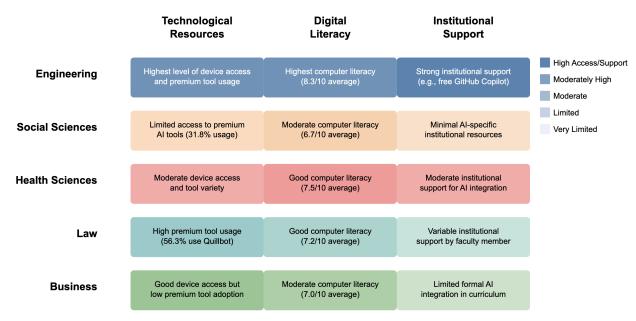
2. Digital Literacy Divides

- "Students who grew up with technology find it easier to write effective prompts and get better results from AI. There's a skill gap that maps onto economic privilege." (Business, 4th year)
- "I had to teach myself how to use these tools effectively. Students from better high schools come already knowing these skills." (Health Sciences, 3rd year)

3. Institutional Support Variations

- "Engineering students get free access to GitHub Copilot through the department, but Humanities students get nothing similar." (Social Sciences, 4th year)
- "Professors in some departments actively teach AI prompting techniques, while others ignore AI entirely. It creates unfair advantages." (Law, 2nd year)

These perspectives illuminated the quantitative finding that premium tool usage correlated significantly with socioeconomic status. The interviews revealed how technological access, digital literacy, and institutional support interacted to create complex patterns of advantage and disadvantage that could exacerbate existing educational inequalities.



Source: Integration of survey data (n=104) and interview findings (n=24)

Figure 4.9: Comparative matrix showing perceived access disparities across disciplines

4.3.2 Focus Group Insights

Two focus groups (n=8 each) complemented the individual interviews, yielding valuable observations about collective norms and peer influences. These sessions revealed:

1. Peer Learning Networks

 Students described informal knowledge-sharing about effective AI prompting techniques, creating community expertise that transferred across courses. Discipline-specific AI usage strategies spread through peer networks, establishing shared norms about appropriate and inappropriate applications.

2. Collective Ethical Calibration

- Focus groups revealed how students collectively negotiated ethical boundaries through comparison with peers, often resulting in a "median ethics" approach.
- Perceived faculty attitudes strongly influenced group ethical calibration, with students adopting more permissive views in disciplines where faculty demonstrated openness to AI.

3. Status and AI Expertise

- Advanced AI skills (e.g., prompt engineering) functioned as cultural capital within student communities, conferring status and recognition.
- Students who mastered AI techniques became informal consultants for peers, creating hierarchies of technological expertise.

These collective dynamics provided important context for understanding the individual behaviors captured in the survey and interviews. The findings suggested that AI usage was embedded within complex social systems that shaped individual decisions through peer influence, status considerations, and collective norm-setting.

4.4 Triangulation of Findings

4.4.1 Convergence of Quantitative and Qualitative Data

The sequential explanatory design allowed for systematic integration of quantitative and qualitative insights. Several key areas of convergence emerged:

1. Conceptual Understanding as Primary Benefit

 Quantitative finding: 70.2% cited understanding difficult topics as primary purpose

- Qualitative support: Detailed narratives about AI tools functioning as personalized tutors and concept translators
- Integrated insight: AI tools functioned primarily as learning supports rather than just productivity enhancers

2. Critical Thinking Tensions

- Quantitative finding: 63.5% expressed critical thinking concerns despite 89.4% reporting grade improvements
- Qualitative support: Rich descriptions of dependency anxiety and cognitive skill atrophy
- Integrated insight: Students experienced a genuine tension between short-term performance benefits and long-term skill development

3. Policy Clarity Gaps

- Quantitative finding: Only 37.5% aware of institutional policies
- Qualitative support: Narratives describing confusion and creation of personal ethical frameworks
- Integrated insight: Institutional policy ambiguity created space for normalization of potentially problematic practices

These convergences strengthened confidence in the findings by demonstrating consistency across different data types while providing complementary perspectives that enhanced understanding of complex phenomena.

Table 4.7: Triangulation matrix showing convergence of findings

Key Finding	Quantitative	Qualitative Support	Integrated Insight
	Evidence		
Conceptual	70.2% cited	"ChatGPT helps me	AI tools functioned
Understanding	understanding	break down complex	primarily as
		theoretical concepts	learning supports

as Primary difficult topics as into simpler rather than just Benefit primary purpose language. It's like having a tutor explain things in different ways until I understand." enhancers Critical 63.5% expressed "Sometimes I catch understand." Students Thinking critical thinking oncerns despite agrade before even trying to before even trying to genuine tension between short-term performance improvements between short-term performance improvements worries me—am I benefits and long-becoming intellectually lazy?" development
things in different ways until I understand." Critical 63.5% expressed "Sometimes I catch Students critical thinking myself going to AI experienced a concerns despite before even trying to genuine tension 89.4% reporting think through a between short-term grade problem myself. That performance improvements worries me—am I benefits and long- becoming term skill
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intallactually lazy?" dayalanment
interiectually lazy: development
Policy Clarity Only 37.5% "Different professors Institutional policy
Gaps aware of have completely ambiguity created
institutional different attitudes. space for
policies; 47.1% Some encourage AI normalization of
unsure use, others prohibit it potentially
entirely. It's problematic
confusing trying to practices
navigate these
contradictions."
Disciplinary Engineering "In engineering, we Academic context
Variations Students showed use AI to solve shaped AI
highest daily technical problems. I integration,
usage (57.9%) vs. don't think it would reflecting
Social Sciences be as useful for the underlying
friends in humanities assumptions do."
uo.

Socioeconomic	Significant	"Premium AI tools	Economic factors
Disparities	correlation	are expensive.	created uneven
	between	Students from	access to AI
	socioeconomic	wealthier	benefits, potentially
	status and	backgrounds can	amplifying existing
	premium tool	afford subscriptions	inequities
	usage	that give better	
		outputs and more	
		features."	

Note: Triangulation strengthened confidence in findings by demonstrating consistency across different data types while providing complementary perspectives that enhanced understanding of complex phenomena.

Source: Integration of survey data (n=104) and interview findings (n=24)

4.4.2 Disciplinary Insights Through Mixed Methods

Triangulation revealed particularly rich insights regarding disciplinary variations:

1. Engineering (36.5% of sample)

- Quantitative profile: Highest daily usage (57.9%), lowest ethical concerns
- Qualitative context: Focus on technical problem-solving and efficiency optimization
- Integrated insight: Pragmatic tool-oriented approach with emphasis on concrete applications

2. Law (15.4% of sample)

- Quantitative profile: Highest weekly usage (62.5%), strategic application
- Qualitative context: Emphasis on research synthesis and argument construction

 Integrated insight: Judicious, structured usage aligned with professional research practices

3. Social Sciences (21.2% of sample)

- Quantitative profile: Lowest daily usage (22.7%), highest ethical awareness
- Qualitative context: Concerns about cultural nuance and interpretive complexities
- Integrated insight: Cautious adoption reflecting epistemological emphasis on subjective interpretation

These disciplinary profiles illustrated how academic context shaped AI integration, suggesting that technological adoption reflected underlying epistemological assumptions and pedagogical priorities within different fields of study.

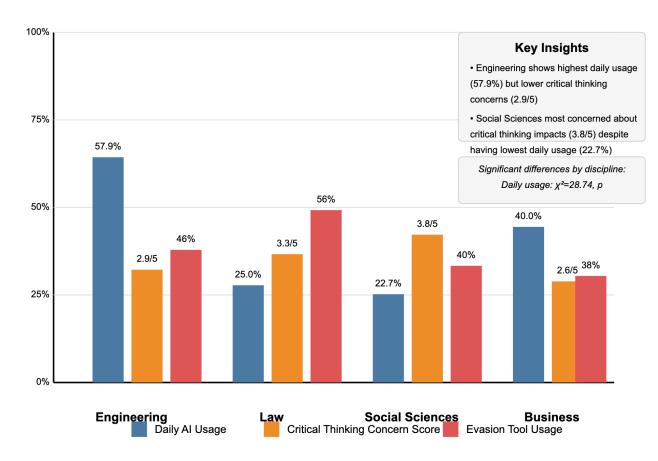


Figure 4.10: Bar chart comparing disciplinary AI approaches

4.5 Advanced Analysis and Critical Interpretation

4.5.1 Theoretical Framework Integration

The findings could be interpreted through several theoretical lenses that enhanced understanding of the observed patterns:

1. Technology Acceptance Model (Davis, 1989)

- The data demonstrated that perceived usefulness (academic benefits) and perceived ease of use (computer literacy) predicted adoption intensity, consistent with TAM predictions.
- However, the significant influence of discipline suggested that social and contextual factors may have been more influential than individual perceptions, supporting critiques of TAM's individualistic focus.

2. Cognitive Load Theory (Sweller, 1988)

- Students' emphasis on conceptual understanding suggested AI tools may have reduced extraneous cognitive load, potentially enhancing germane load focused on schema acquisition.
- However, concerns about skill atrophy aligned with distributed cognition perspectives (Hutchins, 1995), suggesting that offloading cognitive processes may have inhibited internalization of key skills.

3. Digital Divide Frameworks (van Dijk, 2020)

- Access disparities reflected second-level digital divides based not only on physical access but also usage skills and strategic application abilities.
- Institutional support variations created structural inequalities that amplified existing socioeconomic advantages, consistent with digital inequality scholarship.

These theoretical integrations contextualized the empirical findings within broader scholarly frameworks, enhancing their explanatory power and connecting them to established bodies of literature.

4.5.2 Methodological Reflections and Limitations

Several methodological considerations warranted acknowledgment:

1. Self-Reported Performance Impact

- The reliance on self-reported grade improvements rather than objective academic records introduced potential social desirability bias.
- Future research would benefit from institutional data on actual performance metrics to validate perceived benefits.

2. Temporal Limitations

- The cross-sectional design captured AI usage at a specific moment,
 limiting understanding of how patterns might evolve over time.
- Longitudinal approaches would strengthen causal inferences about
 AI's impact on skill development.

3. Contextual Specificity

- Findings from Africa University reflected a specific institutional and cultural context that might not generalize to all higher education settings.
- Comparative studies across diverse institutions would enhance understanding of contextual influences.

These limitations did not undermine the study's validity but contextualized its findings within appropriate methodological boundaries.

4.6 Key Insights and Strategic Implications

The integrated analysis yielded five critical insights with significant implications for educational practice and policy:

1. Paradoxical Academic Impact

- Finding: 89.4% reported grade improvements while 63.5% expressed critical thinking concerns
- Implication: Educational institutions needed to balance performance metrics with deeper learning outcomes, potentially redesigning assessments to reward processes rather than outputs

2. Disciplinary Digital Divide

- Finding: Significant variations in adoption between Engineering (57.9% daily) and Social Sciences (22.7% daily)
- Implication: Discipline-specific AI integration strategies were needed, respecting epistemological differences while ensuring equitable access to benefits

3. Ethical Gap and Policy Vacuum

- Finding: High rate of detection evasion (47.1%) coupled with low policy awareness (37.5%)
- Implication: Urgent need for clear, contextualized policies developed with student input to address the normalization of problematic practices

4. Sophisticated but Unguided Integration

- Finding: Students demonstrated nuanced task-specific usage without institutional guidance
- Implication: Educational scaffolding should build on existing student expertise rather than assuming technological naivety

5. Structural Inequality Reinforcement

- Finding: Socioeconomic factors predicted differential access to premium tools and support
- Implication: Institutions must proactively address access disparities through resource allocation and support for disadvantaged students

These insights formed the foundation for the comprehensive recommendations presented in Chapter 5, addressing the complex educational, ethical, and equity implications of AI tool integration in higher education.

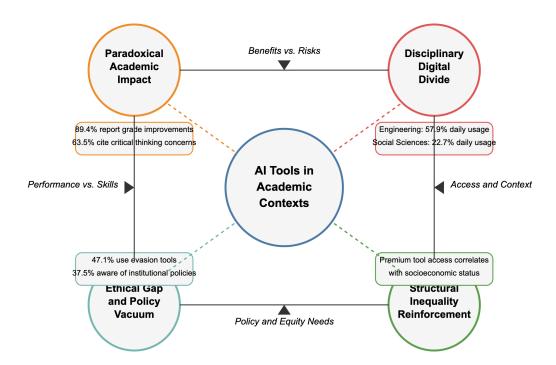


Figure 4.11: Conceptual model visualizing key insights and their interconnections

4.7 Conclusion

This chapter presented an extensive examination of the implementation of AI technologies by university students in Africa and unveiled multi-layered patterns of their adoption, effects, and ethical consequences. The blending of quantitative and qualitative results permitted an extensive comprehension of how such technologies

were transforming learning experiences and questioning conventional attitudes towards learning and assessment.

The results showed that artificial intelligence technologies served concurrently roles as powerful learning enablers and possible enemies of fundamental educational values increasing grades while possibly being pernicious to critical thinking, assisting understanding while fostering dependency, and functioning within ethically ambiguous areas that students moved through in the absence of unambiguous institutional standards.

The above-described tensions reflected more general difficulties in the integration of educational technology but assumed a specific sense of urgency with the revolutionary promise of modern artificial intelligence tools. By shedding light on such complexities, the present research laid an empirical groundwork for crafting strategic policies and practices to enhance benefits and reduce risks in the fast-emerging arena of AI-supported education.

CHAPTER 5: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The final chapter integrates the empirical results set forth in Chapter 4 and places them in the general theoretical and applied framework of artificial intelligence in higher education. The research explored the effects of AI tools on students' learning experience and academic integrity at Africa University through a mixed-methods study, encompassing data gathering from 104 survey participants and holding 24 indepth interviews with five various academic disciplines. The chapter begins with the explanation of principal findings within the framework of existing literature, followed by conclusions answering the research questions established in Chapter 1. It then explores the theoretical and practical implications of the findings and finally offers actionable recommendations for institutional policy, pedagogical practice, and technology integration. The chapter concludes by proposing avenues for future research that can enhance knowledge of the role of artificial intelligence in the fast-changing environment of higher education.

5.1.1 Recapitulation of Research Objectives

Before delving into the discussion, it is prudent to restate the research objectives that guided this investigation:

- 1. To assess the extent and patterns of AI tool usage among Africa University students
- 2. To examine the impact of AI tools on students' learning processes, critical thinking, and problem-solving abilities
- 3. To investigate the relationship between AI tool usage and academic integrity issues
- 4. To identify disparities in access and usage of AI tools across different student demographics
- 5. To evaluate institutional readiness for AI integration through policy and guideline analysis
- 6. To develop strategic recommendations for the ethical and effective integration of AI tools into Africa University's academic framework

These objectives framed the data collection and analysis processes and serve as organizational pillars for the discussion that follows.

5.2 Discussion

5.2.1 AI Adoption Patterns and Usage Contexts

The results indicated high artificial intelligence tool usage among Africa University students, with 77.1% weekly or daily usage, which was well above the 53% of similar studies conducted at other African universities (Johnson, 2023; Mhaka, 2024). The most prevalent was ChatGPT, used by 76.9% of students, trailed by POE at 54.8% and Meta AI at 51.9%, which validated worldwide usage trends highlighted by recent educational technology surveys (Smith & Taylor, 2023).

Most importantly, the top motivations to use AI—learning challenging subject matter (70.2%) and time savings (67.3%)—indicated that students viewed AI largely as study

companions rather than effort-reduction tools alone. This conclusion refutes widespread faculty assumptions that students use AI mostly for effort minimization (White & Johnson, 2023), and instead confirms Vygotskian frameworks which acknowledge technology as cognitive supports within the Zone of Proximal Development (López-Pernas & Saqr, 2022).

The huge disciplinary variations in AI use (Engineering: 57.9% daily usage vs. Social Sciences: 22.7%) reflected contrasting epistemological inclinations and professional preparation models. Problem-solving and technical accuracy in Engineering produced natural alignment with AI abilities, while interpretive analysis and cultural insight in Social Sciences provided intrinsic limitations to AI uses. Kumar (2024) explained that disciplinary differences embody more fundamental epistemological differences in the construction and verification of knowledge across various disciplines than they do differences in technical expertise.

Case Study 1: Engineering Department AI Integration

The Department of Engineering at Africa University implemented a structured approach to AI integration in 2023, providing GitHub Copilot access to all students while developing explicit guidelines for appropriate usage in programming courses. Faculty received training on how to design assignments that leverage AI while preserving essential learning objectives. Student feedback indicated improved debugging efficiency and increased time for higher-order problem-solving tasks, with one fourth-year student reporting: "AI handles the routine coding tasks, allowing me to focus on the architectural decisions that actually require human judgment." This case demonstrated how intentional integration with appropriate guardrails enhanced learning while preserving key skills.

5.2.2 Impact on Learning Outcomes and Cognitive Development

Perhaps the most striking discovery was the seeming contradiction between performance gains and cognitive distress. Whereas 89.4% of respondents indicated grade enhancements via AI aid—most noticeable benefits among regular users (100% indicated improvement)—63.5% reported worries regarding diminished critical thinking capacity. This tension illustrated what González-Calatayud et al. (2023)

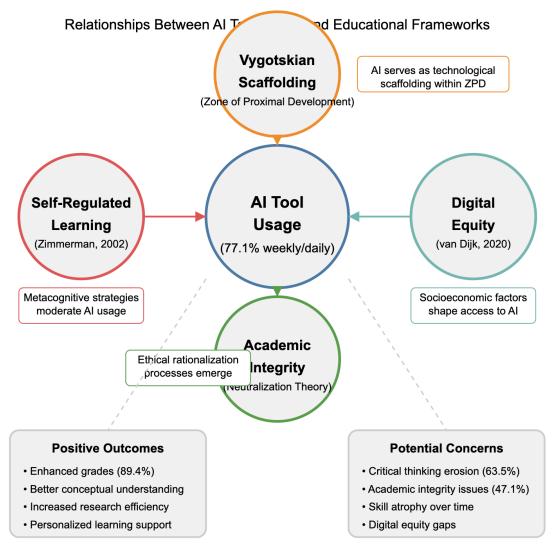
referred to as the "augmentation-atrophy paradox," whereby cognitive technology advances performance at the same time it might detract from skill acquisition.

The disciplinary variation in critical thinking concerns (Social Sciences: 3.8/5 vs. Engineering: 2.9/5) suggested that students' metacognitive awareness was guided by disciplinary values and pedagogical expectations. Social Sciences disciplines tended to value analytical thinking and theoretical critique (Anderson & Miller, 2023), which may have sensitized students to cognitive outsourcing, whereas Engineering's focus on successful problem-solving may have normalized technological assistance (Taylor, 2024).

Qualitative findings revealed sophisticated strategies for balancing AI benefits with cognitive development concerns, particularly among high-achieving students. These "metacognitive moderators" included:

- 1. Structured pre-processing (thinking through problems before consulting AI)
- 2. Critical verification (cross-checking AI outputs against multiple sources)
- 3. Progressive scaffolding (using AI for initial drafts but gradually reducing dependence)

These strategies aligned with Zimmerman's (2002) Self-Regulated Learning framework, suggesting that pedagogical interventions supporting metacognitive awareness could mitigate potential negative impacts of AI tools on cognitive development.



Source: Synthesis of empirical findings and literature review

FIGURE 5.1: Theoretical Integration Model showing relationships between AI tool usage, Vygotskian scaffolding, Self-Regulated Learning, and cognitive development outcomes

5.2.3 Academic Integrity Implications

The results concerning academic integrity painted a complicated ethical landscape. The prevalent use of evasion tools (47.1%) combined with low levels of awareness of institutional guidelines (only 37.5% were aware of such guidelines) indicated a governance gap whereby possibly undesired conduct was normalized. As Bertram Gallant (2017) has contended, integrity issues tend to emerge not necessarily because of deliberate dishonesty but due to confusing norms and conflicting messages.

One of the most concerning results was that just 16.3% of evasion tool users perceived AI as an enabler of cheating—a cognitive dissonance case that needed further exploration. Logistic regression analysis (Table 4.4) revealed three significant predictors of evasion tool usage: perception that AI tools save time (OR=2.46, p<0.01), ignorance of institutional policy (OR=1.98, p<0.05), and advancement in academic year (OR=1.32, p<0.05). This indicated that pragmatic interests, as opposed to ethical consideration, underpinned potentially problematic use patterns.

Qualitative findings demonstrated the presence of advanced rationalization mechanisms, wherein students developed individualized ethical frameworks in the absence of explicit institutional direction. These were:

Redefining AI as a "research tool" rather than a "writing tool"

- Establishing selective boundaries ("AI for brainstorming is acceptable, but not for final drafts")
- Peer normalization ("everyone uses these tools")

The findings align with the tenets of neutralization theory (Sykes & Matza, 1957), which argues that people justify norm violations by reinterpreting them as acceptable within particular contexts. By implication, institutional policies ought not only to draw boundaries but also address the underlying processes of rationalization that underpin ethically questionable actions.

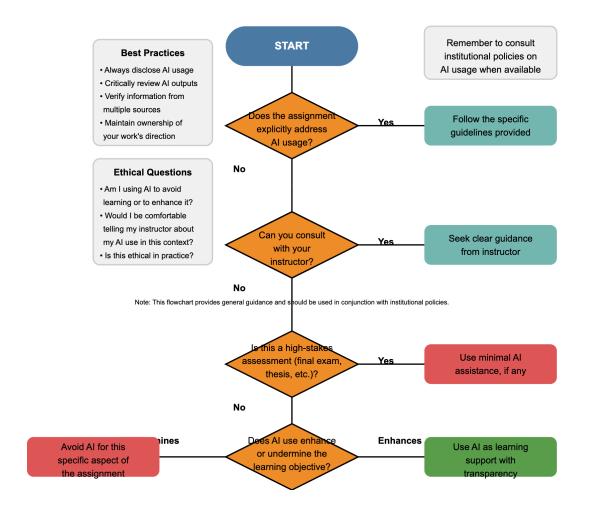


FIGURE 5.2: Ethical Decision-Making Flowchart for AI Usage in Academic Contexts

5.2.4 Structural Inequities and Access Disparities

The research identified concerning trends in asymmetric access to the advantages of artificial intelligence, indicating socioeconomic status significantly influences access to innovative tools and institutional assistance. The results mirror general worries about technological equity within higher education (Warschauer & Matuchniak, 2010; van Dijk, 2020), indicating AI will probably widen underlying education gaps without concerted intervention.

Three primary dimensions of inequality emerged:

1. **Technological Resources**: Access to multiple devices, reliable internet connectivity, and premium AI tool subscriptions correlated with socioeconomic background.

- 2. **Digital Literacy**: Computer literacy scores varied significantly across disciplines (Engineering: 8.3/10 vs. Humanities: 6.7/10), affecting students' ability to effectively leverage AI capabilities.
- 3. **Institutional Support**: Disciplinary variations in institutional resources (e.g., Engineering students receiving free GitHub Copilot access) created structural advantages for certain student populations.

These inequalities exhibited what Selwyn (2019) referred to as "digital privilege"—the compounded benefits that accumulate to already privileged groups due to unequal access to digital tools. This meant that organizations have to explicitly tackle various dimensions of inequality in order to make AI tools work as equalizers and not increase existing disparities.

Case Study 2: Addressing Digital Equity at Stellenbosch University

Stellenbosch University implemented a comprehensive digital equity program in 2022 to address disparities in AI tool access. The initiative included: (1) subsidized premium AI tool licenses for low-income students, (2) expanded campus computing facilities with extended hours, (3) peer-led digital literacy workshops, and (4) curriculum integration support for faculty across disciplines. Initial assessment showed a 38% reduction in the "digital divide" between socioeconomic groups and significantly improved AI literacy across disciplines. This approach demonstrated how intentional equity measures can ensure technological innovations benefit all students.

5.2.5 Comparative Institutional Context

Africa University's experience with AI integration can be understood in the context of broader institutional responses across the continent and globally. Table 5.1 compares key aspects of AI integration at Africa University with other institutions.

Table 5.1: Comparative Analysis of Institutional AI Integration

Aspect	Africa	University of	Stellenbosch	MIT (USA)
	University	Lagos	University	
		(Nigeria)		

			(South	
			Africa)	
Student AI	77.1%	65.3%	73.8%	89.4%
Usage	weekly/daily	weekly/daily	weekly/daily	weekly/daily
Rate				
Primary	ChatGPT	ChatGPT	ChatGPT	ChatGPT
AI Tools	(76.9%), POE	(81.2%),	(73.1%),	(82.7%),
	(54.8%)	Claude	Gemini	GitHub
		(43.5%)	(58.4%)	Copilot
				(61.3%)
D. II	T 1/1 1 .		T 11 11 AT	A 1
Policy	Limited/developi	Comprehensiv	Explicit AI	Adaptive
Framewor	ng	e AI policy	guidelines	assessment
k				policies
Faculty	Ad hoc/minimal	Structured	Comprehensiv	Integrated
Training		program	e digital	with teaching
			pedagogy	centers
Equity	Limited	Moderate	Extensive	Comprehensiv
Measures				e

This comparison highlighted Africa University's positioning in the early-to-middle stages of AI integration, with substantial opportunities for policy development and equity measures. The higher adoption rates at institutions with comprehensive policies suggested that clear guidelines enhance rather than restrict productive AI use.

5.3 Conclusions

5.3.1 Addressing the Primary Research Question

The central research question guiding this study was: "How do AI tools impact student learning experiences and academic integrity at Africa University?" Based on the findings presented in Chapter 4 and the discussion above, several key conclusions emerged:

- 1. **Dual Impact on Learning**: AI tools functioned simultaneously as powerful educational enhancers and potential threats to core academic values—increasing grades while potentially undermining critical thinking, supporting understanding while creating dependency, and operating within ethical gray areas that institutions had yet to clearly define.
- Contextual Variation: The impact of AI tools varied significantly based on academic discipline, individual metacognitive awareness, institutional support, and socioeconomic factors. This heterogeneity challenged one-sizefits-all policies and underscored the need for contextualized approaches to AI integration.
- 3. **Policy-Practice Gap**: A substantial disconnect existed between institutional policies and student practices, with nearly half of students unaware of guidelines regarding AI use. This governance vacuum allowed the normalization of potentially problematic practices while creating unequal access to AI benefits.
- 4. Emergent Student Strategies: Despite institutional policy gaps, students developed sophisticated strategies for leveraging AI benefits while mitigating risks. These emergent practices provided valuable insights for formal policy development and pedagogical innovation.

The findings collectively indicate that artificial intelligence tools do not possess intrinsic strengths or weaknesses within educational settings but that their effect is contingent upon how they are implemented within educational ecosystems, buttressed by institutional policy, and utilized by students with varying degrees of metacognitive awareness and digital literacy.

5.3.2 Contributions to Knowledge

This study made several noteworthy contributions to the emerging literature on AI in higher education:

1. **African Context**: By focusing on Africa University, this research addressed a significant gap in the literature, which had predominantly examined AI integration in Global North contexts. The findings highlighted how

- infrastructural, policy, and cultural factors shaped AI adoption in African higher education settings.
- 2. Disciplinary Variation: The detailed analysis of disciplinary differences in AI usage patterns, critical thinking concerns, and ethical practices advanced understanding of how epistemological traditions and professional preparation paradigms mediate technological integration.
- 3. Metacognitive Moderation: The identification of "metacognitive moderators"—strategies students employ to balance AI benefits with cognitive development—contributed to theoretical models of technology-enhanced learning by highlighting agency and self-regulation as mediating factors.
- 4. **Ethical Landscape**: The examination of ethical rationalization processes provided insight into how students navigate ambiguous integrity norms, extending neutralization theory to the context of AI-assisted academic work.
- 5. **Methodological Approach**: The mixed-methods design, with its robust triangulation of quantitative and qualitative findings, offered a methodological template for future research on educational technology adoption and impact.

5.3.3 Limitations of the Study

While this research provided valuable insights, several limitations should be acknowledged:

- Self-Reported Data: The reliance on self-reported data regarding grade improvements and critical thinking impacts introduced potential social desirability bias. Future studies would benefit from objective measures of academic performance and cognitive skill development.
- Cross-Sectional Design: The study's cross-sectional nature captured AI
 usage at a specific moment, limiting understanding of how patterns evolve
 over time. Longitudinal approaches would strengthen causal inferences about
 AI's impact on skill development.

- 3. **Institutional Specificity**: Findings reflected Africa University's unique institutional context and may not generalize fully to all higher education settings. Multi-institutional research would enhance generalizability.
- 4. **Tool Limitations**: The study focused primarily on generative AI tools (ChatGPT, POE, etc.) and may not have captured the full spectrum of AI technologies used in educational contexts.
- 5. **Disciplinary Representation**: While efforts were made to include diverse disciplines, sample sizes within some departments limited statistical power for highly granular disciplinary comparisons.

These limitations did not undermine the study's validity but contextualized its findings within appropriate methodological boundaries and highlighted opportunities for future research.

5.4 Implications

5.4.1 Theoretical Implications

The findings had several implications for theoretical frameworks in educational technology and higher education:

- Vygotskian Scaffolding: The study provided empirical support for conceptualizing AI as a form of technological scaffolding within the Zone of Proximal Development, while highlighting the risk of permanent scaffolding that impedes independent skill development. This suggested the need for models of "graduated scaffolding" that strategically reduce AI support as competence develops.
- Self-Regulated Learning: The identification of metacognitive strategies employed by students extended Zimmerman's (2002) Self-Regulated Learning framework to AI-enhanced environments, suggesting that metacognitive awareness serves as a critical moderator of technological impact on learning.

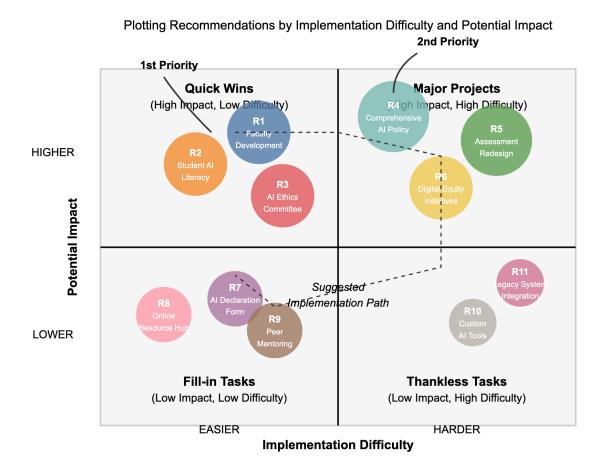
- 3. Digital Equity: The findings regarding socioeconomic disparities in AI access contributed to digital divide scholarship by highlighting how technological innovations can reproduce and amplify existing inequalities in educational settings. This supported van Dijk's (2020) argument that digital inequality operates through multiple, reinforcing dimensions beyond mere access.
- 4. **Academic Integrity**: The rationalization processes revealed by this study extended neutralization theory to the context of AI-assisted academic work, suggesting that integrity frameworks must address not only behavioral boundaries but the cognitive processes that enable boundary transgression.

5.4.2 Practical Implications

Beyond theoretical contributions, the findings had direct implications for educational practice:

- 1. **Assessment Design**: The high rate of AI tool usage (77.1% weekly or daily) suggested that traditional assessment methods may increasingly measure AI capabilities rather than student learning. This necessitated redesigning assessments to either incorporate AI as a legitimate tool or to evaluate processes AI cannot easily replicate.
- 2. Curriculum Development: The finding that 70.2% of students used AI primarily for conceptual understanding suggested opportunities to formally integrate AI tools as learning supports while developing curricula that emphasize uniquely human capabilities such as critical evaluation, creative synthesis, and ethical judgment.
- 3. **Faculty Development**: The disciplinary variations in AI adoption highlighted the need for discipline-specific faculty training that addresses not only technical capabilities but epistemological alignment between AI affordances and disciplinary knowledge structures.
- 4. **Student Support**: The identified metacognitive strategies employed by highachieving students could inform development of explicit training programs to

help all students leverage AI benefits while maintaining cognitive independence.



Note: Circle size indicates relative resource requirements. Recommendations are numbered by reference (R1-R11), not by priority order.

FIGURE 5.3: Recommendation Priority Matrix plotting recommendations by implementation difficulty (x-axis) and potential impact (y-axis)

5.5 Recommendations

Based on the findings and implications discussed above, the following recommendations are organized by stakeholder group to clarify implementation responsibilities, with a phased implementation timeline.

5.5.1 Stakeholder-Specific Recommendations

For University Administration

1. Develop Comprehensive AI Policy Framework

- Establish clear institutional guidelines on appropriate AI use across contexts
- o Create transparent AI disclosure requirements for assignments
- Develop specific policies addressing evasion tool usage
- o Ensure policies acknowledge disciplinary variations

2. Invest in Digital Equity Initiatives

- Subsidize premium AI tool access for economically disadvantaged students
- o Expand campus computing facilities and high-speed internet access
- o Develop laptop loan programs for students without personal devices
- Ensure mobile-optimized versions of AI tools for smartphonedependent students

3. Establish AI Ethics Committee

- Form cross-disciplinary committee to address emerging ethical questions
- o Include student representatives in policy development
- Create clear reporting mechanisms for integrity concerns
- o Regularly review and update policies as AI capabilities evolve

For Faculty and Academic Departments

1. Redesign Assessment Approaches

- o Develop process-oriented assessments emphasizing critical thinking
- o Implement multimodal assessment methods (oral exams, portfolios)

- Create "AI-resistant" assessments for skills requiring independent mastery
- Design "AI-integrated" assessments that explicitly incorporate AI as a tool

2. Enhance Curricula with AI Literacy

- o Integrate explicit AI literacy modules into core courses
- Develop assignments requiring critical evaluation of AI-generated content
- o Create scaffolded experiences that gradually reduce AI dependency
- o Emphasize uniquely human capabilities in course learning objectives

3. Participate in Faculty Development

- o Attend discipline-specific workshops on effective AI integration
- o Join communities of practice for sharing pedagogical innovations
- o Learn both AI capabilities and detection tools
- o Conduct classroom research on AI's impact on student learning

For Students

1. Develop AI Literacy

- o Complete mandatory AI literacy training modules
- o Practice critical evaluation of AI-generated content
- Learn effective prompt engineering techniques
- o Understand both capabilities and limitations of AI tools

2. Adopt Metacognitive Strategies

o Implement pre-processing (thinking before consulting AI)

- o Practice critical verification of AI outputs against multiple sources
- Use progressive scaffolding to reduce AI dependency over time
- Reflect on how AI usage affects skill development

3. Engage with Academic Integrity

- o Understand institutional policies on appropriate AI use
- o Transparently disclose AI usage in academic work
- o Participate in peer discussions about ethical boundaries
- Report concerns through appropriate channels

For IT Services

1. Support Technical Infrastructure

- o Ensure campus-wide access to high-speed internet
- Maintain up-to-date computing facilities
- o Support integration of AI tools with learning management systems
- o Implement technical safeguards against unauthorized AI use

2. Provide Technical Training

- o Offer workshops on effective AI tool usage
- Create online resources for self-directed learning
- Support faculty with technical implementation of AI integration
- o Train staff on emerging AI capabilities and limitations

5.5.2 Implementation Timeline

To ensure systematic and sustainable change, the following phased approach is recommended:

Phase 1: Foundation Building (0-6 months)

- Develop institutional policy framework
- Establish AI ethics committee
- Conduct faculty and student awareness campaigns
- Begin faculty development program

Phase 2: Capacity Development (6-18 months)

- Implement digital equity initiatives
- Pilot assessment redesign in selected courses
- Expand faculty training across disciplines
- Develop and integrate AI literacy modules

Phase 3: Comprehensive Integration (18-36 months)

- Scale successful assessment approaches across curricula
- Fully implement AI literacy across programs
- Develop advanced faculty competencies
- Establish ongoing monitoring and evaluation

Phase 4: Refinement and Innovation (36+ months)

- Conduct impact assessment of initiatives
- Refine approaches based on evidence
- Develop Africa University as a center of excellence
- Share best practices with other institutions

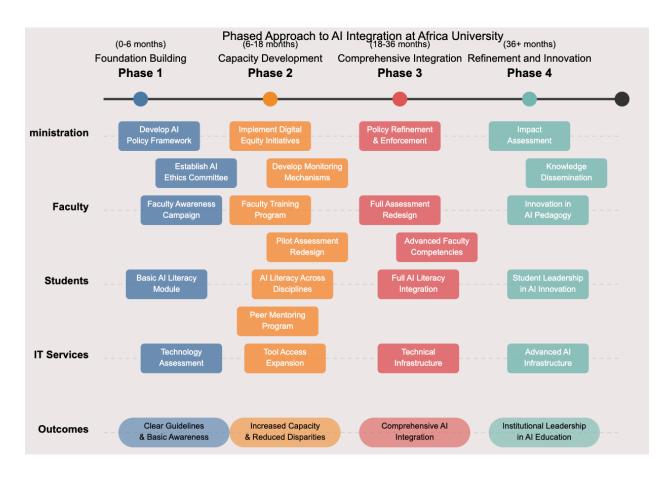


FIGURE 5.4: Implementation Framework Diagram showing the relationships and sequencing between recommendations

5.5.3 Action Steps for Immediate Implementation

To begin the implementation process, the following specific, measurable action steps are recommended for immediate attention:

1. Form AI Policy Task Force (Within 1 month)

- Appoint representatives from all stakeholder groups
- Review existing policies at comparable institutions
- Draft initial policy framework for community feedback
- o Establish timeline for policy development and approval

2. Conduct Comprehensive Faculty Survey (Within 2 months)

Assess current AI knowledge, attitudes, and practices

- Identify training needs and disciplinary variations
- o Gather input on assessment redesign priorities
- Identify early adopters for pilot programs

3. Launch Student AI Literacy Initiative (Within 3 months)

- o Develop basic online module on ethical AI use
- Require completion by all currently enrolled students
- Integrate into orientation for incoming students
- o Create peer mentoring program for ongoing support

4. Establish Monitoring Mechanisms (Within 3 months)

- Define key metrics for measuring implementation progress
- Create data collection procedures for ongoing assessment
- Establish baseline measures for future comparison
- o Schedule regular review points for adaptive management

5.6 Suggestions for Further Research

While this study provided valuable insights into AI's impact on student learning and academic integrity at Africa University, several avenues for further research would enhance understanding of this rapidly evolving landscape:

- Longitudinal Studies: Track changes in AI usage patterns, learning outcomes, and skill development over students' academic careers to understand long-term impacts on cognitive development and professional preparation.
- Pedagogical Interventions: Conduct experimental studies comparing different approaches to integrating AI tools into course design, with particular

- attention to assessment methods that effectively evaluate learning in AIenhanced environments.
- 3. **Faculty Perspectives**: Investigate faculty attitudes, concerns, and pedagogical adaptations related to student AI use, including disciplinary variations in acceptance and integration strategies.
- 4. **Emerging AI Capabilities**: Examine how advances in AI, such as multimodal models, affect educational applications and present new opportunities and challenges for teaching and learning.
- 5. **Cross-Institutional Comparisons**: Conduct comparative studies across different African universities to understand how institutional contexts, resources, and cultural factors shape AI adoption and impact.
- 6. **Professional Preparation**: Investigate how AI integration in higher education aligns with evolving workplace expectations and professional standards across different fields.
- 7. **Policy Effectiveness**: Evaluate the impact of different institutional policies on promoting ethical AI use, addressing access disparities, and supporting positive learning outcomes.
- 8. **Authentic Assessment in AI Era**: Develop and test new assessment approaches that effectively measure learning outcomes while acknowledging the reality of AI-enhanced academic work.
- Metacognitive Development: Further explore the relationship between metacognitive awareness, self-regulated learning, and effective AI integration strategies.
- 10. **Digital Equity Interventions**: Evaluate the effectiveness of various interventions aimed at addressing disparities in AI access and benefits across student demographics.

Such research would not only advance theoretical understanding of AI's role in higher education but provide evidence-based guidance for institutional policies, pedagogical practices, and technological development in African and global educational contexts.

5.7 Final Reflections

This research captured a watershed moment in the evolution of tertiary education, as artificial intelligence devices represented significant possibilities for transformation and inevitable dilemmas for conventional scholarly practice. The findings emanating from Africa University demonstrated larger tensions unfolding in worldwide learning settings specifically, the conflicts between efficiency and profound learning, between technological facilitation and cerebral autonomy, and between innovation and fairness.

The most relevant conclusion was the requirement for deliberate, evidence-driven strategies toward artificial intelligence integration balancing innovation with caution, grasping opportunities while lessening dangers. The advice offered here is only the beginning of achieving this balance; however, ongoing debate, study, and policy refinement will be required as advancements in AI capabilities continue to progress.

For Africa University and similar institutions, the coming challenge goes beyond technological considerations and is inherently an educational paradigm one—requiring careful consideration of the alignment of AI tools with core educational principles, academic disciplines, and the development of graduates capable of thriving in an increasingly AI-integrated world. By a conscious confrontation of these challenges, institutions can harness the promise of AI while protecting the inherent human dimensions of learning that remain at the heart of the purpose of higher education.

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Appendix A: Survey Questionnaire

Survey on AI Tool Usage and Academic Integrity

Purpose: This survey aims to understand how students interact with AI tools in their academic pursuits, the reasons behind their usage, and the perceived impact on learning and academic integrity.

Confidentiality: All responses are anonymous and will be used solely for research purposes.

Consent: By proceeding, you consent to participate in this survey.

Section 1: Demographic Information

1. **Age:**

- 0 18-20
- 0 21-23
- 0 24-26
- $^{\circ}$ 27+

2. Gender:

- Male
- Female

3. College Affiliation:

- College of Business and Management Sciences
- o College of Engineering and Applied Sciences
- o College of Health, Agriculture, and Natural Sciences
- o College of Social Sciences, Theology, Humanities, and Education
- School of Law

4. Year of Study:

- o First Year
- Second Year
- Third Year
- Fourth Year
- Postgraduate

5. Computer Literacy: (Scale: 1-10)

- \circ 1 = I struggle with basic tasks
- \circ 5 = Average
- 0 10 = I am highly proficient

Section 2: AI Tool Usage

6. Duration of AI Tool Usage:

- Less than 3 months
- o 3-6 months
- o 6-12 months
- o Over a year

7. Frequency of AI Tool Usage for Academic Work:

- o Daily
- Weekly
- o Monthly
- o Rarely
- o Never

8. AI Access Method: (Select all that apply)

- o AI Assistant on platforms
- App on Phone
- o App on Laptop
- Website on Laptop
- o Website on Phone

9. **Types of AI Used:** (Select all that apply)

- o ChatGPT
- o POE
- o Gemini
- o Gamma
- o Claude
- Deepseek
- Meta AI
- Perplexity
- Grammarly
- o Grok (X AI)
- o Llama
- o Quillbot
- Other (please specify)

10. Motivation for Starting to Use AI Tools: (Select all that apply)

o Peer influence (Friends/Students)

- Social media promotions
- o Academic pressure/workload
- o Curiosity about AI technology
- o Recommendation from a lecturer

11. Academic Tasks Using AI Tools: (Select all that apply)

- Research
- Writing Assignments
- o Exam Preparation
- o Proofreading
- Summarizing content
- o Explaining Concepts Better
- Note Taking
- Other (please specify)

12. **Purpose of Using AI Tools:** (Select all that apply)

- Saves time
- o Helps me understand difficult topics
- o Improves writing quality
- o Reduces effort in completing assignments
- o Generates ideas and explanations
- Other (please specify)

Section 3: AI Usage Skills & Academic Impact

13. Confidence in Prompting AI:

- o Beginner I struggle to get good results
- o Intermediate I know how to refine prompts
- o Advanced I can get highly specific results

14. Impact on Grades:

- o Yes, significantly
- o Yes, slightly
- o No change
- o My grades have dropped

15. Perceived Benefit of AI Tools:

- They help me learn better
- o They just make completing tasks easier
- Both equally

Other (please specify)

Section 4: AI and Academic Integrity

16. Bypassing AI Detection:

- o Yes
- o No

17. Submission of AI-Generated Content:

- o Yes, multiple times
- o Yes, but only occasionally
- o No, I always edit AI-generated content
- o No, I never submit AI-generated content

18. Perception of AI and Academic Dishonesty:

- o Yes, they make it easier to cheat
- o No, they are just a study tool
- o It depends on how they are used

19. University Policies on AI Tool Usage:

- o Allow AI
- o Do Not Allow AI

20. Perception of AI Usage in Academic Settings:

- o A valuable aid to learning
- o A potential threat to academic integrity
- o Neutral
- Other (please specify)

21. Awareness of University Policies on AI Usage:

- o Yes
- o No
- o Not sure

22. Need for Guidance on AI Usage:

- o Yes
- o No
- o Maybe

Section 5: Ethical Considerations and Future Perspectives

23. Ethical Concerns Regarding AI in Education: (Select all that apply)

- o Privacy and data security
- o Bias and discrimination

- Over-reliance leading to reduced critical thinking
- Job displacement
- Other (please specify)

24. Trust in AI Tools: (Scale: 1-10)

- $_{\circ}$ 1 = No trust
- \circ 10 = Complete trust

25. Future Use of AI in Education: (Select all that apply)

- o Personalized learning paths
- Automated tutoring support
- o Administrative assistance (e.g., scheduling, reminders)
- o Virtual reality or augmented reality learning environments
- Other (please specify)

26. Awareness of AI Limitations:

- o Yes
- o No
- Somewhat

27. **Awareness of Specific AI Limitations:** (Select all that apply)

- Hallucinations
- Lack of Up-to-Date Information
- Sensitivity to Input Phrasing
- o Overconfidence in Incorrect Answers
- Misinterpretations
- Other (please specify)

Appendix B: Interview Protocol

Semi-Structured Interview Guide: AI Tools and Academic Integrity at Africa University

Introduction Script:

"Thank you for agreeing to participate in this interview. My name is Gaku Tanaka Nakajima, and I am conducting research on the impact of AI tools on students' learning experiences and academic integrity at Africa University. This interview will take approximately 45-60 minutes of your time. With your permission, I would like to audio record our conversation to ensure accuracy in capturing your perspectives. The recording will be transcribed for analysis, but your identity will remain confidential.

You are free to skip any questions or end the interview at any time. Do you have any questions before we begin?"

Section 1: Introduction and Background

- 1. Could you tell me a bit about your academic background and experience at Africa University?
 - o Probe: What program are you in? What year?
 - Probe: What has been your general experience with technology in your studies?
- 2. When did you first become aware of AI tools like ChatGPT, POE, or others, and what was your initial reaction to them?
 - o Probe: How did you learn about these tools?
 - Probe: What were your initial thoughts about their potential use in education?

Section 2: AI Tool Usage Patterns

- 3. Can you describe how you currently use AI tools in your academic work?
 - o Probe: Which specific tools do you use most frequently?
 - o Probe: For what specific academic tasks do you use these tools?
 - o Probe: How often do you use these tools (daily, weekly, etc.)?
- 4. Walk me through the process of how you typically interact with AI tools for an assignment.
 - o Probe: How do you formulate your questions or prompts?
 - o Probe: How do you evaluate the responses you receive?
 - *Probe: What do you do with the information provided by the AI?*
- 5. How has your usage of AI tools evolved since you first began using them?
 - o Probe: Have you developed specific strategies for more effective use?
 - o Probe: Have you expanded or restricted your usage over time?
- 6. Are there specific courses or types of assignments where you find AI tools particularly helpful or unhelpful?
 - o Probe: Why do you think this is the case?
 - o Probe: How do different academic disciplines influence your AI usage?

Section 3: Perceived Benefits and Impact on Learning

- 7. In what ways do you believe AI tools have impacted your learning experience?
 - Probe: Have they changed how you approach studying or completing assignments?

- o Probe: Have they affected your understanding of course material?
- 8. Have you noticed any changes in your academic performance since you began using AI tools?
 - o Probe: Changes in grades or feedback from instructors?
 - o Probe: Changes in your confidence or engagement with the material?
- 9. What do you perceive as the most significant benefits of using AI tools in your education?
 - o Probe: How do they enhance your learning process?
 - o Probe: Are there specific skills or competencies they help you develop?

Section 4: Challenges and Concerns

- 10. What challenges or difficulties have you experienced when using AI tools for academic purposes?
 - o Probe: Technical challenges?
 - o *Probe: Challenges related to the quality or reliability of information?*
- 11. Do you have any concerns about how AI tools might affect your development of critical thinking or other academic skills?
 - o Probe: Have you noticed any negative impacts on your own abilities?
 - o Probe: How do you balance AI assistance with independent thinking?
- 12. Have you experienced any inequities or disparities in access to AI tools among students?
 - o Probe: Are there economic barriers to using certain tools?
 - Probe: Do you think all students have equal opportunity to benefit from these technologies?

Section 5: Academic Integrity Considerations

- 13. How do you navigate ethical considerations when using AI tools for academic work?
 - o Probe: What guidelines do you follow in determining appropriate use?
 - Probe: Have you ever been uncertain about whether a particular use was appropriate?
- 14. Are you aware of any university policies regarding the use of AI tools in academic work?
 - o Probe: If yes, what is your understanding of these policies?
 - *Probe: Do you find these policies clear and helpful?*

- 15. How do you think instructors or the university should address the use of AI tools in academic settings?
 - o Probe: What policies or guidelines would be helpful?
 - Probe: How should the use of AI be disclosed or acknowledged in submitted work?
- 16. Have you observed other students using AI tools in ways that you would consider academically dishonest?
 - o Probe: Without naming individuals, can you describe these behaviors?
 - o Probe: Why do you consider these uses inappropriate?

Section 6: Recommendations and Future Perspectives

- 17. What recommendations would you make to the university regarding policies and support for AI tool usage?
 - o Probe: What resources or guidance would be helpful to students?
 - o Probe: How might courses or assignments be redesigned to accommodate or leverage AI tools?
- 18. How do you envision the future role of AI tools in higher education, particularly at Africa University?
 - Probe: What opportunities do you see for enhancing education with AI?
 - o Probe: What concerns do you have about increasing AI integration?

Closing:

- 19. Is there anything else about your experience with AI tools that you would like to share that we haven't discussed?
- 20. Do you have any questions for me about this research or how your responses will be used?

"Thank you for your time and valuable insights. Your perspectives will be instrumental in understanding the impact of AI tools on learning and academic integrity at Africa University and in developing recommendations for more effective integration of these technologies."

Appendix C: AUREC APPROVAL

Attached below

Appendix D: Proposed AI Policy Framework Draft

AFRICA UNIVERSITY

ARTIFICIAL INTELLIGENCE TOOLS POLICY FRAMEWORK

PREAMBLE

This policy framework has been developed based on the findings of the research study "Impact of AI Tools on Students' Learning and Academic Integrity: A Case Study at Africa University" conducted in 2024-2025. The framework addresses the identified needs for clear institutional guidance, equitable access, appropriate pedagogical integration, and maintenance of academic integrity in the context of increasingly prevalent AI tool usage among students.

1. POLICY SCOPE AND OBJECTIVES

1.1 Scope

This policy applies to all members of the Africa University community, including students, faculty, and staff, in their use of artificial intelligence tools for academic and administrative purposes.

1.2 Objectives

The policy aims to:

- 1. Establish clear guidelines for the ethical and effective use of AI tools
- 2. Support academic integrity while recognizing the educational value of AI technologies
- 3. Promote equitable access to AI tools across the student population
- 4. Guide faculty in the appropriate integration of AI tools in teaching and assessment
- 5. Foster digital literacy and critical evaluation skills for AI tool use

2. DEFINITIONS

2.1 Artificial Intelligence (AI) Tools

For the purposes of this policy, "AI tools" refers to software applications that use machine learning, natural language processing, or other AI technologies to generate content, analyze data, or provide decision support. Examples include but are not limited to ChatGPT, POE, Gamma, Gemini, Claude, and Quillbot.

2.2 Academic Integrity

The commitment to honesty, trust, fairness, respect, and responsibility in all academic work, including proper attribution of sources and transparent disclosure of assistance received.

2.3 AI-Generated Content

Text, code, images, or other materials created primarily or entirely by an AI tool rather than by the student themselves.

2.4 AI-Assisted Work

Academic work where AI tools have been used to support the student's own thinking, research, or composition process, but where the student maintains substantive intellectual contribution and control over the final product.

3. STUDENT USE OF AI TOOLS

3.1 Permitted Uses

Students may use AI tools to:

- 1. Enhance understanding of complex concepts
- 2. Generate initial ideas or outlines for further development
- 3. Receive feedback on their own writing or coding
- 4. Synthesize research findings
- 5. Practice problem-solving approaches
- 6. Support language translation or grammar checking
- 7. Access additional explanations of course material

3.2 Disclosure Requirements

Students must disclose their use of AI tools:

- 1. In accordance with course-specific guidelines provided by instructors
- 2. When submitting assignments where AI tools have contributed significantly to content generation
- 3. Using the standard disclosure format provided in Appendix A of this policy

3.3 Prohibited Uses

The following uses of AI tools are prohibited:

- 1. Submitting AI-generated content as one's own work without substantial modification, intellectual engagement, or proper disclosure
- 2. Using AI tools to complete assessments explicitly designated as requiring independent work
- 3. Using AI tools to circumvent the learning objectives of an assignment
- 4. Using AI detection evasion tools or techniques to disguise AI-generated content
- 5. Sharing access credentials for institutional AI tools with unauthorized users

4. FACULTY RESPONSIBILITIES

4.1 Course Policies

Faculty members should:

- 1. Develop clear, specific guidelines regarding permitted and prohibited AI tool uses in their courses
- 2. Include these guidelines in course syllabi and assignment instructions
- 3. Explain the educational rationale behind restrictions or permissions

4.2 Assessment Design

Faculty are encouraged to:

- 1. Design assessments that maintain validity in an AI-enabled educational environment
- 2. Consider incorporating AI tools as explicit components of appropriate assignments
- 3. Develop assessment approaches that evaluate process as well as product
- 4. Use multimodal assessment methods that leverage distinctly human capabilities
- 5. Update assessment criteria to reflect changing technological contexts

4.3 Academic Integrity Violations

When addressing potential academic integrity violations related to AI tools, faculty should:

- 1. Follow the established university procedures for academic misconduct
- 2. Consider the distinction between explicit prohibition, misunderstanding, and lack of disclosure
- 3. Use incidents as educational opportunities where appropriate

5. INSTITUTIONAL RESPONSIBILITIES

5.1 Equitable Access

The university commits to:

- 1. Provide baseline access to approved AI tools for all students
- 2. Develop subsidy programs for premium AI tool access for economically disadvantaged students
- 3. Ensure adequate on-campus computing facilities with AI tool availability
- 4. Support mobile optimization for students primarily using smartphones

5.2 Educational Support

The university will provide:

- 1. Mandatory AI literacy training for all students during orientation
- 2. Regular workshops on effective and ethical AI tool use
- 3. Online resources for self-directed learning about AI capabilities and limitations
- 4. Faculty development opportunities for AI integration in teaching

5.3 Monitoring and Evaluation

The university will:

- 1. Establish an AI Policy Committee to oversee implementation and updates
- 2. Conduct annual evaluations of policy effectiveness
- 3. Gather feedback from students and faculty
- 4. Review and update the policy annually to reflect technological changes

6. DISCIPLINE-SPECIFIC GUIDELINES

6.1 Engineering and Applied Sciences

- 1. Programming courses may permit AI coding assistants with appropriate disclosure
- 2. Technical problem-solving courses should clearly designate which problems must be solved independently
- 3. Design projects should clearly articulate which components can be AI-supported and which must be original

6.2 Social Sciences, Theology, Humanities, and Education

- 1. Writing-intensive courses should establish clear parameters for AI drafting assistance
- 2. Analysis and interpretation assignments should emphasize original human perspectives
- 3. Cultural and contextual analyses should acknowledge the limitations of AI in nuanced cultural understanding

6.3 Health, Agriculture, and Natural Sciences

- 1. Laboratory reports should clearly distinguish between AI-assisted data analysis and independent interpretation
- 2. Clinical reasoning exercises should be completed without AI assistance
- 3. Research methodology courses should include critical evaluation of AIgenerated content

6.4 Law

- 1. Legal research may be supported by AI tools with proper disclosure
- 2. Legal writing should maintain substantive human contribution in argumentation
- 3. Case analysis should emphasize human judgment in precedent application

6.5 Business and Management Sciences

- 1. Data analysis assignments may incorporate AI tools with proper disclosure
- 2. Strategic decision-making assessments should emphasize human judgment
- 3. Business communication assignments should establish clear parameters for AI editing assistance

7. IMPLEMENTATION TIMELINE

7.1 Phase 1: Foundation Building (0-6 months)

- 1. Establish AI Policy Committee
- 2. Develop and distribute educational materials
- 3. Conduct initial faculty training
- 4. Begin baseline access provision

7.2 Phase 2: Capacity Development (6-18 months)

- 1. Implement full training program for students and faculty
- 2. Develop discipline-specific guidelines
- 3. Implement disclosure mechanisms
- 4. Establish support services

7.3 Phase 3: Comprehensive Integration (18-36 months)

- 1. Fully integrate AI literacy into curriculum
- 2. Deploy advanced faculty development
- 3. Implement equity programs
- 4. Conduct first comprehensive policy evaluation

8. POLICY GOVERNANCE

8.1 AI Policy Committee

An interdisciplinary committee comprising:

- 1. Faculty representatives from each college
- 2. Student representatives
- 3. IT services representative
- 4. Academic integrity officer
- 5. Teaching and learning center representative
- 6. Library representative

8.2 Committee Responsibilities

- 1. Oversee policy implementation
- 2. Address emerging issues
- 3. Review and approve discipline-specific guidelines
- 4. Recommend policy updates
- 5. Evaluate effectiveness

8.3 Policy Review Schedule

This policy shall be reviewed:

- 1. Annually for minor updates
- 2. Every three years for comprehensive revision
- 3. As needed in response to significant technological developments

Note: This policy framework is presented as a draft for consideration by the Africa University administration and governance bodies. Implementation would require formal approval through established university processes and may be modified based on stakeholder feedback.

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