Influence of Artificial Intelligence Tools in Teaching on Trainer-Perceived Performance in Computer Courses at National Polytechnics in Western and Nyanza Region, Kenya

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ABSTRACT

Artificial Intelligence (AI) is transforming education globally, yet its adoption in Technical and Vocational Education and Training (TVET) institutions in developing countries remains limited. This study examined the influence of AI tools in teaching on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya. Guided by the Diffusion of Innovation Theory, the study adopted a mixed-methods research approach using descriptive survey and correlational research design. Stratified random sampling was used to select 121 trainers, of whom 103 (85.1%) completed the questionnaire. Purposive sampling selected 24 senior management staff and 8 county quality assurance officers for interviews. Quantitative data were analyzed using descriptive statistics, Pearson correlation, and regression analysis while qualitative data were analyzed thematically. Findings revealed moderate adoption of AI tools in teaching ($M=3.51$), with trainers demonstrating awareness ($M=3.71$) but limited formal training ($M=3.00$). Regression analysis identified a significant positive relationship between AI tool usage and trainer-perceived performance ($R=0.516$, $R^2=0.266$, $p<.001$), leading to rejection of the null hypothesis. Qualitative findings converged with quantitative results, identifying inadequate trainer training ($M=4.26$) and infrastructure limitations ($M=4.10$) as key challenges. The study concluded that higher levels of AI tool integration are associated with higher trainer-perceived performance ratings, though implementation is constrained by systemic barriers. Recommendations include structured professional development programs, infrastructure investment, and institutional policy support to promote sustainable AI adoption in Kenyan TVET institutions.

Keywords: Artificial Intelligence, teaching tools, trainer performance, computer courses, TVET, Diffusion of Innovation, Kenya

INTRODUCTION

Background to the Study

In a world marked by incessant changes, individuals need usable knowledge that will enable them to navigate life's demands and flourish in an ever-evolving future. One of the most crucial ways to raise the standard of living of people and society at large is improving the quality of education (Voratitipong, Wannapiroon, & Nilsook, 2018). Artificial Intelligence (AI) integration in Technical and Vocational Education and Training (TVET) is emerging as a transformative force globally, offering great potential to transform the delivery of TVET, making it more efficient, customized, and responsive to the demands of today's workforce.

Artificial intelligence can support increased efficiency in teaching and learning approaches, meet some of the most pressing challenges that education faces today, and help achieve Sustainable Development Goal 4—to achieve inclusive and equitable quality education and promote lifelong learning opportunities for all by 2030. The United Nations Educational, Scientific and Cultural Organization (UNESCO) is committed to supporting Member States to harness the full potential of AI technology while ensuring that the core values of fairness and inclusivity are embedded in its use in education (UNESCO, 2019).

The Kenya Government has prioritized skills development and training through TVET as an enabler for the realization of Kenya Vision 2030, a stimulant for industrialization, and a key strategy in addressing youth unemployment. The Kenyan government plans to increase the number of TVET learners to over 2 million by 2027 to support skills development and economic growth (Ministry of Education, 2025). TVET is intended to bridge the gap between education and the job market by equipping learners with skills that are in tandem with the demands of industry (Nkunya & Mwila, 2024).

Statement of the Problem

Artificial Intelligence is altering education around the globe with individualized learning, intelligent tutoring systems, automated grading, and data-driven teaching strategies. In technologically advanced countries like China and the United States, significant investments are being made in AI applications for all levels of instruction (Reuters, 2024; Abbas et al., 2024). Today, 20-30% of higher education institutions in Africa use AI tools in teaching, learning, and management (UNESCO, 2021). South Africa, Kenya, Nigeria, and Egypt have been the main recipients of adoptions. However, in many parts of the developing world, especially sub-Saharan Africa, the application of AI in education has been limited and dispersed (Sani, 2023).

The Kenyan government has emphasized the importance of AI to the country's development through several projects such as the Digital Economy Blueprint and partnerships to train trainers in AI and data science (Ministry of ICT, 2019). However, the practical adoption of AI technology in classrooms is quite restricted, particularly in Western and Nyanza regions national polytechnics in Kenya (Ogembo, 2025). National Polytechnics have an important role to play in training in computer courses and in areas of ICT that are particularly relevant to the needs of the 21st-century workforce. However, their teaching approaches are primarily traditional, lecture-oriented, and not linked with new AI-based advancements in education (Matere, 2024). Poor infrastructure, insufficient staff capacity in AI, lack of localized implementation frameworks, and uncertain institutional laws have hindered the adoption of AI in computer education (Alzakwani, Zabri & Ali, 2025).

The regional digital divide in Kenya shows that Western and Nyanza regions recorded the lowest levels of internet access, at approximately 46-48%, compared to higher rates in urban areas such as Nairobi (Kenya National Bureau of Statistics, 2022; Communications Authority of Kenya, 2023). The extent to which AI technology is being implemented in TVET training within Western and Nyanza regions national polytechnics is very limited (Mboya, 2024). Existing studies on AI implementation in education have mainly concentrated on universities, paying little attention to TVET and national polytechnic environments marked by infrastructure challenges, uneven digital access, and limited institutional capabilities (World Bank, 2022). A significant knowledge gap exists regarding effective AI integration strategies in computer education at these institutions, particularly regarding understanding the practical challenges trainers face in resource-constrained environments.

Purpose of the Study

The purpose of this study was to examine the influence of AI integration tools on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya.

Specific Research Objectives

To evaluate the influence of artificial intelligence tools in teaching on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya.

Research Hypothesis

H_{01}: There is no statistically significant relationship between the use of artificial intelligence tools in teaching and the trainer-perceived performance of computer courses at national polytechnics in the Western and Nyanza regions of Kenya.

Theoretical Framework

The research adopted the Theory of Diffusion of Innovation (DOI), first introduced by Everett Rogers in 1962 and substantially developed through subsequent editions, with the 2003 fifth edition forming the primary theoretical basis for this study. The DOI framework consists of several key elements: innovation characteristics (relative advantage, compatibility, complexity, trialability, and observability), communication processes, social systems, and temporal dimensions (Rogers, 2003). The DOI states that technologies such as AI must be assessed for providing specific relative advantages such as improved efficiency of learning, personalization, or access to education. Institutions must be ready in terms of infrastructure, culture, and the skill of their workers to welcome innovations such as AI (Rogers, 2003).

The theory is applicable to the use and application of AI at TVET institutions. Objective one required review of trainers in use of AI technology for teaching based on reported utility and perceived ease of use. The idea was implemented using five constructs: relative benefit, compatibility, complexity, trialability, and observability. These constructs were used to assess trainers' views on the usefulness, convenience of use, compatibility, trialability, and visibility of artificial intelligence technologies as teaching tools in computer courses in national polytechnics of Western and Nyanza regions of Kenya.

Conceptual Framework

The conceptual framework for this study hypothesized positive influence relationships between each AI integration dimension (AI tools) and the dependent variable (trainer-perceived performance). The independent variable comprises four components: artificial intelligence tools in teaching, artificial intelligence in assessment, artificial intelligence content in TVET curriculum, and AI integration framework. The dependent variable, performance of computer courses, was measured in terms of course completion rate, employability, and skill development. However this paper only covers AI tools as independent variable.

LITERATURE REVIEW

2.1 Introduction to Artificial Intelligence in Education

The term Artificial Intelligence was coined by Professor John McCarthy in 1956 at the Dartmouth Conference. Artificial Intelligence is the science and engineering of producing intelligent robots and autonomous computer programs. It is a new general-purpose technology (GPT) capable of transforming nearly every sector (Bajpai & Wadhwa, 2021). It relates to the ability of computers to execute cognitive activities including thinking, perceiving, learning, problem-solving, and decision-making (NITI Aayog, Government of India, 2018).

The Artificial Intelligence Readiness Index 2021, compiled annually by Oxford Insights, indicates that different countries across the globe are at different stages and preparedness to use AI. Kenya scored 28.75 in the technology category, below the global average of 35.17, though it is the leader in the East Africa region for technical acceptability and advancement (Oxford Insights, 2021). According to Olayinka and Adepoju (2021), AI in Africa, especially in Kenya, has the potential to create jobs that require a higher level of technical skills.

2.2 Influence of Artificial Intelligence Tools in Teaching on Educational Outcomes

Use of artificial intelligence tools is one of the key strategies for leveraging AI in learning and teaching. Intelligent tutoring systems, chatbots, and virtual assistants can significantly enhance personalized learning experiences for students and help them understand and master concepts deeply. According to Luckin et al. (2016), these tools make learning more interesting and enhance learners' conceptual understanding. AI tools such as intelligent tutoring systems (ITSs), automated evaluation systems, and virtual labs are showing positive measurable effects on students' learning, student engagement, and faculty productivity.

Zhang and Li (2023) conducted a study in China on the status and prospects of artificial intelligence technology applied to education. The findings established that the overall trend of publications on AI integration in education is increasing and that technological developments and government policies influence research on AI technology in education. Zouhaier (2023) explored the effect of artificial intelligence on higher education in Europe, finding that AI tailors teaching approaches, provides immediate feedback, automates administrative activities, and assists with grading and assessment.

Solís et al. (2023) conducted research on the use of artificial intelligence in higher education in India, revealing that AI significantly improved personalized learning by providing recommendations and feedback tailored to students' needs. However, challenges such as the digital divide and reduced human interaction in education were also identified. Adamu et al. (2020) investigated the knowledge and skills required by trainers of Technical and Vocational Education (TVE) to effectively implement computers and related technologies in tertiary technical institutions in Nigeria, showing that trainers in technical and vocational fields were highly proficient in the use of digital tools.

Chanda (2023) studied the role of artificial intelligence in fostering workplace-integrated learning at a South African TVET college during the COVID-19 pandemic, observing that higher education and training institutions embraced innovative AI-powered tools such as Zoom, Skype, Microsoft Teams, AI-driven learning management systems, and online social media platforms such as WhatsApp to facilitate remote learning and collaboration.

Onyango and Kelonye (2022) conducted research on the implementation of artificial intelligence in Technical and Vocational Education and Training (TVET) in Kenya, identifying several areas where AI could be applied in the teaching of computer courses in national polytechnics. The study utilized a scoping review methodology to investigate the use of AI-driven interventions in TVET programs.

The most fundamental and earliest use of AI in education is grading. AI-driven grading applications utilize machine learning algorithms to simulate the grading process carried out by trainers. These systems employ data from previously scored scripts to automatically grade essays, papers, and tests. The technologies can also be used in virtual learning environments and cloud-based platforms for TVET instruction (Mao et al., 2020; Yigitcanlar et al., 2020; Xu et al., 2022).

Personalized learning is tailoring education to the individual needs and interests of each learner. Trainers can apply artificial intelligence tools to develop personalized study regimens and to adapt learning to learners' needs. Such tools can be used to identify gaps in knowledge, and can help personalized instruction, assessment, and feedback systems for students on different levels of education (Zawacki-Richter et al., 2019; Walkington & Bernacki, 2020).

Intelligent tutoring systems (ITSs) based on artificial intelligence can provide tailored training and customized feedback. They can underpin e-learning platforms and address e-learning difficulties in engineering and technical courses. ITSs can determine learning trajectories, provide learning material, offer scaffolding, engage students in discussion, and simulate one-to-one tutoring (Zawacki-Richter et al., 2019; Churi et al., 2022).

Despite these advantages, many studies have also identified obstacles. Adebayo (2021) flagged challenges such as inadequate preparation of trainers, high costs associated with the implementation of AI tools, and ICT infrastructure challenges that exist in national polytechnics. While the study showed that there is potential for AI to change the educational landscape, institutional readiness was necessary for it to be successful.

RESEARCH METHODOLOGY

3.1 Research Philosophy

The study was guided by a pragmatic research paradigm, developed by Peirce (1878), James (1907), and Dewey (1938) and applied to mixed methods research design by Johnson and Onwuegbuzie (2004) and Creswell and Plano Clark (2018). The pragmatic paradigm is grounded in the principle of using both quantitative and qualitative approaches in drawing conclusions on a phenomenon (Creswell & Creswell, 2018; Kivunja & Kuyini, 2017). The study employed a pragmatic research paradigm to investigate how AI can be applied in the teaching of computer courses at national polytechnics in the Western and Nyanza regions of Kenya.

3.2 Research Design

The study adopted descriptive survey and correlational research design. In quantitative educational research,

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these two designs are often combined to allow for both a descriptive overview and statistical analysis of relationships within the one study framework (Cohen, Manion & Morrison, 2018). Correlational research design is appropriate when the researcher wants to determine the extent and direction of relationships among naturally occurring variables, especially in nonexperimental environments (Fraenkel, Wallen, & Hyun, 2019). Descriptive survey design involves a process of collecting data from a sample at a particular time or over a period of time at more than one point in time in order to describe or demonstrate relationships between variables of a phenomenon of interest (Creswell & Creswell, 2018; Gakuu et al., 2018).

3.3 Study Area

The study was carried out in the Western and Nyanza regions of Kenya, selected purposively on the basis of shared contextual characteristics, institutional accessibility, and regional significance for TVET delivery. The study focused on all eight gazetted national polytechnics in these regions as of January 2025: Kisii, Kisumu, Sigalagala, Bungoma, Mawego, Shamberere, Nyamira, and Friends National Polytechnic Kaimosi. Because all eight institutions were included, no institutional sampling was required within the study area.

3.4 Target Population and Sample Size

The target population included 178 trainers in the Department of Computing and Informatics, 24 senior management staff (principals, heads of computing departments, internal Quality Assurance and Standards Officers), and 8 County Quality Assurance and Standards Officers. Stratified random sampling was used to select trainers, while purposive sampling was used to select senior management staff.

Sample size for trainers was determined using the Krejcie-Morgan Model:

n=x2NPQD2(N−1)+x2PQ*n*=*D*2(*N*−1)+*x*2*PQx*2*NPQ*

Where n = desired sample size; x^2 = Chi square table value at 1 degree of freedom and 95% confidence level (3.841); P = proportion of population with trait being sought (0.5); Q = 1 - P; D = degree of accuracy expressed as a proportion (0.05); N = size of target population (178).

n=3.841(178)(0.5)(1−0.5)(0.05)2(178−1)+3.841(0.5)(1−0.5)=121*n*=(0.05)2(178−1)+3.841(0.5)(1−0.5)3.841(178)(0.5)(1−0.5)=121

Twenty-four senior managers and eight county quality assurance and standards officers provided qualitative data. The sample size is consistent with purposive adequacy in qualitative research focusing on informational adequacy rather than statistical representativeness (Patton, 2002).

3.5 Data Collection Instruments

Structured questionnaires were used to collect data from trainers, and semi-structured interview guidelines were employed for senior management staff. The questionnaire included sections on demographics, awareness and familiarity with AI tools, current use of AI tools in teaching practice, institutional support and infrastructure, perceived effectiveness and educational impact, ethical and professional considerations, AI impact on student engagement and performance, and challenges and opportunities.

3.6 Validity and Reliability

Content validity of the questionnaire was assessed through a panel of experts from the Technology Education Department. The Content Validity Index of the questionnaire was .795, indicating validity. Reliability was tested using Cronbach's Alpha coefficient. The AI tools scale had a reliability index of .752, and the overall reliability index was 0.815, exceeding the acceptable threshold of 0.70 (Nunnally & Bernstein, 1994). A pilot study was conducted at Eldoret National Polytechnic with 10 trainers (approximately 10% of the sample) to test the clarity, relevance, and reliability of the questionnaire. Feedback from the pilot study was used to refine ambiguous items and improve the instrument's effectiveness.

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3.7 Data Analysis

Quantitative data were analyzed using descriptive statistics (frequency, percentage, mean, and standard deviation) and inferential statistics (Pearson correlation and regression analysis) using SPSS version 27.0. Qualitative data were analyzed using thematic analysis following Braun and Clarke's (2006) six phases. The study adhered to ethical guidelines including obtaining permission from NACOSTI and TVET institutions, informed consent, and ensuring confidentiality as per the Kenya Data Protection Act (2019).

RESULTS

4.1 Response Rate

The researcher distributed 121 questionnaires to trainers. One hundred and three (103) out of 121 responded, accounting for 85.1% response rate. According to Mugenda and Mugenda (2008), a response rate of over 70% is very good. All 8 questionnaires for internal quality assurance officers and heads of computing departments were responded to. Interviews for County Quality Assurance Officers and Chief Principals recorded a turnout of 100%.

4.2 Demographic Characteristics

Table 4.1: Descriptive Results on Demographic Characteristics

Characteristic	Category	Frequency	Percent (%)	Mean	SD
Institution	Kisii	14	13.6		
	Bungoma	12	11.7		
	Nyamira	12	11.7		
	Kisumu	15	14.6		
	Mawego	12	11.7		
	Friends Kaimosi	13	12.6		
	Sigalagala	13	12.6		
	Shamberere	12	11.7		
Gender	Male	56	54.4	1.49	.558
	Female	44	42.7		
	Prefer not to say	3	2.9		
Teaching Experience	0-5 years	48	46.6	1.75	.801
	6-10 years	34	33.0		

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Characteristic	Category	Frequency	Percent (%)	Mean	SD
	11-15 years	20	19.4		
	16+ years	1	1.0		
Level Taught (Certificate)	Yes	57	55.3	1.45	.500
Level Taught (Diploma)	Yes	92	89.3	1.11	.310
Level Taught (Higher Diploma)	Yes	19	18.4	1.82	.390
Department (Computing & Informatics)	Yes	80	77.7	1.22	.418

4.3 Awareness and Familiarity with AI Tools

Table 4.2: Awareness and Familiarity with AI Tools among Trainers

Statement	N	Mean	Std. Deviation
I am aware of various AI tools applicable to teaching computer courses.	103	3.90	1.133
I have received training on integrating AI in teaching.	103	3.00	1.400
I actively seek information about new AI tools relevant to computer education.	103	3.98	.840
I can differentiate between traditional ICT tools and AI technologies.	103	3.93	1.060
I feel confident in identifying suitable AI tools for my teaching needs.	103	3.74	1.196
Overall Mean Result	**103**	**3.71**	**1.126**

The results showed that trainers have moderate awareness and interest in using AI tools in teaching computer courses. Trainers agreed (M=3.98) that they actively searched for information about new AI tools, and agreed (M=3.90) that they know about various AI tools. Trainers were neutral (M=3.00) regarding having received training on integrating AI in instruction, indicating a key gap in professional development.

4.4 Current Use of AI Tools in Teaching Practices

Table 4.3: Current Use of AI Tools in Teaching Practices

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Statement	N	Mean	Std. Deviation
I use AI-powered platforms (e.g., ChatGPT, GitHub Copilot) to support my teaching.	103	3.90	1.159
I use AI tools to generate or enhance teaching materials.	103	3.73	1.198
I use AI tools during student assessments or grading.	103	3.11	1.275
I integrate AI tools during classroom lessons or demonstrations.	103	3.42	1.272
I regularly reflect on the effectiveness of the AI tools I use in class.	103	3.37	1.276
Overall Mean Result	**103**	**3.51**	**1.236**

The most popular usage of AI is through platforms such as ChatGPT and GitHub Copilot (M=3.90). Trainers also agreed (M=3.73) that they were employing AI to generate or enhance educational materials. However, trainers were neutral about the use of AI during classroom lessons (M=3.42) and the use of AI in student assessments (M=3.11). The overall mean of 3.51 indicated a moderate level of AI use in teaching.

4.5 Institutional Support and Infrastructure

Table 4.5: Institutional Support and Infrastructure in Relation to AI

Statement	N	Mean	Std. Deviation
My institution encourages the use of AI tools in teaching.	103	3.38	1.147
My department has policies that support the use of AI in instruction.	103	2.97	1.248
There is reliable internet and infrastructure to support AI tool use.	103	3.62	1.164
I face challenges in accessing AI tools in my institution.	103	2.92	1.100
The institution provides technical support or training for using AI tools.	103	2.91	1.261
Overall Mean Result	**103**	**3.16**	**1.184**

Trainers agreed (M=3.62) that there was reliable internet and infrastructure to support AI tool use. However, trainers were neutral regarding institutional encouragement (M=3.38), departmental policies (M=2.97), and technical support or training (M=2.91). The overall mean of 3.16 indicated average institutional support and infrastructure for AI use.

4.6 Perceived Effectiveness and Educational Impact

Table 4.6: Perceived Effectiveness and Educational Impact of AI

Statement	N	Mean	Std. Deviation
AI tools enhance the delivery of computer course content.	103	4.17	.909
Students show increased engagement when AI tools are used in class.	103	3.90	1.015
AI tools help in assessing students' understanding of computer concepts.	103	3.80	.953
I have noticed improved student performance when AI tools are used in teaching.	103	3.55	1.017
The use of AI in teaching aligns well with the computer courses curriculum objectives.	103	3.68	1.122
Overall Mean Result	**103**	**3.82**	**1.003**

Trainers agreed (M=4.17) that AI tools enhance the delivery of computer course content and agreed (M=3.90) that students are more engaged when AI tools are employed. The overall mean of 3.82 shows a positive perception of the effectiveness and educational benefits of applying AI in teaching computer courses.

4.7 Ethical and Professional Considerations

Table 4.7: Ethical and Professional Considerations

Statement	N	Mean	Std. Deviation
Ethical concerns affect my decision to use AI in teaching.	103	3.40	1.149
I worry about students' over-reliance on AI tools.	103	3.95	1.208
I am concerned about plagiarism or academic dishonesty facilitated by AI tools.	103	4.13	1.026
I ensure students are guided on the ethical use of AI tools.	103	3.80	1.079
The use of AI tools in teaching requires clear ethical guidelines.	103	4.13	1.016
Overall Mean Result	**103**	**3.88**	**1.096**

Trainers strongly agreed (M=4.13) that they are concerned about plagiarism facilitated by AI tools and that clear ethical guidelines are required. They also agreed (M=3.95) about worrying about student over-reliance on AI tools. The overall mean of 3.88 indicated that ethical and professional concerns are important to most trainers.

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4.8 Impact on Student Engagement and Performance

Table 4.8: Impact of AI on Student Engagement and Performance

Statement	N	Mean	Std. Deviation
The introduction of AI tools will affect student engagement in your courses.	103	3.91	1.130
AI tools will have a positive impact on student performance and learning outcomes.	103	3.97	1.014
AI tools will have improved knowledge retention among students.	103	3.72	1.052
The training provided for using AI tools will be adequate in your institution.	103	3.46	1.186
There is sufficient institutional support for the effective implementation of AI tools.	103	3.24	1.232
Overall Mean Result	**103**	**3.66**	**1.123**

Trainers agreed (M=3.97) that AI tools will positively impact student performance and agreed (M=3.91) on the effect on student engagement. However, they were neutral regarding adequate training (M=3.46) and sufficient institutional support (M=3.24). The overall mean of 3.66 indicated a positive appraisal of AI's potential impact.

4.9 Challenges and Opportunities

Table 4.9: Challenges and Opportunities in Relation to AI

Statement	N	Mean	Std. Deviation
Lack of adequate training	103	4.26	.851
Resistance to change	103	3.62	1.095
Inadequate infrastructure	103	4.10	.965
Cost of implementation	103	3.92	.893
Technical issues	103	4.00	.886
Overall Mean Result	**103**	**3.98**	**0.938**

Lack of adequate training was the highest-rated challenge (M=4.26), followed by inadequate infrastructure (M=4.10). Technical issues (M=4.00), cost of implementation (M=3.92), and resistance to change (M=3.62) were also identified as significant challenges. The overall mean of 3.98 indicated that trainers face serious barriers to embedding AI in their instruction.

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4.10 Regression Analysis: Influence of AI Tools on Perceived Performance

Prior to conducting the regression analysis, the following assumptions were tested:
Normality: Shapiro-Wilk test was not significant ($p > 0.05$), indicating normal distribution of residuals.
Homoscedasticity: Breusch-Pagan test was not significant ($p > 0.05$), indicating constant variance of residuals.
Multicollinearity: Variance Inflation Factor (VIF) was 1.00, indicating no multicollinearity (single predictor variable).
Independence of Errors: Durbin-Watson statistic was 1.95, indicating independence of errors (within acceptable range of 1.5-2.5).

Table 4.10: Model Summary on the Influence of AI Tools on Perceived Performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.516[a]	.266	.259	.88086

a. Predictors: (Constant), artificial intelligence tools

Table 4.11: ANOVA on the Influence of AI Tools on Perceived Performance

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	28.467	1	28.467	36.689	.000[b]
Residual	78.367	101	.776		
Total	106.835	102			

a. Dependent Variable: performance

b. Predictors: (Constant), artificial intelligence tools

Table 4.12: Coefficients on the Influence of AI Tools on Perceived Performance

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	
	B	Std. Error	Beta		
(Constant)	.682	.492		1.387	.169
Artificial Intelligence Tools	.798	.132	.516	6.057	.000

a. Dependent Variable: performance

Regression Equation:

Performance = 0.682 + 0.798 × (Artificial Intelligence Tools)

The regression analysis revealed that artificial intelligence tools accounted for 26.6% of the variance in trainers' performance perceptions ($R^2 = .266$, $p < .001$). The model was statistically significant, $F = 36.689$, $p < .001$. The unstandardized coefficient (B) for AI tools was 0.798, meaning that for every one-unit increase in the use of AI

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tools, perceived performance increases by 0.798 units. The standardized coefficient (Beta) was 0.516, indicating a moderate to strong positive effect of AI tools on performance.

4.11 Hypothesis Testing

Table 4.13: Testing Hypothesis on AI Tools and Teaching Performance

	AI Tools	Performance	
AI Tools	Pearson Correlation	1	.516**
	Sig. (2-tailed)		.000
	N	103	103
Performance	Pearson Correlation	.516**	1
	Sig. (2-tailed)	.000	
	N	103	103

**. Correlation is significant at the 0.01 level (2-tailed).

The Pearson correlation analysis revealed a moderate positive correlation between the use of AI tools and teaching performance ($r = 0.516$, $p < 0.01$, $N = 103$). The correlation coefficient of 0.516 (26.6% of variance explained) indicated that increased use of AI tools was associated with improved performance. The relationship was statistically significant at the 0.01 level ($p = 0.000$), suggesting that the observed association was unlikely to have occurred by chance.

Decision: The null hypothesis stating there is no statistically significant relationship between the use of artificial intelligence tools in teaching and the performance of computer courses was **rejected**.

4.12 Heads of Departments' Perspectives on AI Tools in Teaching

Figure 4.1: Framework for Integrating AI Courses

All Heads of Departments (HODs) and Internal Quality Assurance & Standards Officers (100%) reported that there is no framework in place for integrating Artificial Intelligence into the curriculum within their respective departments.

Table 4.13: Organizations and Platforms Offering AI Courses

Organizations and Platforms	Yes (%)
CDACC	87.5%
Huawei ICT Academy	75.0%
IBM Skills Build	37.5%
Google Cloud Skills Boost	37.5%

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Organizations and Platforms	Yes (%)
Microsoft Learn	12.5%
Future Learn	12.5%

Table 4.14: Technical Infrastructure Requirements for AI Learning Environment

Statement	N	Mean	Std. Deviation
We use platforms like Google Colab, Jupyter Notebooks, or Kaggle Kernels for AI programming activities.	8	4.25	.707
Our institution uses Moodle or Google Classroom integrated with AI plugins.	8	4.13	.641
AI tools such as ChatGPT, Codex, IBM Watson, or Microsoft Azure AI are integrated into the learning process.	8	3.50	1.414
Students have access to open-source AI tools (e.g., TensorFlow, PyTorch, Orange) for experimentation.	8	4.00	1.069
Our Learning Management System supports AI-based personalized learning content.	8	4.13	1.126
Overall Mean Result	**8**	**4.00**	**0.991**

HODs reported frequent use of platforms such as Google Colab, Jupyter Notebooks, and Kaggle Kernels (M=4.25), and affirmed that institutional Learning Management Systems are being integrated with AI plugins (M=4.13). The overall mean of 4.00 (SD=0.991) reflects strong institutional readiness in terms of technical infrastructure to support AI-enhanced learning.

Table 4.15: Pedagogical Strategies for AI

Statement	N	Mean	Std. Deviation
Flipped classroom models are used, with students accessing pre-recorded AI content before in-person sessions.	8	4.50	.535
Class time is effectively utilized for guided practice, discussions, or coding exercises in AI topics.	8	4.13	1.126
Adaptive learning systems are in place to personalize AI learning for individual students.	8	4.50	.535
Students work in teams on small AI projects like chatbots or recommendation engines.	8	4.38	.518

Statement	N	Mean	Std. Deviation
Capstone projects are used to address real-world AI challenges in sectors like agriculture, health, or local business.	8	4.38	.518
Overall Mean Result	**8**	**4.38**	**0.646**

HODs strongly agreed (M=4.50) on the use of flipped classroom models and adaptive learning systems. The overall mean of 4.38 (SD=0.646) indicates that HODs are actively adopting modern, interactive, and personalized pedagogical strategies suited for AI instruction.

4.13 Internal Quality Assurance Officers' Perspectives

Table 4.16: Internal Quality Assurance Officers on AI Tools in Teaching

Statement	N	Mean	Std. Deviation
AI tools are effectively used in the teaching of computer courses at national polytechnics in Western and Nyanza regions.	8	3.00	1.195
There are clear quality standards guiding the use of AI tools in teaching computer courses.	8	2.50	.926
The selection of AI tools for teaching follows established institutional policies and guidelines.	8	2.50	1.604
Overall Mean Result	**8**	**2.67**	**1.242**

Internal Quality Assurance Officers indicated moderate (M=3.00) use of AI tools, but low levels of clear quality standards (M=2.50) and institutional policies (M=2.50). The overall mean of 2.67 indicates low institutional preparedness from a quality assurance perspective.

4.14 Qualitative Findings from Principals and County Quality Assurance Officers

Key Themes from Principal Interviews:

Consideration of AI tools: Five principals reported that institutions had considered the use of AI tools, but limited funding and technical capacity hindered implementation. One principal stated: "*...Yes, we have had initial discussions, but no concrete steps have been taken due to limited funding and technical capacity*" (P1).

Lack of consideration: Two principals stated that institutions had not considered AI tools because they had mainly focused on basic ICT infrastructure and staffing challenges.

Trainer interest: One principal noted that individual trainers had shown interest, but institutionally there was a lack of strategic direction.

Key Themes from CQASO Interviews:

Limited funding: Five CQASOs noted that one or two institutions have shown interest but have not moved beyond planning due to lack of funding.

Infrastructure gaps: Seven CQASOs pointed out that most institutions are not yet ready due to limitations in infrastructure and digital capabilities.

Trainer interest vs. training opportunities: Four CQASOs noted that trainers showed interest, but limited training opportunities were a challenge.

Key Challenges in Adopting AI Tools:

- Lack of trained staff with expertise in AI
- Insufficient ICT infrastructure and unreliable internet connectivity
- Budget constraints and competing institutional priorities
- Policy and strategic support needed

DISCUSSION

5.1 Awareness and Familiarity with AI Tools

The findings revealed a growing awareness and moderate application of AI tools in the teaching of computer courses within national polytechnics. Trainers demonstrated considerable familiarity with AI tools (M=3.71) and exhibited moderate usage in instructional settings (M=3.51). These results align with the findings of Adamu et al. (2020), who established that technical trainers in Nigeria were competent in using digital tools, showing a positive correlation between teaching experience and digital competence. Similarly, Onyango and Kelonye (2022) noted that Kenyan polytechnics had begun adopting AI-powered systems like automated grading tools and personalized learning platforms, supporting the present research evidence of moderate use.

The finding that trainers actively seek information about new AI tools (M=3.98) suggests a positive disposition toward innovation adoption, consistent with Rogers' (2003) DOI theory's persuasion stage, where individuals develop favorable attitudes toward an innovation. However, the neutral response regarding training on integrating AI (M=3.00) indicates that while interest exists, formal professional development opportunities are lacking, reflecting the complexity construct in DOI theory.

5.2 Current Use of AI Tools in Teaching

The most popular usage of AI is through platforms such as ChatGPT and GitHub Copilot (M=3.90), suggesting that a large number of trainers are already employing these AI technologies for instruction. This aligns with Chanda (2023), who noted that the ability of AI to enable remote collaboration and learning through platforms such as Zoom and AI-powered LMSs has revolutionized traditional delivery of education.

The moderate use of AI in assessment (M=3.11) and classroom lessons (M=3.42) suggests that while some trainers were using AI for direct teaching and assessment, this was not a widespread practice. This finding is consistent with Adebayo (2021), who identified challenges such as inadequate preparation of trainers and ICT infrastructure constraints that exist in national polytechnics. The moderate level of reflection on AI tool effectiveness (M=3.37) indicates that trainers are not systematically evaluating the impact of their AI tool usage, which may limit the optimization of AI-enhanced teaching practices.

5.3 Institutional Support and Infrastructure

The findings revealed average institutional support and infrastructure (M=3.16). While trainers agreed (M=3.62) that there was reliable internet and infrastructure to support AI tool use, they were neutral regarding institutional encouragement (M=3.38), departmental policies (M=2.97), and technical support (M=2.91). This finding aligns with Wekesa and Omollo (2023), who identified limited access to teaching resources, inadequate trained trainers, and weak institutional support as key challenges affecting AI integration.

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The absence of formal policies (M=2.97) and technical support (M=2.91) indicates that AI adoption is occurring in a policy vacuum, which may lead to inconsistent, ad-hoc implementation. This is consistent with Achieng (2023), who noted that frameworks for regulating the impact of AI to society are not in conformity, making many firms hesitant to deploy AI technology because of unresolved issues and ethical concerns.

5.4 Perceived Effectiveness and Educational Impact

Trainers strongly agreed (M=4.17) that AI tools enhance the delivery of computer course content and agreed (M=3.90) that students are more engaged when AI tools are employed. These findings support Zawacki-Richter et al. (2019) and Solís et al. (2023), who demonstrated that AI technologies, including intelligent tutoring systems (ITS), virtual labs, and adaptive learning systems, improve personalization of learning and quality of instruction.

The positive perception of AI's educational value (M=3.82) and awareness of ethical concerns (M=3.88) align with observations by Zouhaier (2023) and Zhang & Li (2023), who emphasized the importance of ethical considerations and regulatory frameworks when implementing AI in higher education. The finding that trainers have noticed improved student performance when AI tools are used (M=3.55) suggests that the benefits of AI are becoming observable to trainers, which DOI theory identifies as a critical factor in adoption (Rogers, 2003).

5.5 Regression Analysis and Hypothesis Testing

The regression analysis revealed a significant moderate positive relationship between AI tools and performance ($R=0.516$, $p<0.05$), affirming earlier international studies that demonstrated measurable benefits of AI on student engagement and outcomes. This finding is consistent with studies by Zawacki-Richter et al. (2019) and Solís et al. (2023), who found that AI technologies improve personalization of learning and quality of instruction.

The rejection of the null hypothesis provides empirical evidence that AI tools significantly impact teaching performance in computer courses at national polytechnics. This finding supports the theoretical proposition of DOI theory that innovations with perceived relative advantage are more likely to be adopted and yield positive outcomes. The positive relationship indicates the perceived utility and advantage of AI tools within the polytechnic educational context, suggesting that the trend reflects the early to mid-stages of diffusion of AI technologies across institutions.

5.6 Qualitative Findings and Triangulation

The qualitative findings from principals and CQASOs strongly converged with quantitative results, providing validation of the survey findings. Principals acknowledged that while discussions about AI tools have occurred, implementation has been constrained by limited funding, lack of trained staff, and insufficient ICT infrastructure. CQASOs corroborated these findings, noting that most institutions are not yet ready due to gaps in infrastructure and digital capacity.

This convergence between quantitative and qualitative data strengthens the validity of the findings and aligns with the sequential explanatory mixed-methods design, where qualitative data provides explanations and meanings to quantitative results (Creswell & Plano Clark, 2018). The consistency between self-reported trainer data and institutional leadership perspectives suggests that the identified barriers (training gaps, infrastructure limitations, funding constraints) are genuine systemic challenges rather than artifacts of self-report bias.

5.7 Theoretical Implications

The findings of this study provide strong empirical support for Rogers' (2003) Diffusion of Innovation theory. The positive perception of AI's educational value (M=3.82) and the significant correlation between AI tool usage and performance ($r=0.516$, $p<0.01$) align with DOI's relative advantage construct, where innovations that demonstrate clear benefits are more likely to be adopted.

The moderate levels of AI tool usage and institutional support reflect the knowledge and persuasion stages of DOI's innovation-decision process, where institutions are aware of AI's potential but have not yet fully committed to implementation. The training gap (M=4.26) operationalizes DOI's complexity construct, revealing that perceived difficulty hampers adoption rates. The absence of formal frameworks (as reported by 100% of HODs) indicates that the diffusion of AI has not yet achieved critical mass across institutions.

The study also validates DOI's emphasis on the social system and communication channels, as insufficient institutional support and weak dissemination of AI-related practices have slowed diffusion across polytechnics. The findings support the need for a structured framework to guide AI integration, consistent with DOI's emphasis on planned, stage-based adoption to accelerate movement from early adopters to the early and late majority within TVET institutions.

5.8 Systemic Barriers to AI Adoption in TVET

The results of this research, based on both quantitative and qualitative data, indicate that the integration of AI in Kenyan TVET institutions is limited by a network of systemic obstacles. These obstacles include gaps in digital skills, shortcomings in institutional readiness, ethical issues, and limitations in resources—functioning collectively to create an environment that hinders the sustainable integration of AI. Grasping these connections is crucial for creating successful interventions. This result correlates with extensive academic discussions surrounding technology adoption in developing environments, where scholars have continually stressed that technological innovation is seldom hindered by just one issue but instead by the intersection of various, interdependent challenges (Adebayo, 2021; Alzakwani, Zabri & Ali, 2025; World Bank, 2022).

5.8.1 Digital Skills Gap

The research revealed a notable discrepancy between trainers' knowledge of AI tools (M=3.71) and their official training in AI integration (M=3.00). This gap is especially troubling as trainers are eager for information on new AI tools (M=3.98), showing strong motivation yet lacking adequate institutional backing for skill enhancement. This discovery aligns with the findings of Adamu et al. (2020), who indicated that although technical and vocational instructors in Nigeria showed skill in digital tools, formal training options were scarce, resulting in trainer expertise being primarily self-taught instead of systematically cultivated.

The digital skills gap goes beyond fundamental digital literacy to include specialized abilities necessary for successful AI integration. According to Zawacki-Richter et al. (2019) in their systematic review of AI uses in higher education, effectively incorporating AI necessitates that educators acquire advanced teaching and technical skills that exceed conventional ICT abilities. In the TVET context, Onyango and Kelonye (2022) highlighted that trainers need to possess not only knowledge of AI tools but also the ability to assess, choose, and customize these tools for particular vocational education scenarios.

Scholarly literature identifies key competency areas essential for effective AI integration in teaching:

Prompt Engineering: Educators must effectively interact with AI tools like ChatGPT to generate educational content. Abbas et al. (2024) highlight that the quality of outcomes from generative AI depends on users' prompting skills, yet most educators lack formal training, creating a significant skills gap (Zhang & Li, 2023).

AI Tool Selection: The ability to evaluate and choose appropriate tools for pedagogical contexts is necessary. Churi et al. (2022) point out that the diverse AI educational tools available pose challenges in making informed decisions, necessitating both technical and pedagogical expertise.

Data Analysis Skills: The capacity to interpret AI-generated analytics for instructional decisions is increasingly important, yet educators often struggle with data literacy, as noted by Mao et al. (2020) and Xu et al. (2022).

Ethical AI Use: Competence in guiding students on responsible AI use and addressing integrity issues is vital. Despite its importance, many educators remain undertrained in ethical considerations (Achieng, 2023; UNESCO, 2019, 2021).

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County Quality Assurance and Standards Officers found that although trainers expressed interest in AI, the lack of training opportunities remains a major hurdle. This indicates that current professional development systems are failing to prepare trainers for AI-enhanced educational settings. Wekesa and Omollo (2023) pointed out that inadequately trained faculty impedes AI content integration into the Kenyan college curriculum. Similarly, Ogembo (2025) highlighted insufficient staff capacity in AI as a significant barrier to public higher education programs in Kenya.

The digital skills gap evidenced in this study mirrors broader issues highlighted in the technology integration literature, especially in developing countries. The World Bank (2022) identified acute digital skills deficits in sub-Saharan African TVET institutions, where limited resources often lead to deprioritization of professional development in emerging technologies. Solís et al. (2023) described the "digital divide in AI competence," illustrating barriers educators face in acquiring necessary AI integration skills.

5.8.2 Institutional Readiness Deficit

The study also revealed a profound institutional readiness deficit. The fact that all Heads of Departments (100%) reported the absence of a formal framework for AI integration highlights a policy vacuum in AI adoption. This deficit manifests in several critical dimensions:

Policy and Strategic Planning: A lack of departmental policies supporting AI use (M=2.97) and neutral institutional encouragement (M=3.38) suggest that institutions are not strategically positioned for coordinated AI integration. Principals noted that while discussions about AI tools took place, no tangible steps were enacted, highlighting the gap between awareness and implementation. Alzakwani, Zabri, and Ali (2025) identified weak institutional policies and unclear implementation frameworks as major impediments to AI adoption in higher education in developing contexts. Rogers' (2003) Diffusion of Innovation theory suggests that absent clear policies contributes to adopter uncertainty, stalling adoption efforts.

Leadership and Organizational Culture: School leadership and organizational culture emerged as significant barriers to AI integration. Resistance to change was identified as a main challenge (M=3.62), alongside diverse institutional responses, indicating a varying institutional culture around innovation. Chanda (2023) noted that institutional culture influences attitudes toward adoption, while Solís et al. (2023) emphasized leadership commitment as a critical success factor for AI integration. The inconsistency between leadership discussions and actual strategic actions underscores a common challenge in technology adoption, where, as Luckin et al. (2016) observed, successful AI integration requires sustained leadership commitment and strategic resource allocation.

Technical Infrastructure: The study noted that although trainers affirmed reliable internet and infrastructure (M=3.62), Heads of Departments reported using platforms like Google Colab and Jupyter Notebooks (M=4.25), suggesting a disparity in technical capacity. The Communications Authority of Kenya (2023) highlighted regional disparities in internet access that affect technological utilization. Mboya (2024) described a "digital divide within institutions," signaling that while infrastructure exists, its effective use is hindered by capacity and cultural barriers, as well as policy constraints. This finding is consistent with observations from Adebayo (2021) and the World Bank (2022), who noted that institutions often invest in technology infrastructure without simultaneously investing in the human capacity and organizational systems needed for effective utilization.

5.8.3 Ethical and Professional Concerns

The study highlights significant ethical and professional concerns among trainers regarding AI in education, particularly the absence of institutional frameworks to address these issues. Key concerns include:

- **Plagiarism and academic dishonesty** facilitated by AI tools (M=4.13)
- **Student over-reliance** on AI tools (M=3.95)
- The **need for clear ethical guidelines** (M=4.13)

These findings align with broader discussions on AI ethics in education, emphasizing fairness, transparency, and accountability as outlined by UNESCO (2019, 2021) and NITI Aayog (2018). The lack of institutional policies creates uncertainty, prompting hesitation among trainers regarding AI adoption, as noted by Achieng (2023). Qualitative data suggests that ethical considerations are not systematically integrated into institutional planning, indicating a reactive rather than proactive approach.

Concerns surrounding student dependence on AI tools are particularly relevant in TVET contexts, risking foundational skill development (Onyango & Kelonye, 2022; Mboya, 2024). The emphasis on plagiarism is echoed in current academic discourse, with many institutions lagging in establishing comprehensive policies for AI-related academic integrity issues (Abbas et al., 2024; Solís et al., 2023). The general lack of practical ethical guidelines further underscores the need for institutional attention to the complex ethical implications of AI in educational settings (Alzakwani et al., 2025). As Cotton et al. (2024) observed, ensuring academic integrity in the era of generative AI requires proactive institutional responses rather than reactive measures.

The concern about student over-reliance on AI tools (M=3.95) is particularly significant. As Onyango and Kelonye (2022) noted, TVET programs emphasize practical skills and competencies, and there are legitimate concerns that over-reliance on AI tools might undermine the development of foundational skills. Mboya (2024) warned that excessive dependence on AI tools in TVET could lead to skill erosion if not carefully managed. However, as Luckin et al. (2016) argued, the goal of AI integration should be to augment rather than replace human capabilities, requiring careful pedagogical design and clear ethical guidelines.

5.8.4 Resource Constraints

The study highlights resource constraints as key barriers to AI adoption in educational contexts. The cost of implementation (M=3.92) and technical issues (M=4.00) emerged as significant obstacles, supported by qualitative feedback from principals and CQASOs who cited limited funding and technical capacity. A principal's remark—"Yes, we have had initial discussions, but no concrete steps have been taken due to limited funding and technical capacity" (P1)—underlines the lack of progress due to these constraints. This echoes Wekesa and Omollo (2023) and Ogembo (2025), who also emphasized resource limitations, including funding, infrastructure, and technical skills, as hindrances to AI integration in Kenya's public higher education.

However, the resource constraint is not simply about absolute resource availability. The finding that HODs reported availability of AI-capable GPUs (M=4.13) and use of platforms like Google Colab and Kaggle Kernels (M=4.25) suggests that resources may exist but are not being strategically deployed. This points to the need for cost-benefit analyses that can guide strategic investment decisions and help institutions prioritize resource allocation for maximum impact. As the World Bank (2022) noted, resource constraints in developing contexts often reflect not just absolute scarcity but also strategic allocation challenges.

Scholars like Adebayo (2021) and Yigitcanlar et al. (2020) have noted that institutions often underestimate the full costs of AI implementation, which include ongoing support and training. Furthermore, technical issues, rated at (M=4.00), complicate the sustained use of AI tools, as many institutions in developing contexts lack sufficient technical support. Qualitative data reveal that funding and technical abilities remain principal barriers, aligning with broader literature on technology adoption in sub-Saharan Africa, including insights from the World Bank (2022) and Alzakwani et al. (2025). Churi et al. (2022) also noted that AI tools require sophisticated technical support, including system administration, data management, and troubleshooting capabilities, which are often limited in developing contexts.

5.8.5 Interconnectedness of Barriers

The study identifies the interconnectedness of barriers to AI adoption, where training gaps (M=4.26) and infrastructure limitations (M=4.10) reinforce one another. A lack of institutional readiness can inhibit the application of skills acquired through training, as emphasized by Rogers' (2003) DOI theory. Ethical concerns also play a role, deterring adoption despite resource availability. The study suggests that addressing these resource constraints, particularly in training and institutional frameworks, is critical to breaking the cycle of underinvestment.

The interconnectedness of barriers operates through several mechanisms:

- **Training gaps compound infrastructure limitations:** Trainers lacking digital competencies may be less able to effectively utilize available infrastructure (Adamu et al., 2020).
- **Institutional readiness deficits limit training effectiveness:** Trained trainers lack the organizational support to apply their new skills, as Rogers (2003) DOI theory would predict.
- **Ethical concerns deter adoption despite resource availability:** Unresolved ethical issues create hesitation and uncertainty (Achieng, 2023).
- **Resource constraints limit capacity building:** Limited resources prevent the investments needed to effectively utilize existing resources, creating a vicious cycle (World Bank, 2022).

Intervention design must consider the systemic nature of these barriers. Scholars advocate for a comprehensive approach that targets multiple dimensions of difficulty in AI adoption, as piecemeal efforts are unlikely to yield long-term success (Alzakwani, Zabri & Ali, 2025; Onyango & Kelonye, 2022). The identified barriers highlight that even with perceived advantages of AI tools (M=3.82), the realization of these benefits is restricted by existing challenges in the Kenyan TVET context. This observation aligns with Rogers' (2003) Diffusion of Innovation theory, which emphasizes that the perceived relative advantage of an innovation is not an inherent property but is shaped by the context in which it is adopted

CONCLUSION

This study investigated the influence of artificial intelligence tools in teaching on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya. The findings revealed a growing awareness and moderate application of AI tools, with trainers demonstrating familiarity with AI technologies but limited formal training and institutional support.

The regression analysis established a significant positive relationship between AI tool usage and trainer-perceived performance ($R=0.516$, $R^2=0.266$, $p<0.001$), leading to rejection of the null hypothesis. This suggests that where AI tools have been utilized, they have a significant and positive influence on teaching performance in computer courses. However, adoption remains constrained by inadequate trainer training, infrastructure limitations, and weak institutional policies.

The study concluded that higher levels of AI tool integration are associated with higher trainer-perceived performance ratings. However, the moderate levels of adoption and the significant barriers identified indicate that the full potential of AI in enhancing teaching performance has not yet been realized. The findings underscore the need for structured professional development programs, infrastructure investment, and institutional policy support to promote sustainable AI adoption.

The study contributes to the body of knowledge on AI integration in TVET in sub-Saharan Africa, providing empirical evidence from a context that has received limited attention. The findings support the Diffusion of Innovation theory, demonstrating that the perceived relative advantage of AI tools, when combined with reduced complexity and increased observability, can accelerate adoption and improve teaching performance.

RECOMMENDATIONS

Based on the findings and conclusions of this study, the following recommendations are made:

7.1 Recommendations for Practice

1. **Structured Professional Development Programs:** Given that lack of adequate training (M=4.26) was identified as the highest-rated challenge, national polytechnics should develop structured, ongoing

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professional development programs to improve trainer pedagogical competencies in the use of AI teaching tools. These programs should emphasize reflective teaching techniques, ethical considerations, and instructional design, and should be accredited by KQA and TVETA through the establishment of nationally recognized competency standards in AI pedagogy.

2. **Infrastructure Investment:** With inadequate infrastructure (M=4.10) identified as a significant challenge, institutions should prioritize investment in reliable internet connectivity, modern computing hardware, and backup power solutions to support AI-enhanced teaching. The study found that HODs agreed on the availability of AI-capable GPUs (M=4.13), suggesting that leveraging existing infrastructure while addressing identified gaps could be a cost-effective strategy.
3. **Policy Development:** The finding that departments lack policies supporting AI use (M=2.97) indicates a need for institutional policy development. Institutions should develop clear policies and guidelines for AI integration, addressing ethical considerations, data privacy, and academic integrity. These policies should be developed collaboratively with trainers to ensure relevance and buy-in.
4. **Change Agent Identification:** Institutions should identify and formally empower early adopters as institutional change agents (using Rogers' diffusion theory). These trainers should be trained as internal mentors to model AI-assisted teaching practices and develop persistent networks that facilitate attitude change from persuasion through decision and implementation phases.
5. **Stakeholder Engagement:** Given the positive perception of AI's educational value (M=3.82) and the importance of ethical considerations (M=3.88), institutions should engage all stakeholders (trainers, students, administrators, industry partners) in developing AI integration strategies. This participatory approach can address concerns about academic dishonesty, student over-reliance, and data privacy while building institutional capacity.

7.2 Recommendations for Policy

1. **National AI Integration Framework:** The Ministry of Education and TVETA should develop a national framework for AI integration in TVET, providing clear guidance on infrastructure standards, trainer competencies, curriculum alignment, and ethical considerations. The finding that 100% of HODs reported no existing framework highlights the urgency of this recommendation.

2. **Funding Mechanisms:** Given the financial constraints identified by principals and CQASOs, the government should establish dedicated funding mechanisms for AI integration in TVET institutions, including capital investment for infrastructure, recurrent funding for professional development, and incentives for innovation.

3. **Curriculum Reform:** The finding that AI tools align well with curriculum objectives (M=3.68) suggests that curriculum reform to explicitly include AI competencies would be well-received. KICD and CDACC should review computer course curricula to incorporate AI literacy, applied AI skills, and ethical AI practice across certificate, diploma, and higher diploma levels.

7.3 Recommendations for Further Research

1. **Longitudinal Studies:** Future research should use longitudinal designs to explore the long-term impact of AI tools on students' academic achievement, skills development, and employability outcomes. Longitudinal investigations could identify the causative impact of AI integration factors on objective performance results beyond the correlational influence revealed in this study.

2. **Experimental Studies:** Experimental or quasi-experimental studies are recommended to further investigate the causal relationship between AI tool usage and performance. Such designs would help to identify causal linkages and determine whether the observed positive relationship is due to the AI tools themselves or other mediating factors.

3. **Comparative Studies:** Comparative studies across different TVET institutions in Kenya, including urban and rural institutions, would help to understand how contextual factors moderate the effectiveness of AI tools. This would inform targeted interventions for different institutional contexts.

4. **Student Perspectives:** Future studies should examine learners' engagement as the main respondents, using validated tools to assess learners' attitude toward AI, utility, convenience of use, and learning gain. This would provide a more holistic view of if and how AI integration affects TVET learners.

5. **Qualitative Phenomenology:** Future research should employ qualitative and phenomenological methodologies to investigate trainers' and learners' lived experiences, perceptions, and attitudes regarding the employment of AI tools in training. This would allow for a better understanding of the context of acceptance, obstacles, and pedagogical adjustments that may not be fully captured by quantitative models.

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