A Comparative Analysis of Artificial Intelligence Learning and In-Class Learning in Kenyan Universities

Kariuki Thomas N. [1], Ruto Paul [2], Gichanga Ruth W. [3], Wainaina Hesborn [4]
St. Paul's University

Abstract

This study presents a comparative analysis of Artificial Intelligence (AI) learning and traditional in-class learning in Kenyan universities, focusing on learning outcomes, student engagement, and accessibility. The study was conducted across six universities—three public and three private—and the study involved 424 undergraduate students and 35 instructors, utilizing a mixed-methods approach. Quantitative data from surveys and performance records were complemented by qualitative insights from interviews and focus group discussions. The results revealed that students using AI learning platforms outperformed those in traditional settings, particularly in Science, Technology, Engineering, and Mathematics (STEM) disciplines, with AI learners achieving an average score of 78.4% compared to 72.9% for in-class learners. Engagement levels were also higher among AI learners, who reported more frequent interaction with learning materials and instructors, especially during asynchronous sessions. However, significant challenges were identified in terms of accessibility, especially in rural universities where unstable internet and a lack of digital infrastructure hindered AI adoption. In contrast, in-class learning was more accessible in these regions but faced issues of overcrowded classrooms and limited resources. The study suggests that while AI learning offers significant advantages in terms of personalization and flexibility, a blended learning model combining both AI and in-class methods may provide the most effective educational experience. This model could address the strengths and limitations of each approach, especially in addressing the digital divide and fostering critical thinking. The findings suggest policy reforms to improve digital infrastructure, promote instructor training, and ensure inclusive access to AI-driven education in Kenyan universities.

Key Words: *Artificial Intelligence (AI) Learning, In-Class Learning, Kenyan Universities, Blended Learning Model, Inclusive Education.*

1.0 Introduction

Kenyan Universities face significant challenges, including overcrowded classrooms, limited access to qualified instructors, and strained resources, which often hinder the effectiveness of traditional in-class learning. AI learning systems, on the other hand, have been proposed as a solution to address these challenges by providing personalized learning experiences, scalability, and flexibility. As universities increasingly adopt AI-driven technologies, understanding the benefits and limitations of both learning methods is critical for ensuring that the integration of AI technologies enhances, rather than detracts from, educational quality and equity.

Wanjiku (2021); Mutisya & Mwangi (2020) exploring the roles and approaches of AI in enhancing higher education in Kenya examine the challenges and opportunities that AI offers and compares the effectiveness of AI-enhanced learning with traditional in-class learning. Owino (2019), examining the impact of artificial intelligence on student learning outcomes in Kenyan Universities provides a detailed analysis of the ways AI is reshaping how students learn and compares performance metrics from both AI-assisted and conventional classroom environments. Whereas, Njuki (2022), explores the advantages and limitations of AI-driven educational tools and methodologies in Kenyan universities, offering insights into how AI compares to traditional classroom setups. However, the studies fail to provide cogent data on the comparative effectiveness of AI and traditional in-class learning and whether AI learning can significantly improve learning outcomes, student engagement, and accessibility compared to in-class learning in Kenyan universities.

The study objectives were to compare the learning outcomes of students engaged in AI learning platforms with those of students in traditional in-class learning settings in selected Kenyan universities. To assess the level of student engagement in AI-based learning systems versus in-class learning environments. To evaluate the accessibility of AI learning platforms in comparison to in-class learning, particularly for students in remote and underprivileged regions of Kenya and to examine the strengths and limitations of AI learning and in-class learning in relation to pedagogical effectiveness and overall student experience.

This study was guided by the following hypotheses that AI learning platforms result in superior learning outcomes compared to in-class learning in Kenyan universities. AI learning platforms engage students more effectively than in-class learning environments and AI learning platforms provide greater accessibility to students, especially those in remote or disadvantaged regions, compared to in-class learning. The study aimed to offer a comprehensive understanding of how these learning methods affect students across various fields of study.

2.0 Methodology

The study was conducted across multiple Kenyan universities, including both public institutions (Muranga University of Technology, Kenyatta University, and Karatina University) and three private universities (St. Paul’s University, Kenya College of Accounts University, and United States International University). The selected universities are located in urban and rural settings, providing a comprehensive understanding of how AI learning and in-class learning function in diverse educational environments. The study primarily focuses on undergraduate students, instructors, and administrators who have experience with both AI-driven learning systems and traditional face-to-face learning. These institutions were selected based on their adoption of AI technologies in their curriculum and their geographical diversity.

Kenyan universities are increasingly incorporating AI learning platforms to supplement in-class instruction, particularly in response to the challenges posed by overcrowded classrooms, limited teaching resources, and the need to provide equitable access to higher education. The study setting included both the physical classrooms used for in-person learning and the online platforms used for AI-based learning, with data collection taking place within these environments.

Study Design

This study employed a comparative cross-sectional study design. The aim was to compare learning outcomes, engagement levels, and accessibility between students exposed to AI learning platforms and those who primarily experience in-class learning. A mixed-methods approach was used, combining both quantitative (surveys, academic performance data) and qualitative (interviews, focus group discussions) data collection techniques. This design allowed for a comprehensive analysis of the two learning methods, capturing both measurable outcomes and personal experiences.

Population

The target population for the study included undergraduate students enrolled in universities. These students came from a variety of academic disciplines, including Science, Technology, Engineering, and Mathematics (STEM) as well as Social Sciences and Humanities. Instructors and university administrators involved in both AI and in-class learning, including those who have implemented or manage AI learning platforms within their institutions. The inclusion criteria for students were based on enrollment in an undergraduate program in a university that uses both AI and in-class learning methods, participation in courses that utilize AI learning tools or platforms and availability and willingness to participate in the study.

Sampling Strategy

The sampling strategy involved stratified random sampling to ensure representation from various strata, including university type (public and private), geographical location (urban and rural), academic discipline (STEM vs. Social Sciences), and year of study (first year through final year). This strategy ensured a diverse and representative sample of students across multiple variables.

Using Cochran's formula, the sample size was determined to be 424 students, adjusted for potential non-responses, ensuring a sufficient sample size for reliable statistical analysis. A smaller, separate sample of 30-50 instructors and administrators was also selected using stratified sampling.

Variables

The primary independent variable include the mode of instruction (AI learning vs. in-class learning) and the dependent variables included the learning outcomes measured through student grades, performance on assessments, and retention rates, student engagement, evaluated using metrics such as class participation (in-class), interaction with AI tools, time spent on learning tasks, and engagement during lessons and accessibility examined based on access to learning materials, availability of digital infrastructure, and the inclusivity of AI systems (especially for students in rural or underserved areas). The control variables included student demographics based on age, gender, socioeconomic background, course complexity looking at the difficulty and rigor of the academic subjects studied and instructor quality exploring the consistency in teaching methodology and experience across both AI and traditional in-class learning.

Data Collection Instruments

To ensure comprehensive data collection, the study used both quantitative and qualitative instruments. A structured survey was administered to students and instructors. The survey included both closed-ended and Likert-scale questions to capture data on learning outcomes (grades, retention rates), student engagement (participation, interaction with content), accessibility and inclusivity of learning platforms. The survey also captured demographic data to control for potential confounding variables. Qualitative data were gathered through semi-structured interviews and FGDs with both students and instructors. These discussions explored experiences with AI learning tools, perceived effectiveness and challenges of in-class learning, insights into the advantages and limitations of each method in different academic settings. The interviews allowed for deeper exploration of issues such as the integration of AI systems and their effect on learning behavior. Academic records were also reviewed (with participant consent) to compare the performance outcomes of students who engaged in AI-based learning versus those in traditional settings. This included their exam results, coursework, and completion rates. Classroom observations were conducted for both in-class and AI-driven courses to observe student participation, interaction, and the learning environment's overall dynamics.

Data Collection Procedures

The data collection procedures included a pilot study that was conducted to test the reliability and validity of the survey instrument. Ethical approval was obtained from the relevant university research committees before data collection. Informed consent was collected from all participants and data were collected over a 12-week period, ensuring adequate time to gather data from all selected institutions and participants.

Quantitative Analysis

The collected data were analyzed using both quantitative and qualitative methods. The quantitative analysis included data from the surveys that were analyzed using descriptive statistics (mean, median, mode, standard deviation) to summarize student performance, engagement, and accessibility. Inferential statistics were also used to test the hypotheses. A t-test and ANOVA were employed to compare mean differences in learning outcomes and engagement between AI and in-class learning. Chi-square tests were used to examine categorical data such as accessibility and inclusivity. Multivariate regression models were used to control for confounding variables, such as student demographics and course complexity.

Qualitative Analysis

On qualitative analysis, data from the interviews and FGDs were transcribed and analyzed using thematic analysis. The transcripts were coded for recurring themes related to the experiences of students and instructors with AI learning and in-class teaching. Patterns in responses were identified, and findings were compared across different institutions and academic disciplines.

Performance Data Analysis

On the performance data analysis, performance data from academic records were analyzed to compare the grades, retention rates, and completion rates between students in AI-based learning systems and traditional in-class environments. A paired sample t-test was used to determine if significant differences existed in performance outcomes between the two groups.

3.0 Results and Discussion

Response Rates:

- **Students:** 424 invited; 398 responded (94% response rate).
- **Instructors and Administrators:** 35 invited; 30 responded (86% response rate).

Participants' Demographic Information

The demographic characteristics of the participants were as follows:

1. **Students:**
    - Gender Distribution: 54% female (215 participants), 46% male (183 participants).
    - Age Range: The majority of participants were aged between 18-25 years (85%), with the remaining 15% being between 26-35 years.
    - Year of Study:

- First-year students: 23% (92 participants),
- Second-year students: 25% (100 participants),
- Third-year students: 26% (103 participants),
- Final-year students: 26% (103 participants).

- Disciplines:
  - STEM: 43% (171 students),
  - Social Sciences and Humanities: 57% (227 students).

2. **Instructors and Administrators:**
   - Gender Distribution: 60% male (18 participants), 40% female (12 participants).
   - Academic Disciplines Taught:
     - STEM: 40% (12 instructors),
     - Social Sciences and Humanities: 60% (18 instructors).
   - Experience in AI Learning: 65% of instructors had experience with AI-based learning systems for at least one year.

Key Findings

1. Comparison of Learning Outcomes

The study found a significant difference in academic performance between students using AI learning platforms and those in in-class learning environments. The mean performance scores for the two groups were as follows:

a) **AI Learning Students:** Mean score = **78.4%** (SD = 6.3).
b) **In-Class Learning Students:** Mean score = **72.9%** (SD = 7.8).

A t-test conducted showed that the difference in mean scores between the two groups was statistically significant ($p < 0.05$). Students in the AI learning group demonstrated higher average performance, particularly in STEM disciplines, where AI platforms were more interactive and adaptive to individual learning needs.

Subgroup Analysis (STEM vs. Social Sciences):

a) STEM students using AI learning tools performed better (mean = 80.5%) compared to their peers in traditional classrooms (mean = 74.1%).
b) In contrast, Social Sciences and Humanities students showed less significant differences between AI and in-class learning performance (AI mean = 76.2%, in-class mean = 71.8%).

2. Student Engagement and Interaction

Engagement levels were measured using self-reported metrics and classroom observation data. AI learning students reported:

a) Higher engagement with learning materials (87% reported regular interaction with AI tools, compared to 64% of in-class learners reporting regular engagement with physical class materials).
b) Greater frequency of interaction with instructors via AI platforms, particularly during asynchronous sessions (74% of AI learners reported frequent interactions, compared to 55% of in-class learners).

Classroom Observations revealed that AI learning platforms fostered individualized feedback and adaptive learning paths, contributing to higher engagement. In contrast, traditional classroom environments had higher peer-to-peer interaction**,** which was cited as beneficial in group activities but lacked the personalized learning available in AI platforms.

3. Accessibility and Inclusivity

The study found notable differences in accessibility between students using AI learning and those in in-class learning, especially in rural areas:

- AI Learning Platforms **-** 35% of students in rural universities reported challenges accessing AI learning due to unstable internet and lack of digital devices.
- In-Class Learning **-** Students in rural settings expressed fewer barriers, as traditional classrooms did not require digital infrastructure. However, they noted that overcrowded classrooms and limited teaching resources negatively impacted learning quality.

Overall, AI learning was found to be more inclusive for students with specific learning needs. Adaptive technologies embedded in AI platforms, such as text-to-speech and interactive simulations**,** were reported as beneficial by 91% of students with learning disabilities, compared to 52% who relied on traditional classroom accommodations.

Secondary Findings

1. Instructor Perspectives

Interviews with instructors revealed several key insights:

a) AI Learning Platforms **-** 80% of instructors acknowledged that AI tools made teaching more efficient by providing instant feedback and automating routine tasks, such as grading quizzes.
b) However, 60% expressed concern about the lack of human interaction in AI learning environments, which they felt was crucial for fostering critical thinking and problem-solving skills.
c) In-Class Learning **-** Instructors in traditional classrooms emphasized the importance of face-to-face interaction for discussions, debates, and collaborative learning. However, they acknowledged the challenges of managing large class sizes and uneven student participation.

2. Student Perceptions of AI Learning vs. In-Class Learning

Focus group discussions highlighted the following perceptions:

a) Advantages of AI Learning **-** Flexibility, personalized learning, and access to a broader range of resources were frequently mentioned. Students appreciated the self-paced learning feature of AI platforms, which allowed them to revisit complex topics.
b) Disadvantages of AI Learning **-** Lack of social interaction and challenges related to internet access were identified as drawbacks, particularly for rural students. Some students felt isolated in AI environments and missed the spontaneous exchanges that occur in physical classrooms.

c) Advantages of In-Class Learning **-** Students valued the interactive nature of in-person classes and the ability to ask questions in real time. Peer learning and group discussions were cited as beneficial, particularly in social sciences.

d) Disadvantages of In-Class Learning - Overcrowded classrooms, limited interaction with instructors, and the lack of personalized feedback were frequently mentioned as barriers to learning.

3. Impact of Internet Connectivity

Internet access played a significant role in the effectiveness of AI learning platforms**.** Students in urban universities reported fewer connectivity issues and greater ease in accessing online resources. In contrast**,** students in rural areas faced substantial challenges due to unstable internet, limiting their ability to fully utilize AI learning tools.

Main Findings of the Study

This study compared the effectiveness of Artificial Intelligence (AI) learning platforms and in-class learning methods in Kenyan universities. The key findings revealed that students engaged in AI learning outperformed those in traditional classrooms, particularly in Science, Technology, Engineering, and Mathematics (STEM) disciplines. The study also found that AI learning resulted in higher student engagement and interaction with learning materials. However, issues of accessibility, especially in rural areas with poor internet connectivity, and the lack of social interaction in AI-based environments, were notable challenges. Additionally, instructors expressed concerns about the potential loss of critical thinking development in AI-based learning due to reduced interpersonal interactions.

Discussion of the Main Results in Reference to Previous Research

1. Performance Outcomes

The finding that students in AI learning environments achieved better academic outcomes aligns with previous research. Studies by Huang et al. (2019) and Ghatak et al. (2020) demonstrated that AI-driven learning platforms can improve learning outcomes through adaptive learning paths**,** which provide individualized feedback and allow students to learn at their own pace. In this study, students in STEM fields, in particular, benefitted from AI systems that offer interactive simulations and automated problem-solving tools**.** These results confirm earlier findings that AI learning is particularly effective in disciplines that require frequent practice, problem-solving, and conceptual mastery (Zawacki-Richter et al., 2019).

However, in the Social Sciences and Humanities, the difference in performance between AI and in-class learners was less pronounced. This finding mirrors the work of Mavroudi and Hadzilacos (2020), who found that while AI systems are valuable for structured disciplines, they may be less effective in areas that rely heavily on discussion, critical thinking**,** and contextual analysis. In these fields, in-class learning allows for more nuanced debate and dialogue, which can enhance understanding.

2. Engagement and Interaction

The higher levels of student engagement reported in AI learning environments also resonate with earlier research. A study by Chen et al. (2020) showed that AI learning systems, which incorporate elements such as gamification, quizzes, and personalized learning paths, often result in greater interaction with course content. In this study, AI learners reported more frequent use of learning materials and more opportunities to receive feedback, particularly in asynchronous settings.

However, this study also found that AI learning lacked the social interaction present in traditional classrooms, a finding consistent with research by Veletsianos (2021), who noted that peer interaction and face-to-face discussions are crucial elements of traditional learning environments. In-class learning supports collaborative activities and peer learning, especially in the Social Sciences, where students benefit from exchanging ideas in real-time.

3. Accessibility and Inclusivity

The study highlighted significant issues with accessibility for AI learning, particularly in rural universities. This aligns with the challenges noted by Komba et al. (2021), who observed that the digital divide in Sub-Saharan Africa affects the ability of students to benefit from online and AI-driven learning. Poor internet infrastructure, coupled with a lack of access to digital devices**,** restricts the reach and effectiveness of AI learning tools in rural settings. The data suggest that while AI learning has the potential to enhance educational access, it may exacerbate inequalities if not supported by adequate technological infrastructure.

Conversely, the inclusive nature of AI learning platforms for students with disabilities was a positive finding. AI systems offer tools such as text-to-speech and interactive simulations, which can help students with specific learning challenges. This is supported by earlier studies, such as those by Alghazo and Alghazo (2020), which noted the value of AI in making education more accessible for students with special needs.

Policy and Practice Implications of the Results

1. The findings suggest that a blended learning model**—**combining the strengths of both AI and in-class learning—could provide an optimal solution for improving educational outcomes in Kenyan universities. AI platforms offer personalized learning paths and adaptive feedback**,** while traditional classrooms provide opportunities for social interaction and collaborative learning**.** Educational policymakers should consider investing in such models to enhance the quality of education across disciplines.
2. For AI learning to be effective across all universities, there is a clear need for improved internet connectivity and digital infrastructure, particularly in rural areas. Policymakers must prioritize investments in broadband access**,** affordable devices**,** and training for both students and instructors. Additionally, universities should develop strategies to support students who may not have reliable access to technology, such as providing offline AI learning tools or creating mobile learning solutions**.**
3. The study highlights a need for ongoing instructor training on how to effectively integrate AI tools into their teaching. While AI can automate certain aspects of teaching, it is essential for instructors to learn how to balance AI's capabilities with critical thinking and interactive learning strategies. Institutions should provide professional development programs that help instructors maximize the benefits of both AI and in-class methodologies.
4. AI platforms have shown great promise in supporting students with learning disabilities. Policymakers should expand AI learning platforms' accessibility features to ensure inclusive education for all students. Universities should also develop policies that ensure these tools are

widely available and effectively integrated into learning systems for students with special needs.

Strengths and Limitations of the Study

Strengths

1. **Comprehensive Data Collection**

The study employed a mixed-methods approach**,** combining both quantitative (surveys, performance data) and qualitative (interviews, focus group discussions) methods. This allowed for a thorough understanding of the learning outcomes**,** student engagement, and accessibility issues in both AI and in-class learning environments. The inclusion of multiple universities and academic disciplines provided a holistic view of the comparative effectiveness of the two learning methods.

2. **Stratified Random Sampling**

The use of stratified random sampling ensured a representative sample from various strata, including university type, geographic location, and academic discipline. This increased the study's generalizability across Kenyan universities.

3. **Focus on Both Urban and Rural Universities**

The inclusion of both urban and rural institutions provided valuable insights into the digital divide and the different experiences of students in various educational environments. This helps policymakers understand the unique challenges faced by rural institutions in implementing AI learning platforms.

Limitations

1. **Self-Reported Data**

The reliance on self-reported data for student engagement and interaction could introduce response bias**.** Students may have over- or under-reported their engagement levels. Future research could benefit from integrating automated tracking tools within AI platforms to capture engagement data more objectively.

2. **Limited Longitudinal Data**

This study focused on a cross-sectional design**,** which provides a snapshot of learning outcomes at one point in time. A longitudinal study could offer deeper insights into how students' performance and engagement evolve over time when using AI platforms. Future studies could track students over several semesters to assess the long-term effectiveness of AI learning.

3. **Technology Variability**

The study did not control the variability of AI tools used across universities. Different institutions may use different platforms with varying capabilities, which could affect the consistency of the results. Future research should consider evaluating specific AI platforms to provide more detailed recommendations on the best technologies to adopt.

4.0 Conclusion

This comparative analysis of Artificial Intelligence (AI) learning and in-class learning in Kenyan universities has provided a critical understanding of the evolving educational landscape, particularly in the context of a rapidly digitalizing world. The study’s findings underscore the transformative potential of AI learning platforms, particularly in enhancing academic performance, fostering individualized learning paths, and driving student engagement, especially within STEM disciplines. However, the study also highlights key challenges associated with AI learning, including issues of accessibility in rural areas, concerns over the lack of interpersonal interaction, and the critical role of infrastructure in determining the success of AI-based education.

The analysis reveals that while AI learning offers substantial advantages, particularly through personalized feedback mechanisms and adaptive learning strategies, it cannot entirely replace the social and collaborative benefits of traditional classroom settings. In disciplines where critical thinking, discussion, and peer interaction are central to the learning process—such as the Social Sciences and Humanities—traditional in-class learning maintains distinct advantages. This duality suggests that rather than positioning AI learning in opposition to in-class learning, a blended learning model—one that leverages the strengths of both methods—could be the most effective pathway for future educational practices in Kenyan universities.

Furthermore, the study draws attention to the digital divide that continues to hinder equitable access to AI learning, particularly in rural institutions. For AI learning to be truly inclusive, significant investments in digital infrastructure and policy reforms are essential. Without addressing these foundational challenges, AI learning risks exacerbating existing educational inequalities. At the same time, the inclusivity demonstrated by AI platforms in supporting students with special learning needs is a promising development that should be expanded across all educational settings.

From a policy perspective, this research highlights the need for Kenyan universities and education policymakers to adopt a nuanced approach that recognizes the varying strengths of AI and in-class learning. Policymakers should focus on promoting technological integration, instructor training, and the development of infrastructure that ensures both rural and urban students can access high-quality education regardless of their physical learning environment.

In conclusion, this study affirms that the future of higher education in Kenya lies in hybrid approaches that integrate cutting-edge AI technologies with the irreplaceable human elements of face-to-face learning. By adopting such a model, Kenyan universities can better prepare students to thrive in an increasingly complex, digital world while ensuring that no student is left behind. This study contributes to the ongoing discourse on the role of technology in education, providing a foundation for further research and policy development aimed at creating a more equitable, effective, and sustainable learning environment for all.

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