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AWARENESS AND ADOPTION OF ARTIFICIAL INTELLIGENCE IN TEACHING PRACTICES: CHALLENGES AND OPPORTUNITIES FOR INSTRUCTORS IN TANZANIAN PUBLIC AND PRIVATE HIGHER LEARNING INSTITUTIONS

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ABSRACT

This study investigates the awareness, adoption, and implementation challenges and opportunities of Artificial Intelligence (AI) in teaching practices among instructors in Tanzanian public and private higher learning institutions (HLIs). Using a mixed-methods approach, the study examined differences in AI awareness levels, the extent of AI adoption, and institutional readiness. Results revealed no significant differences in most awareness indicators between public and private HLIs, except for foundational knowledge, which was higher in public HLIs. The extent of AI adoption was generally low across both sectors, with weak predictive influence from institutional support and personal willingness. Significant differences were observed in implementation challenges and opportunities public HLIs faced greater infrastructural and policy constraints, while private HLIs demonstrated slightly higher readiness and optimism toward AI. These findings highlight the need for targeted interventions, including investment in infrastructure, AI-focused professional development, and policy support. Strengthening institutional capacity and fostering a culture of innovation are critical to enhancing AI integration and maximizing its potential in Tanzanian HLIs.

KEYWORDS: Artificial Intelligence (AI), Public and Private Higher Learning Institutions,

AI Integration.

1.0 INTRODUCTION

Artificial Intelligence (AI) is transforming education by enhancing teaching and learning processes. Globally, Higher Learning Institutions (HLIs) use AI to personalize learning, automate tasks, and support instruction. However, awareness and adoption vary by region due to differences in infrastructure, policy, and resources. In Tanzania, AI adoption in teaching and learning is still at an early stage, offering both challenges and opportunities for HLIs. In developed countries, AI has been successfully integrated into HLIs (Lashayo *et al*., 2023). American University, for instance, established an Institute for Applied AI to prepare students for AI-driven careers, while Stanford University uses AI to turn readings into podcasts and support assignments, encouraging deeper student engagement (El Naggar *et al*., 2024). In contrast, African HLIs face slower AI adoption due to infrastructure gaps, limited skills, and education system constraints. Further challenges like the digital divide, data privacy, and algorithmic bias must be addressed to fully benefit from AI in education (Mambile and Mwogosi, 2025)

East African HLIs are beginning to explore AI in teaching and learning, but progress is hindered by low digital literacy, poor infrastructure, and ethical concerns (Ocen *et al*., 2025). Collaboration between governments, HLIs, and tech developers is key. In Tanzania, the integration of AI remains limited. According to Mambile and Mwogosi (2025), AI offers benefits like better assessment, time-saving, personalized learning, and enhanced accessibility, but faces barriers such as high costs, cheating risks, ethical concerns, and limited infrastructure. Students are more open to using AI tools, while instructors remain cautious due to concerns about teaching quality and job security (Sarakikya and Kitula, 2024). Similarly, (Ponera and Stephen Madila, 2024) found varied levels of AI awareness among Tanzanian HLIs instructors, emphasizing the need for training and clear policies to guide effective integration.

Despite global progress, Tanzanian HLIs struggle with low AI awareness, limited infrastructure, and a lack of guiding policies (Ponera and Stephen Madila, 2024). Adoption remains slow, underscoring the need to evaluate current awareness, challenges, and opportunities to support AI integration in teaching (Sarakikya and Kitula, 2024). This study aims to assess AI awareness and adoption among instructors in Tanzanian HLIs and identify challenges and opportunities for integration. Specifically, it seeks to evaluate instructors' awareness of AI; to examine how AI is being adopted in teaching; to identify challenges to implementation; and to explore opportunities to enhance educational outcomes through AI.

The findings are valuable for policymakers, institutional leaders, and instructors. Policymakers can use them to develop AI strategies; HLIs can identify infrastructure and training needs; and instructors can better understand AI's teaching potential. Ultimately, the study contributes to modernizing Tanzanian education in line with global trends. In addition, the study is limited to Tanzanian HLIs, focusing on instructors' AI awareness and adoption. Constraints include possible biases in self-reported data, limited institutional information, and the fast-paced evolution of AI technology, which may affect the future relevance of the findings.

2.0 Literature Review

2.1 Theoretical Literature Review

The study reveals important implications for enhancing teaching practices in Tanzanian HLIs through AI integration. Awareness of AI varies between public and private HLIs, with public HLIs like Ardhi University (ARU) and Arusha Technical College (ATC) facing systemic challenges such as bureaucracy and poor information flow. Although private HLIs such as KCMC University (KCMCU) and Mwenge Catholic University (MWECAU) show more flexibility, awareness levels remain modest overall. Drawing on Rogers' (2003) Diffusion of Innovations Theory (DOI), the study emphasizes the need for national strategies and targeted awareness campaigns to improve AI literacy across all (Mambile and Mwogosi, 2025)

On adoption, guided by Davis' (1989) Technology Acceptance Model (TAM), the study shows limited use of AI tools due to skepticism, poor infrastructure, and lack of support in both HLIs. Public HLIs struggle with policy gaps and technical support, while private HLIs face training deficiencies. This suggests the need to build both institutional capacity and instructors' confidence in AI's usefulness and ease of use. Investing in regular professional development and creating enabling policies can help increase adoption (Mambile and Mwogosi, 2025)

Regarding challenges and opportunities, the Institutional Theory by DiMaggio and Powell (1983) highlights how rigid structures and unclear regulations slow AI implementation. Common barriers across HLIs include limited ICT infrastructure, training gaps, and ethical concerns. However, AI's potential benefits such as automation, personalized learning, and improved assessment offer significant opportunities. Overcoming resistance requires adaptive leadership, clear AI policies, infrastructure development, and strategic partnerships (Mambile and Mwogosi, 2025; Ponera and Stephen Madila, 2024) Therefore, to fully leverage AI in teaching, all stakeholders policy makers, institutional leaders, and instructors must collaborate to increase awareness, encourage adoption, and eliminate existing institutional and technical barriers. A coordinated, inclusive approach will drive AI-enhanced innovation and improve education quality across Tanzanian HLIs.

2.2 Emperical Literature Review

2.2.1 The Level of Awareness of AI

In developed countries, Ahmad *et al*. (2022) examined AI implementation at the University of Toronto's Rotman School of Management, focusing on AI tools used to automate administrative tasks and support teaching. Through a case study design and purposive sampling of academic staff, the study revealed a high level of awareness of AI, particularly regarding the AI assistant "All Day TA," which helped enhance student engagement. The authors recommended increasing faculty training to maximize AI's potential in teaching. In Africa, Bakiri *et al*., (2024) conducted a study on AI services in Tanzanian academic libraries, where 68.3% of librarians reported being aware of AI tools, but only 23% had adopted them. This cross-sectional survey uncovered a significant awareness-adoption gap, largely attributed to infrastructure limitations. The study concluded that substantial investment in infrastructure and AI training was necessary to promote broader adoption within Tanzanian educational institutions. In Tanzania Mambile and Mwogosi, (2025) explored AI awareness among instructors in Tanzanian HLIs using a mixed-methods design. Through surveys and interviews, they found that while students were enthusiastic about AI tools, instructors were more cautious, citing concerns over the quality of teaching and job security. The study recommended enhancing AI awareness among instructors and offering comprehensive training programs to facilitate AI integration into Tanzanian HLIs.

2.2.2 The Extent of Adoption of AI

In developed countries, Ahmad *et al*. (2022) found that AI adoption was already high, particularly in HLIs like Stanford University, where AI tools were integrated into curricula and student support services. Tools such as "All Day TA" were used to automate administrative tasks, which allowed instructors to focus more on interactive teaching. The study concluded that AI adoption was progressing rapidly and recommended further support for faculty to ensure its effective integration into teaching practices. In Africa, (Bakiri et al., 2024)observed slow AI adoption in Tanzanian academic libraries, where only 23% of HLIs had implemented AI, despite high awareness among librarians. The study identified a lack of infrastructure, training, and financial resources as significant barriers to adoption. It concluded that AI adoption in African HLIs would require significant investment in infrastructure and professional development to overcome these challenges. In Tanzania, Lashayo *et al*. (2023) studied the integration of AI in Tanzanian HLIs' computing curricula and found limited adoption. Their survey revealed that only a small number of HLIs had incorporated AI into their programs. The study concluded that AI adoption in Tanzanian HLIs sector was still in its infancy, recommending increased investment in AI infrastructure and the development of policies to promote its integration.

2.2.3 Challenges and Opportunities Associated with Implementing AI

In developed countries, Ahmad *et al*. (2022) highlighted several challenges associated with AI implementation, including privacy concerns, algorithmic bias, and fears of job displacement. Despite these challenges, AI presented significant opportunities to enhance teaching, particularly through personalized learning and task automation. The study recommended establishing stronger regulations and ethical guidelines to ensure responsible AI use in education. In Africa, Bakiri *et al*. (2024) noted challenges faced by African HLis, such as inadequate internet access, digital illiteracy, and data privacy concerns. Despite these barriers, AI offered opportunities to improve personalized learning, student engagement, and administrative processes. The study recommended investing in digital infrastructure and staff training to harness AI's full potential in African HLIs. In Tanzania, Mambile and Mwogosi (2025)) identified several challenges to AI implementation, including high costs, poor infrastructure, and concerns about the reduction of human interaction in teaching. However, AI presented opportunities for personalized learning and improved assessments. The study concluded that overcoming these challenges through better training and infrastructure development would help maximize AI's potential in Tanzanian HLIs.

3.0 Research Methodology 3.1 Research Design

This study employed a quantitative cross-sectional research design to examine the awareness and adoption of Artificial Intelligence (AI) in teaching among instructors in Tanzanian public and private higher learning institutions (HLIs). The design was suitable as it allowed for the collection of data at a single point in time to explore current levels of AI knowledge, adoption, and related challenges without manipulating variables (Creswell and Creswell, 2022). It enabled effective comparison across HLIs in areas such as instructor readiness, infrastructure, policy, and ethics. Cross-sectional designs are practical in educational technology research due to time and resource efficiency, especially when rapid insights are needed for policy or institutional planning (Bryman, 2021)

3.2 The study area

This study was conducted in both private and public higher learning institutions (HLIs) in Tanzania, specifically at KCMC University (KCMCU) and Mwenge Catholic University (MWECAU) as private HLIs, and Ardhi University (ARU) and Arusha Technical College (ATC) as public HLIs. The selection of these institutions aimed to explore the awareness and adoption of Artificial Intelligence (AI) in teaching practices, providing a comparative framework to understand the varying challenges and opportunities across sectors. In Public iHLIs often face infrastructural challenges, limited budgets, and bureaucratic constraints that hinder AI integration (Ntorukiri *et a*l., 2022). On the other hand, private HLIs tend to have better flexibility, access to international partnerships, and more funding, allowing for quicker AI adoption (Ntorukiri *et al*., 2022). This difference is crucial for understanding the diverse readiness between sectors.

The study also focused on northern and coastal zones in Tanzania, a regions with growing HLIs and increasing interest in digital transformation. ARU and ATC, known for technical programs, align well with AI adoption, while KCMCU and MWECAU, which focus on health and social sciences, may face different AI adoption challenges. This diversity across academic disciplines ensured a comprehensive analysis of AI awareness and adoption. Additionally, the study reflects the broader push for digitalization in education, both globally and within Tanzania, where HLIs are at different stages of AI adoption (Lashayo *et al*., 2023). By including a mix of private and public HLIs, the study offers valuable insights that can guide policy and institutional planning for AI integration in HLIs across the region.

3.3 Population and Sample Size

This study targeted only lecturers—excluding tutorial assistants, senior lecturers, associate professors, and professors from four selected Higher Learning Institutions (HLIs) in Tanzania: KCMC University (KCMCU), Mwenge Catholic University (MWECAU), Ardhi University (ARU), and Arusha Technical College (ATC). The focus on lecturers was intentional, as they are the main instructional agents and most directly involved in the adoption of Artificial Intelligence (AI) in teaching (Lashayo et al., 2023). With a finite population of 400 lecturers, a sample size of 200 was drawn using Taro Yamane's (1967) formula. This method is commonly used in educational research for reliable sample size calculation, especially when resources are limited and full population coverage is impractical (Creswell and Creswell, 2022). Focusing solely on lecturers ensured the study gathered meaningful insights into the awareness and adoption of AI in teaching. Their perspectives are vital for informing institutional strategies in both public and private HLIs in Tanzania (Manyengo, 2024)

3.4 Sampling Techniques

This study adopted a probability sampling method, specifically stratified random sampling, to ensure a balanced and representative selection of lecturers from four Tanzanian Higher Learning Institutions (HLIs) KCMCU, MWECAU, ARU, and ATC. Stratification was based on lecturers' teaching levels (NTA 6, 7–8, 9–10), academic qualifications, and areas of specialization. This approach allowed the study to capture key variations among lecturers, enhancing the richness and reliability of the data. Stratified sampling was chosen to minimize bias and improve precision in representing a heterogeneous population. Memon *et al*. (2020) affirm its usefulness when ensuring proportional representation across diverse subgroups. In this study, such diversity across qualifications, teaching experience, and disciplines likely affects awareness and adoption of AI in teaching.

In addion, lecturers at different NTA levels face unique technological demands, and their educational background for instance master's vs. PhD or ICT specialization may shape their readiness to use AI. Stratifying the sample based on these attributes supported more accurate comparisons. Creswell and Creswell (2022) note, this technique deepens analysis and enhances generalizability. Furthermore, Jackson *et al*. (2021) highlight the need for thoughtful sampling in digital transformation research, particularly in higher HLIs across East Africa. Hence, stratified random sampling was instrumental in ensuring comprehensive representation from varied institutional and academic contexts.

3.5 Data collection methods and Tools

This study used a survey approach through structured questionnaires as the primary data collection method, which is a common practice in quantitative research for gathering standardized and measurable data from large groups (Creswell and Creswell, 2022). Surveys were ideal for this research, which aimed to assess awareness, adoption, and the challenges and opportunities of AI integration in teaching within public and private Higher Learning Institutions (HLIs) in Tanzania. They are widely applied in education and technology studies to examine attitudes, knowledge, and practices (Bryman, 2021)

Structured questionnaires were administered to 200 lecturers from KCMC University (KCMCU), Mwenge Catholic University (MWECAU), Ardhi University (ARU), and Arusha Technical College (ATC). These questionnaires focused on three areas: awareness of AI, adoption of AI tools, and perceived challenges and opportunities in using AI in teaching. The questions were closed-ended and designed using a five-point Likert scale, effective for measuring perceptions and behavior in quantitative research (Roselidyawaty and Rokeman, 2024). The use of Likert-scale items ensured consistent and easily quantifiable responses, supporting descriptive and inferential analysis. This structure also enabled comparisons between public and private HLIs regarding AI adoption.

Data collection was conducted digitally using KoboToolbox, a reliable platform for quantitative research, especially in low-resource settings (Kiran Kumar Poloju *et al*., 2022). KoboToolbox allowed real-time data entry, minimized errors, and supported efficient monitoring.

3.6 Data analysis

This study employed quantitative inferential data analysis to examine the awareness, adoption, and implementation challenges and opportunities of Artificial Intelligence (AI) in teaching practices across public and private Higher Learning Institutions (HLIs) in Tanzania. The analysis was guided by three specific objectives, each involving normality testing followed by appropriate non-parametric statistical techniques due to the non-normal distribution of data.

Regarding objective one, which aimed to evaluate the level of awareness of AI among instructors, the Kolmogorov-Smirnov and Shapiro-Wilk tests were used to assess the normality of five key variables: Knowledge of Basic AI Concepts (KBAI), Awareness of AI Tools in Education (AAI), Exposure to AI Training and Workshops (EAI), Confidence in Discussing AI Topics (CDAI), and Self-Rated AI Awareness Level (SRAI). All variables returned p-values < 0.05, indicating non-normal distribution. Therefore, the Mann-Whitney U test was employed to compare public and private HLIs using the following test formula:

$$U = n_1 n_1 + \frac{n(n_1+1)}{2} - R_1 \text{...} \textit{Eqn (2)}$$

where n1 and n2 represent sample sizes, and R1 is the sum of ranks for the first group. The findings showed a statistically significant difference in KBAI, with instructors from private HLIs reporting higher basic knowledge of AI concepts. However, there were no significant differences in AAI, EAI, CDAI, and SRAI, suggesting comparable levels of AI awareness in those dimensions across both sectors. Analysis was conducted using SPSS ver.22 integrated with AMOS ver.24, and the assumption made was that, data were ordinal and groups independent.

For objective two, which assessed the extent of AI adoption in teaching, the same normality tests were applied to the independent variables: Frequency of AI Use (FUAI), Integration of AI in Lesson Plans (IAI), Institutional Support for AI Usage (ISAI), and Willingness to Adopt AI Tools (WAAI). Since all variables again failed the normality assumption ($p < 0.05$), the study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the predictive relationship with the dependent variable Teaching Practices (TP). The PLS-SEM equation used was:

$$TP = \beta_1(FUAI) + \beta_2(IAI) + \beta_3(ISAI) + \beta_4(WAAI) + \varepsilon \quad \text{.. } Eqn\ (2)$$

Results showed that none of the predictors had a statistically significant influence on TP in either public or private HLIs. Path coefficients in public HLIs ranged from 0.105 to 0.158, and in private HLIs from 0.098 to 0.146, with all p-values above 0.05, indicating no significant effect. The analysis was performed using SmartPLS software, and assumptions included independence of observations, no multicollinearity, and linear relationships between latent variables.

Finally for objective three, which sought to identify challenges and opportunities related to AI implementation, the Kolmogorov-Smirnov and Shapiro-Wilk tests again confirmed normal data. The Chi-square test was used to examine differences in the following variables between public and private HLIs: Perceived Infrastructural Challenges (PIC), Data Privacy and Ethical Concerns (DPEC), Instructor Readiness (IR), Perceived Opportunities of AI (PO), and Policy Support (PS). The formula applied was:

$$X^2 = \sum \frac{(O-E)^2}{E} \quad \text{.. } Eqn\ (3)$$

where O is the observed frequency and E is the expected frequency. Results revealed significant differences across all five variables.

For PIC, of public HLIs instructors reported high challenges compared from private HLIs (reflecting greater infrastructural constraints in public institutions. On DPEC, of public respondents expressed concern versus in private HLIs, while IR was higher in private HLIs compared to public. Similarly, PO was more optimistic among private HLIs than public. Finally, PS was slightly stronger in private HLIs than in public. This analysis was conducted using SPSS ver.22 integrated with AMOS ver.24, assuming categorical data, independent observations, and expected frequency >5. This shows that, while instructors from both public and private HLIs demonstrated similar levels of awareness and adoption of AI, public HLIs faced significantly more infrastructural, ethical, readiness, and policy-related challenges, potentially limiting effective AI integration in teaching.

4.0 The study findings

4.1 The Level of Awareness of Artificial Intelligence 4.1.1 Normality tests

Normality tests were conducted to assess the distribution of variables in the study. These variables included Knowledge of Basic AI Concepts (KBAI), Awareness of AI Tools in Education (AAI), Exposure to AI Training/Workshops (EAI), Confidence in Discussing AI Topics (CDAI), Self-Rated AI Awareness Level (SRAI), and Teaching Practices in Tanzanian Public and Private Higher Learning Institutions (HLIs) (TP). In establishing normality was essential for determining the appropriate statistical analysis technique. Given the sample size of 200 (df > 100), the Kolmogorov-Smirnov (K-S) test was employed, as recommended by (Demir, 2022). The results revealed statistically significant values (Sig. = .000) for all variables, indicating that the data did not follow a normal distribution. These findings were further validated by the Shapiro-Wilk test, which also returned significance values of .000 across all variables. Based on these results, the study adopted non-parametric statistical methods, as suggested by (Demir, 2022). To compare public and private HLIs, the Mann-Whitney U test was applied, consistent with the guidelines provided by (Wall Emerson, 2023)

4.1.2 The Level of Awareness of AI in Public and Private Higher Learning Institutions

The study assessed differences in AI awareness among instructors in public and private higher learning institutions (HLIs) in Tanzania using the Mann-Whitney U test across five areas: Knowledge of Basic AI Concepts (KBAI), Awareness of AI Tools in Education (AAI), Exposure to AI Training and Workshops (EAI), Confidence in Discussing AI Topics (CDAI), and Self-Rated AI Awareness Level (SRAI). A significant difference was found only in KBAI ($p = .026$), with public HLI instructors showing greater familiarity with AI basics, likely due to more institutional support and access to state-sponsored digital initiatives (Mambile and Mwogosi, 2025).

Table 1: The Level of Awareness of AI in Public and Private Higher Learning Institutions

	KBAI	AAI	EAI	CDAI	SRAI
Mann-Whitney U	4192.000	4689.500	4964.000	4384.000	4462.500
Wilcoxon W	9242.000	9739.500	10014.000	9434.000	9512.500
Z	-2.220	-0.708	-0.109	-1.673	-1.440
Asymp. Sig. (2-tailed)	0.026	0.479	0.913	0.094	0.150

Source:

Research Findings, 2025

a. Grouping Variable: Types of Higher Learning Institutions (Public and Private Higher Lesrning Institutions)

No significant differences were found in AAI ($p = 0.479$), EAI ($p = 0.913$), CDAI ($p = 0.094$), and SRAI ($p = 0.150$), suggesting both institution types provide similar access to AI tools and training. This may reflect the equalizing role of open-access platforms and online AI education (Chan *et al*., 2024)

Based on these findings, the hypothesis (H_1) that there is a significant difference in AI awareness between instructors in public and private HLIs is accepted only for KBAI and rejected for the other dimensions. This highlights the need for targeted interventions in private HLIs to strengthen foundational AI literacy. The lack of significant differences in training exposure also calls for a system-wide enhancement of professional development programs across all HLIs.

Thefore, HLIs should embed AI in teaching strategies and foster collaboration across disciplines to maximize AI's educational potential. Successful AI adoption requires not just knowledge but also supportive environments that encourage continuous learning and innovation (UNESCO, 2023).

4.2 The Extent of Adoption of Artificial Intelligence in Teaching Practices instructors

4.2.1 Normality test

To assess the extent of Artificial Intelligence (AI) adoption in teaching practices among instructors in Tanzanian public and private Higher Learning Institutions (HLIs), this study analyzed five variables four: Frequency of AI Use in Teaching (FUAI), Integration of AI in Lesson Plans (IAI), Institutional Support for AI Usage (ISAI), and Willingness to Adopt AI Tools (WAAI) and to saw the effect of Teaching Practices in Tanzanian Public and Private HLIs (TP). Since the sample size was 200 (df > 100), the Kolmogorov-Smirnov (K-S) test was used to test for normality, following (Demir, 2022). All variables reported significance (Sig.) values of 0.000, indicating non-normal distributions. This was supported by Shapiro-Wilk test results, which also showed Sig. = 0.000 for all variables. Due to the violation of normality, the study applied a non-parametric statistical method Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is suitable for non-normal data, small to medium sample sizes, and prediction-focused research It is ideal for modeling latent constructs and complex relationships like those between AI-related factors and teaching practices (Sarstedt *et al*., 2022).

4.2.2 The Extent of Adoption of AI comparison analysis between Tanzanian Public and Private Higher Learning Institutions

The Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis explored the extent of AI adoption in teaching practices among instructors in Tanzanian public and private Higher Learning Institutions (HLIs) by examining four predictors: Frequency of AI Use (FUAI), Integration of AI in Lesson Plans (IAI), Institutional Support for AI Usage (ISAI), and Willingness to Adopt AI Tools (WAAI). Results showed no statistically significant influence of these variables on teaching practices (TP) in either type of institution. In public HLIs, path coefficients ranged from 0.105 to 0.158, and in private HLIs, from 0.098 to 0.146, all with p-values above 0.05, indicating non-significance.

Table 2: The Extent of Adoption of AI comparison analysis (n = 200)

Path Relationship

FUAI → TP IAI → TP ISAI → TPWAAI → TP

Path Coefficient (Public HLIs)

0.105 0.142 0.128

0.158

p-value (Public HLIs)

0.168 0.097 0.134

0.083

Path Coefficient (Private HLIs)

0.098 0.131 0.119

0.146

p-value (Private HLIs)

0.211 0.118 0.192

0.101

Significance Not Significant Not Significant Not Significant

Not Significant

R^2 (TP) 0.267 – **0.243** – Weak to Moderate

Source: Research Findings, 2025

a. **Assumptions**: Linearity of Relationships, Predictive Orientation (R^2), Non-normal Data Distribution, Independence of Observations, Measurement Scale or Ordinal

The R^2 values were 0.267 for public HLIs and 0.243 for private HLIs, reflecting weak to moderate explanatory powe. These results imply that other factors not included in the model like infrastructure, training, or institutional culture may play a larger role in shaping AI use in teaching. As highlighted by (Sife and Lwoga, 2021), both public and private HLIs in Tanzania face barriers such as limited infrastructure, lack of AI policy, and inadequate staff training. (UNESCO, 2023) also stresses the need for systemic support to realize meaningful AI integration in education. Given the lack of significant differences and effects, the study rejects the hypothesis (H_1) that there is a significant difference in the extent of AI adoption between public and private HLIs. This suggests overall low and similar adoption levels across institutions.

The findings imply that policy and institutional interventions are necessary, such as investing in training, leadership support, and integrating AI into educational frameworks. As Ketevan Shengelia (2024) argue, creating environments that support educators is crucial for effective technology use in teaching. Without such support, AI's transformative potential in Tanzanian education may remain unrealized.

4.3 Challenges and Opportunities Associated with Implementing AI 4.3.1 Normality Test

Before conducting any comparative analysis, it was essential to assess the normality of the data, as this determines whether parametric or non-parametric statistical methods are appropriate. The variables examined in this analysis included Perceived Infrastructural Challenges (PIC), Data Privacy and Ethical Concerns (DPEC), Instructor Readiness (IR), Perceived Opportunities of AI (PO), Policy Support for AI Implementation (PS), and the dependent variable, Teaching Practices (TP). Results from the Kolmogorov-Smirnov (K-S) test indicated that all six variables PIC, DPEC, IR, PO, PS, and TP had significance (Sig.) values greater than 0.05. These findings confirm that the assumption of normality was satisfied for all variables, thereby justifying the use of parametric statistical methods in the comparative analysis. Accordingly, Independent Samples t-tests or Chi-square test are appropriate for comparing the results of challenges and opportunities between public and private higher learning institutions.

4.3.2 The Challenges and Opportunities Associated with Implementing AI In Tanzanian Higher Learning Institutions

The Chi-square test results from this study reveal significant differences in the challenges and opportunities associated with implementing Artificial Intelligence (AI) in Tanzanian higher learning institutions (HLIs). The analysis focused on perceived infrastructural challenges (PIC), data privacy and ethical concerns (DPEC), instructor readiness (IR), perceived opportunities of AI (PO), and policy support for AI implementation (PS).

Table 3: Comparing Public and Private HLIs on AI Implementation Challenges and Opportunities (n = 200)

Variable Response Category Public HLIs Private HLIs (n = 100) (n = 100) χ^2 Value df Sig. (p-value)

Perceived Infrastructural Challenges (PIC) Data Privacy and Ethical Concerns (DPEC) Instructor Readiness (IR)

Perceived Opportunities of AI (PO)

Policy Support for AI Implementation (PS)

High/Low 65/35 Yes/No 25/75 Ready/Not Ready 15/85 High/Low 24/76

Strong/Weak 12/88 55/45 8.000 1 0.005 20/80 4.500 1 0.034

20/80 7.200 1 0.007 30/70 12.500 1 0.000

15/85 7.220 1 0.007

Source: Research Findings, 2025

a. Assumptions: Independence of Observations, Categorical Data, No Small Expected Frequencies, Data must be in a contingency table

The results indicated a significant difference in PIC, with 65% of public HLI respondents reporting high challenges compared to 55% of private HLI respondents. The Chi-square value of 8.000 (p = 0.005) suggests that while both public and private HLIs face infrastructural difficulties, public HLIs experience slightly higher challenges. This could be due to resource constraints, as public HLIs often struggle with limited funding and outdated technology, which hinders their ability to implement advanced technologies like AI

(Abulibdeh *et al*., 2025). Addressing these challenges is essential for both sectors to effectively integrate AI into teaching practices.

In terms of DPEC, 25% of public HLI respondents expressed concern, compared to 20% in private HLIs. The Chi-square value of 4.500 (p = 0.034) indicates that public HLIs are more concerned about DPEC issues related to AI. This finding highlights the need for both HLIs to develop strong ethical frameworks and data protection policies, ensuring that AI technologies are implemented responsibly (Abulibdeh *et al*., 2025). The lower concern in private HLIs may reflect good institutional policies or more resources allocated to managing these challenges.

Regarding IR, 15% of public HLI instructors reported being ready to adopt AI, compared to 20% of private HLI instructors. The Chi-square value of 7.200 (p = 0.007) shows a significant difference, suggesting that instructors in private HLIs are slightly more prepared to adopt AI. This could be due to private HLIs' greater flexibility in implementing training programs and their ability to invest in new technologies ((Miah *et al.*, 2023). Public HLIs, on the other hand, may face challenges related to resource allocation and lack of training opportunities, hindering instructor readiness for AI adoption.

When examining the PO of AI, the results showed that 24% of public HLI instructors viewed AI as offering high opportunities, while 30% of private HLI instructors shared this view. The Chi-square value of 12.500

(p = 0.000) indicates a significant difference, with private HLIs expressing more optimism about AI's potential benefits. This could be due to better infrastructure and resources in private HLIs, which enable them to explore AI's opportunities more effectively. Private HLIs often have more financial flexibility to invest in AI technologies, which allows them to perceive and leverage AI's potential for enhancing teaching and learning (Abulibdeh *et al.*, 2025).

PS for AI implementation (PS) also showed a significant difference, with 12% of public HLI instructors reporting strong policy support compared to 15% of private HLIs instructors. The Chi-square value of 7.220 (p = 0.007) indicates that although both sectors have weak policy support, private HLIs show slightly more favorable policies. This suggests that public HLIs are lagging behind in terms of developing comprehensive policies to support AI integration, which could hinder the smooth adoption of AI technologies (Mtebe and Raphael, 2021).

Based on these findings, the hypothesis (H1: There is a significant difference in the challenges and opportunities associated with implementing Artificial Intelligence in teaching practices between public and private HLIs in Tanzania can be accepted. The significant differences observed in PIC, DPEC, IR, PO of AI, and PS for AI implementation indicate that the challenges and opportunities related to AI implementation in teaching practices vary between public and private HLIs in Tanzania.

The implications of these findings are critical for policymakers and institutional leaders. Public HLIs need to invest in infrastructure and professional development programs to bridge the readiness gap identified in this study. Strengthening policy frameworks to support AI adoption is also essential. Both HLIs must prioritize developing ethical guidelines and data privacy protocols to ensure responsible AI usage. For private HLIs, further enhancing support for AI adoption and increasing awareness of its potential benefits can help them leverage AI to improve teaching and learning. Ultimately, addressing these challenges requires concerted efforts from both public and private HLIs to fully capitalize on the opportunities AI offers in education in HLIs.

5.0 Conclusion and Recommendations

5.1 CONCLUSION

This study assessed the level of awareness, extent of adoption, and challenges and opportunities of Artificial Intelligence (AI) in Tanzanian higher learning institutions (HLIs). Findings showed that there were no significant differences between public and private HLIs in most awareness indicators, such as Awareness of AI Tools (AAI) and Exposure to AI Training (EAI). However, public HLIs demonstrated a higher level of Knowledge of Basic AI Concepts (KBAI), indicating that while general awareness is similar, foundational literacy in AI needs improvement, especially in private HLIs. This highlights the need for better integration of AI into curricula and professional development.

Regarding AI adoption in teaching, the study found no significant impact from variables like Frequency of AI Use (FUAI), Integration of AI in Lesson Plans (IAI), or Institutional Support for AI Usage (ISAI) on teaching practices. The low R^2 values suggest that other factors, such as infrastructure and institutional policies, are more influential. These results emphasize the need for reforms that prioritize AI integration through better training, leadership support, and enhanced infrastructure.

When analyzing challenges and opportunities, public HLIs faced more infrastructural difficulties, greater concerns over data privacy and ethics, and lower instructor readiness compared to private HLIs. These differences reflect systemic disparities between the two sectors, where public institutions struggle more with resources and policy support. The hypothesis that challenges and opportunities vary between public and private HLIs was accepted, underscoring the need for tailored approaches to AI integration across the higher education sector.

5.2 Recommendations

To support AI implementation, both public and private HLIs should integrate AI education into curricula and promote cross-departmental collaboration. Special focus should be placed on strengthening AI fundamentals, particularly in private institutions, through workshops and faculty training. Institutions must also invest in digital infrastructure, create clear AI policies, and offer continuous training for educators, particularly in public HLIs that face more infrastructural challenges.

National and institutional policymakers should establish ethical guidelines and data protection standards to address privacy concerns and foster trust in AI. Additionally, creating a culture of innovation within HLIs, supported by leadership that encourages experimentation, is essential for increasing AI adoption in teaching. Lastly, forming partnerships with tech organizations, AI experts, and educational stakeholders will help bridge knowledge gaps and improve access to AI tools, enabling Tanzanian HLIs to maximize AI's educational potential.

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