

# Influence of Artificial Intelligence Technologies in Assessment on Trainer-Perceived Performance in Computer Courses at National Polytechnics in Western and Nyanza Regions, Kenya

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## ABSTRACT

Artificial Intelligence (AI) is transforming educational assessment globally, yet its application in Technical and Vocational Education and Training (TVET) institutions in Kenya remains limited. This study examined the influence of AI technologies in assessment on trainer-perceived performance in computer courses at eight national polytechnics in Western and Nyanza regions. Guided by Rogers' Diffusion of Innovation (DOI) Theory. The study employed a convergent mixed-methods design with a cross-sectional correlational quantitative component and a qualitative interview component. Stratified random sampling selected 121 trainers, of whom 103 (85.1%) completed questionnaires. Purposive sampling selected 24 senior management staff and 8 County Quality Assurance and Standards Officers for qualitative interviews. The findings revealed moderate utilization of AI technologies in assessment (Mean = 3.00), with trainers expressing strong agreement on AI's transformative potential in improving assessment effectiveness (Mean = 4.06) and enabling personalized learning (Mean = 4.06). Regression analysis demonstrated a significant moderate positive relationship between AI technologies and trainer-perceived performance ( $R = 0.606$ ,  $R^2 = 0.368$ ,  $p < 0.001$ ), leading to rejection of the null hypothesis. Qualitative data revealed that while trainers recognized AI's potential, adoption was constrained by inadequate infrastructure, limited technical capacity, lack of institutional policies, ethical concerns regarding data privacy and algorithmic bias, and the absence of national guidelines for AI-based assessments. The study concludes that AI technologies were significantly positively associated with trainer-perceived performance but require systemic support for full implementation. Recommendations include development of institutional AI assessment policies, enhanced trainer training, infrastructure investment, and establishment of national quality assurance standards for AI-based assessments in Kenyan TVET institutions.

**Keywords:** Artificial intelligence, assessment, TVET, computer courses, trainer-perceived performance, Diffusion of Innovation

## INTRODUCTION

### Background to the Study

Artificial Intelligence (AI) refers to technology that enables computers and machines to simulate human abilities such as learning, understanding, problem-solving, decision-making, creativity, and autonomy (Stryker & Kavlakoglu, 2026). Incorporation of Artificial Intelligence (AI) in the assessment of students is a paradigm shift in the current education system (Gardner, O'Leary & Yuan, 2021). AI technologies in assessment include auto-grading, adaptive tests, plagiarism detectors, learning analytics, and AI proctoring systems. Collectively, all such AI technologies transform the process of assessing student learning (Baker et al., 2023). Globally, the use of AI technologies in assessment has shown remarkable improvements in the efficiency of grading and feedback and also learning experiences of students (Müller et al., 2021; García & López, 2020).

Technical and Vocational Education and Training (TVET) environments require the assessment of practical skills and competency. For this reason, AI technologies have potential for transforming the environment of TVET. AI technologies can assess technical competencies objectively and without much administrative burden for trainers (Fischer et al., 2020). In Europe, Asia, and Africa, several studies have documented reductions in assessment time by 40-60% due to the application of AI-assisted grading techniques (Adeoye et al., 2021; Li, Zhao & Wang, 2021; Dintwe et al., 2021).

The Kenyan government has identified the role of skills development through TVET as an enabler of Kenya Vision 2030 with the aim of increasing the TVET enrolment number to over 2 million by 2027 (Ministry of Education, 2025). To this end, Computer courses at the national polytechnics are the foundation towards this vision and would empower trainees with appropriate skills and knowledge for the digital economy. At present, however, evaluation methodologies used by National polytechnics are mostly manual and rely heavily on the interpretation of examiners (Kamau et al., 2021; Mutua & Kihoro, 2021).

Despite the advancements made globally in the field of AI-based evaluation strategies, national polytechnics in Western and Nyanza regions of Kenya have made slow adoption of AI technology for evaluation (Mboya, 2024; Wanjiru et al., 2022).

Three research gaps were identified in the current literature. First, although international literature indicates effectiveness of AI in assessment, research from these settings is from well-endowed educational environments located in Europe, North America and East Asia (Zhang & Li, 2023; Zouhaier, 2023). Secondly, very few studies are available from African countries, often originating from single institutions without considering systemic factors shaping adoption of AI (Onyango & Kelonye, 2022). Thirdly, there is not a single study conducted in Kenya using quantitative regression analysis on the impact of AI technology on trainer perceived performance of Computer courses across several national polytechnics.

The current research study seeks to address these gaps by exploring the influence of AI technologies for assessment on trainer perceived performance of Computer courses in national polytechnics at Western and Nyanza regions, Kenya.

## Statement of the Problem

In the global education landscape, AI is reshaping how educational assessment is being done by providing smart and objective assessment solutions (Salgado-Olvera et al., 2024; Kautz et al., 2021). However, the current practices of assessment in the Kenya National Polytechnic Institutions are predominantly human and traditional based especially when it comes to awarding and process of marks to the learners (Kamau et al., 2021; Wanjiru et al., 2022). Due to lower usage of AI based assessment tool, Kenyan National polytechnics has greater work load during marking, delays in students' feedback, inconsistency and limited ability of assessors to assess some technical skills in digital context required for the Kenyan economy (Mutua & Kihoro, 2021; Okoro & Nwankwo, 2023).

Western and Nyanza regions collectively share a total of 8 gazetted National Polytechnics and major proportion of trainees are in rural settings and they attend these institutions with large size classes. Kenya National Bureau of Statistics (2022) and Communications Authority of Kenya (2023) highlight that internet accessibility in these two regions has been inconsistent with the range 46-48 percent and they had digital divide. Nevertheless, computer departments in these polytechnics have fundamental skill sets that are prerequisite to the deployment of AI such as computing, programming and knowledge of system architectures (Alzakwani, Zabri & Ali, 2025; Mukkala, 2024). There is no comprehensive empirical study that has tested the influence of AI based assessment in the perceived trainers' performance in Kenyan National polytechnics, using systematic and standard statistical analysis. This paper fill in the knowledge gap by examining influence of AI technologies in assessment on trainer-perceived performance, the potential barriers/challenges that might hinder successful implementation of AI based assessment system in the Kenyan National Polytechnics and provides recommended approach for sustainable utilization of these tools in the practice of educational assessment.

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## Purpose of the Study

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

## Research Objective

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

## Research Question

What is the influence of artificial intelligence technologies in assessment on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya?

## Research Hypothesis

Artificial intelligence technologies in assessment have no statistically significant influence on trainer-perceived performance in computer courses at national polytechnics in Western and Nyanza regions, Kenya.

## Theoretical and Conceptual Frameworks

Rogers (2003) Diffusion of Innovation (DOI) theory looks at how new ideas are spread through groups over time. According to DOI theory there are five things that decide if people will start using a new tool. These five things are: advantage, which is how much better the new tool seems compared to the old way; compatibility, which is how well the new tool fits with what people already value and do; complexity, which is how hard the new tool is to learn; trialability, which is whether people can test the new tool out first; and observability, which is how easy it is for others to see the results of the new tool (Rogers, 2003; Williams, E. Lewis, S., Tonde, J., Alonge, M., & Kisuule, P. 2023).

DOI framework was thus very useful for this study. This is because AI assessment approaches are innovations that must be adopted by the people working in national polytechnics. This study specifically used the DOI theory parts of trialability and observability to see if trainers had the chance to test the technology and if trainers could see the results of AI assessment tools. When looking at complexity the trainers will have opportunity to explore the ease or difficulty of using AI tools for assessment. The DOI framework also looks at how people talk to each other and the role of leaders. Both of these parts are important because this study looks not only the polytechnic academic policies but also institution leadership.

The conceptual framework posits AI technologies in assessment (independent variable) and trainer-perceived performance of computer courses (dependent variable).

## LITERATURE REVIEW

### Introduction to AI Technologies in Assessment

AI technologies in assessment encompass algorithms for evaluating student learning, performance, and skills. They include automated grading systems, adaptive testing platforms, ChatGPT detection, automated essay scoring, plagiarism detection software, learning analytics dashboards, and AI-based proctoring systems. This integration marks a significant leap from traditional methods, allowing for processing large data volumes, immediate feedback, and the identification of unseen learning patterns. Tools like Turnitin, Gradescope, Proctorio, and Coursebox illustrate the global adoption of AI in education, offering advantages such as increased grading efficiency, objectivity, and personalized feedback, transforming the landscape of educational assessments. (Gardner, O'Leary & Yuan, 2021).

AI technologies in assessment encompass algorithms for evaluating student learning, performance, and skills. They include:

- Automated grading systems: Gradescope, Crowdmark, Moodle Quiz auto-grading
- Plagiarism detection: Turnitin, Urkund, Grammarly's plagiarism checker
- AI-based proctoring: ProctorU, Honorlock, ExamSoft
- Learning analytics: Moodle Analytics, Blackboard Insights, Google Classroom analytics
- Adaptive testing platforms: Coursebox, ExamSoft's adaptive features
- Automated essay scoring: Tools integrated into platforms like Turnitin Feedback Studio
- AI-generated insights: Predictive analytics systems, automated feedback generation

### International Studies on AI in Assessment

In Europe, AI use in assessment appears to bring several advantages. In their 2021 study in German TVET, Müller et al. identified a 60% time saving in grading, and better feedback for students. Spanish institutions recorded a 20% improvement in performance on AI based adaptive assessments (García & López, 2020). But these studies might not be generalizable, especially to developing regions.

The Asia studies by Li, Zhao, & Wang (2021) recorded a 50% savings in assessment grading time in a Beijing polytechnic while enriching the student experience. They also discovered that students gained an average of 22% in their scores with an AI adaptive test-taking system in Shanghai (Zhang & Wang, 2020). Even in Africa, AI in assessment and graded on a project in a polytechnic in Lagos achieved 55% times savings in grading (Adeoye et al., 2021). A study at an institution in Ibadan showed a 25% score increase after implementing AI enabled test-taking environment (Oluwole & Adebayo, 2020).

AI aided grading systems in Botswana and South Africa show similar trends as European institutions by reducing the grading time by up to 60% while improving the quality of feedback for students and ultimately learning outcomes.

### Kenyan Studies on AI in Assessment

Limited empirical research exists on AI in assessment within Kenyan TVET institutions. Kariuki and Njoroge (2021) studied AI-powered student assist systems at Mombasa National Polytechnic and found a 30% increase in student engagement and satisfaction. Mutua and Kihoro (2021) examined AI-enabled automated grading systems in Kenyan national polytechnics and found trainers could reduce grading time by 50% on programming tasks. Wanjiru et al. (2022) used a mixed-methods approach in three Kenyan polytechnics and reported that AI-assisted grading improved assessment accuracy, reduced grading discrepancies, and promoted academic equity.

Kamau et al. (2021) demonstrated that machine learning techniques to evaluate students' code submissions in Kenyan polytechnics were more accurate at detecting logical errors and plagiarism. Okoro and Nwankwo (2023) conducted a quasi-experimental study in Kenya and found that students receiving adaptive AI feedback scored 15% higher than those receiving traditional feedback on final tests. These studies collectively suggest that AI technologies in assessment have significant potential to improve educational outcomes in Kenyan polytechnics.

### Research Gap

Despite growing evidence of AI's benefits in assessment globally, several gaps remain. First, existing studies in Kenya have focused on single institutions or limited samples, restricting generalizability (Mutua & Kihoro, 2021; Mboya, 2024). Second, most studies have been descriptive rather than inferential, lacking rigorous statistical analysis of the influence of AI technologies on performance (Wanjiru et al., 2022). Third, no study has simultaneously examined the multiple dimensions of AI assessment technologies across multiple national polytechnics in the Western and Nyanza regions. Fourth, the lack of contextual validation of AI assessment frameworks for Kenyan TVET institutions means that generic international models may be inappropriate for local conditions (Wekesa & Omollo, 2023; Ndungu et al., 2021). This study addresses these gaps by providing

confirmatory empirical evidence on the statistical influence of AI technologies in assessment on trainer-perceived performance in computer courses.

## RESEARCH METHODOLOGY

### 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.

### Research Design

The study adopted a convergent mixed-methods design. The quantitative component used a cross-sectional correlational survey to examine the association between trainers' reported use of AI-assisted assessment and trainer-perceived performance in computer courses. The qualitative component used semi-structured interviews with institutional managers, quality-assurance personnel, and relevant officers to explore implementation conditions, perceived benefits, ethical concerns, and barriers to adoption. Quantitative and qualitative data were collected during the same study period, analysed separately, and integrated during interpretation through comparison of convergent, complementary, and divergent findings. Because the data were collected at one point in time, the study estimated associations rather than causal effects.

In this study, the term "influence" is used in the statistical sense of the extent to which AI technologies in assessment are associated with and predict variation in trainer-perceived performance. The term does not imply a causal relationship because the quantitative component employed a cross-sectional correlational design.

### 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.

### 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:

$$n = \frac{x^2 NPQD^2}{(N-1) + x^2 PQ} = \frac{D^2(N-1) + x^2 PQ}{x^2 NPQ}$$

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).

$$n = \frac{3.841(178)(0.5)(1-0.5)(0.05)^2}{(178-1) + 3.841(0.5)(1-0.5)} = 121 \quad n = \frac{(0.05)^2(178-1) + 3.841(0.5)(1-0.5)}{3.841(178)(0.5)(1-0.5)} = 121$$

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).

### 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.

### 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).

### 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

### Use of AI technologies in assessment

The overall level of use was moderate ( $M = 3.00$ ,  $SD = 1.251$ ). The highest-rated use item concerned applying AI-generated insights to improve assessment strategies and learning outcomes ( $M = 3.27$ ). Plagiarism detection ( $M = 3.13$ ) and automated grading ( $M = 3.11$ ) also showed moderate use. The lowest ratings concerned monitoring student behavior during online assessments ( $M = 2.69$ ) and institutional AI-driven assessment platforms ( $M = 2.80$ ). These results indicate that lower-complexity or more familiar applications were more visible than advanced, integrated assessment systems.

| Assessment-use indicator                                         | N   | Mean | SD    |
|------------------------------------------------------------------|-----|------|-------|
| Automated grading systems((e.g., Gradescope, Moodle Auto-Grader) | 103 | 3.11 | 1.228 |
| AI-driven assessment platforms e.g., Coursebox                   | 103 | 2.80 | 1.191 |
| Learning analytics (e.g., Moodle Analytics)                      | 103 | 2.95 | 1.224 |
| Online examinations with AI features e.g., Google Forms          | 103 | 3.03 | 1.310 |
| Plagiarism detectione.g., Turnitin,                              | 103 | 3.13 | 1.234 |
| Monitoring behavior during online assessment e.g., ProctorU      | 103 | 2.69 | 1.358 |
| AI-generated assessment insights e.g., predictive analytics      | 103 | 3.27 | 1.214 |
| Overall                                                          | 103 | 3.00 | 1.251 |

Note. Means are reported on the five-point scale used in the thesis questionnaire.

The highest-rated specific tool was plagiarism detection ( $M = 3.13$ ), with trainers frequently mentioning Turnitin as the primary platform. Automated grading ( $M = 3.11$ ) referred to tools like Gradescope and institution-specific

Moodle auto-graders. The lowest-rated items included AI proctoring tools such as ProctorU ( $M = 2.69$ ) and comprehensive AI assessment platforms like Coursebox ( $M = 2.80$ ). This variation suggests that trainers are more comfortable with familiar, lower-risk tools (plagiarism checkers) than with advanced applications (proctoring, adaptive platforms).

### Perceived effectiveness, personalization and practical assessment

Trainers expressed strong agreement about the potential effectiveness of AI in assessment (overall  $M = 4.06$ ,  $SD = 0.858$ ). The strongest item concerned improved tracking of student progress ( $M = 4.18$ ), followed by timely feedback ( $M = 4.17$ ). Trainers also rated the potential for improving the overall learning experience ( $M = 4.10$ ), fairness and objectivity ( $M = 4.03$ ), assessment efficiency ( $M = 3.96$ ) and grading accuracy ( $M = 3.93$ ) positively.

The customization and personalization scale also received a positive rating ( $M = 4.06$ ,  $SD = 0.933$ ). Trainers agreed that AI tools could be customized for course needs ( $M = 4.13$ ), adapt assessment difficulty ( $M = 4.12$ ) and provide tailored feedback ( $M = 4.07$ ). Suitability for technical and practical skills was positive but comparatively lower ( $M = 3.91$ ).

The technical- and practical-skills scale produced an overall positive rating ( $M = 3.91$ ,  $SD = 0.982$ ). AI was viewed as useful for simulating real-world scenarios ( $M = 4.11$ ) and assessing programming and coding skills ( $M = 3.87$ ). Trainers nevertheless acknowledged limitations in assessing hands-on hardware troubleshooting ( $M = 3.87$ ), while AI-based platforms for evaluating practical laboratory work received a mean of 3.82. Alignment with Competency-Based Education and Training principles was rated at  $M = 3.89$ .

| Construct                         | Overall mean | SD    | Interpretation     |
|-----------------------------------|--------------|-------|--------------------|
| Use of AI technologies            | 3.00         | 1.251 | Moderate use       |
| Perceived effectiveness           | 4.06         | 0.858 | Positive agreement |
| Customization and personalization | 4.06         | 0.933 | Positive agreement |
| Technical and practical skills    | 3.91         | 0.982 | Positive agreement |

### Regression analysis

AI technologies in assessment were positively associated with trainer-perceived performance. The model produced  $R = .606$  and  $R^2 = .368$ , indicating that 36.8% of the variance in perceived performance was statistically accounted for by the AI-assessment-technology predictor in this sample. The adjusted  $R^2$  was .361 and the standard error of the estimate was .81780.

| Model statistic                      | Value  |
|--------------------------------------|--------|
| R                                    | .606   |
| $R^2$                                | .368   |
| Adjusted $R^2$                       | .361   |
| $F(1,101)$                           | 58.742 |
| p                                    | < .001 |
| Unstandardized B for AI technologies | .996   |
| SE(B)                                | .130   |
| Standardized $\beta$                 | .606   |
| t                                    | 7.664  |

The analysis of variance confirmed that the regression model was statistically significant,  $F(1,101) = 58.742$ ,  $p < .001$ . The unstandardized coefficient was positive and statistically significant ( $B = .996$ ,  $SE = .130$ ,  $\beta = .606$ ,  $t = 7.664$ ,  $p < .001$ ). The fitted model was:  $\text{Performance} = -0.126 + 0.996(\text{AI technologies})$ . Accordingly, the null hypothesis was rejected. The result should not be interpreted as proof that AI caused improved performance, because the study used cross-sectional, perception-based measures.

## Qualitative Findings

Heads of Departments said there was agreement that student performance in computer courses is monitored effectively through AI-generated insights, emphasizing outcome-based monitoring. However, agreement on evaluating trainer preparedness was only moderate showing inconsistencies in how readiness tracked. The overall mean was 3.80, which indicates agreement that the institution can monitor AI integration.

Internal Quality Assurance Officers were neutral about whether policies for data privacy and ethical AI use in assessments are available. Their mean score was 2.63 with a spread showing a big policy gap. They also were neutral about the reliability and validity of assessment methods with a mean of 2.38 and a larger spread. This shows they doubt the accuracy of AI tools. The overall mean of 2.63 points to inadequacies in AI-assisted assessment practices.

Interviews with eight principals revealed that five were thinking about using AI technologies to assess students in computer courses. Two principals preferred assessments because they were not aware of AI options. The main concerns about AI assessments were risks of bias and errors mentioned by six principals; data privacy problems, raised by all eight principals; and resistance from staff mentioned by four principals.

Eight County Quality Assurance and Standards Officers said there were no discussions about AI integration. Seven officers called for national guidelines and, for trainer training and certification. They also stressed how vital it is to have data privacy measures and fairness checks to ensure assessments are accurate and not discriminatory.

## DISCUSSION

### Integration of Quantitative and Qualitative Findings

The findings revealed moderate utilization of AI technologies in assessment (Mean = 3.00) despite trainers' strong agreement on AI's transformative potential (Mean = 4.06). This discrepancy between positive attitudes and limited implementation was confirmed by qualitative data. Principals reported that discussions on AI assessment remained exploratory without concrete action, while CQASOs noted the absence of official discussions or pilot initiatives. The convergence between quantitative and qualitative findings validates that barriers to AI adoption in assessment are systemic, including inadequate infrastructure, limited technical capacity, and lack of institutional policies.

### AI Technologies in Assessment and Trainer-Perceived Performance

The model explained 36.8% of the variance in trainer-perceived performance. The strength of the correlation is represented by  $R = .606$  ( $R = 0.606$ ,  $R^2 = 0.368$ ,  $p < 0.001$ ). Accordingly, the null hypothesis was rejected, providing empirical support for the study's alternative hypothesis that AI technologies positively influence trainer-perceived performance in computer courses. This relationship supports the results of international research on the effectiveness of AI assessment applications. According to the research conducted by Muller et al. (2021), the application of AI-enabled assessment systems reduced marking time by 60% and increased immediate feedback provision in German vocational education and training institutions. Similar results were reported by Garcia and Lopez (2020) as they found that the use of AI for assessment in Spanish vocational education improved student performance by 20%. The current finding recorded an  $R^2$  of .368, indicating that AI technologies in assessment account for 36.8% of the variance in trainer-perceived performance. The corresponding effect size (Cohen's  $f^2 = .582$ ) exceeds Cohen's (1988) threshold for a large effect ( $f^2 \geq .35$ ), suggesting a substantial practical significance of AI technologies in assessment.

The results of this study are also comparable with those of studies conducted in other developing countries. For instance, Adeoye et al. (2021) found that AI-enabled assessment systems reduced marking time by 55% and improved learning experiences in Lagos State Polytechnic. On the other hand, Oluwole and Adebayo (2020) found that students who undertook examinations using AI-assisted adaptive assessment scored 25% higher than those who sat traditional examinations in Ibadan. Ndaba and Mthethwa (2020) also found that the adoption of AI grading systems decreased marking time by 50% and increased the level of detail in feedback at the Tshwane University of Technology. Based on these findings, similar improvements in assessment could reasonably be expected in other Kenyan TVET institutions, provided that the critical prerequisites—adequate infrastructure, institutional policies, trainer training, and national quality assurance frameworks—are concurrently addressed. However, given the cross-sectional and perception-based nature of this study, further research using objective performance metrics is necessary to confirm the magnitude and sustainability of these effects.

### Use of AI Technologies in Assessment

The early stage of AI adoption in Kenyan national polytechnics is reflected in the moderate use of AI technologies in assessment (Mean = 3.00). The highest scores were for plagiarism detection (Mean = 3.13) and AI-generated insights to improve assessment strategies (Mean = 3.27), indicating that trainers are starting to use AI for particular assessment tasks. However, the low scores for learning analytics (Mean = 2.95), AI monitoring (Mean = 2.69), and AI-based assessment platforms (Mean = 2.80) show that more extensive and sophisticated use of AI is still scarce. These results are in line with those of Mutua and Kihoro (2021), who discovered that although they were not yet common, AI-enabled automated grading systems were being used in some Kenyan polytechnics. Likewise, Wanjiru et al. (2022) found that while AI-assisted grading was restricted to a few institutions, it increased accuracy and decreased discrepancies.

The specific obstacles preventing AI adoption were identified by the qualitative findings. Inadequate infrastructure, financial limitations, and a shortage of qualified personnel were noted by principals. With neutral ratings for data privacy policies (Mean = 2.63) and AI reliability (Mean = 2.38), internal quality assurance officers identified policy gaps. CQASOs stressed the importance of fairness checks, trainer certification, and national guidelines. These results are consistent with those of Wekesa and Omollo (2023), who noted that two major obstacles to AI integration in Kenyan institutions are restricted access to resources and insufficient institutional support.

The variation in usage scores across specific AI tool categories reveals important adoption patterns. Plagiarism detection tools (M = 3.13) achieved the highest usage, likely because Turnitin has been available in many Kenyan institutions for over a decade, making adoption less threatening. Conversely, AI monitoring and proctoring tools (M = 2.69) received the lowest rating, reflecting trainers' concerns about student privacy, technical reliability, and the ethical implications of automated surveillance—concerns echoed in interviews with principals and CQASOs.

### Effectiveness of AI in Assessment

Trainers strongly agreed that AI has the potential to revolutionize assessment, despite its current limited application. Trainers' positive opinions of AI's capabilities are reflected in the high ratings for timely feedback (Mean = 4.17), better tracking of student progress (Mean = 4.18), and improved learning experience (Mean = 4.10). These results align with global research that has shown AI's capacity to support formative assessment and offer instantaneous, tailored feedback (Gardner, O'Leary and Yuan, 2021; Holmes et al. 2019). In the TVET context, where objective evaluation of practical skills is crucial, the consensus on AI enhancing fairness and objectivity (Mean = 4.03) is especially important. The belief that AI can evaluate technical and practical skills (Mean = 3.91) indicates that trainers are aware of AI's potential in competency-based assessment, which is essential to Kenya's CBET framework. Nonetheless, AI's capacity to evaluate hardware received a neutral rating.

The perception that AI is capable of evaluating technical and practical skills (Mean = 3.91) indicates that trainers are aware of the potential of AI in competency-based assessment, which is essential to Kenya's CBET framework. On the other hand, the neutral rating (Mean = 3.87) for AI's capacity to evaluate hardware

troubleshooting shows an understanding of AI's limitations in evaluating practical skills. This result is consistent with that of Owolabi and Aladejana (2022), who discovered that AI-based grading was more successful for database and programming courses in Nigerian polytechnics than for assessments involving practical hardware.

### **Customization and Personalization**

Trainers concur that AI makes learning more individualized (Mean=4.12) and tailored to the requirements of various courses (Mean=4.13). The potential of AI to support personalized learning was widely acknowledged by trainers. This conclusion supports the Zawacki-Richter et al. argument. (2019) and Walkington and Bernacki (2020) that AI can produce instructional models and personalized learning groups based on specific traits. These instructors also saw how artificial intelligence could be used to tailor instruction to the needs of specific students. Thus, the various learning requirements of students in the national polytechnics can be met by employing AI in TVET institutions.

### **Assessment of Technical and Practical Skills**

Trainers' recognition of AI's potential in developing authentic assessment environments is reflected in the agreement that AI can replicate real-world scenarios for practical assessments (Mean = 4.11). This is important for TVET institutions because competency-based assessment relies heavily on the demonstration of practical skills. The results are consistent with Chanda's (2023) observation that immersive learning experiences can be obtained through AI-powered simulations and virtual environments. The favorable assessment of AI's conformity to CBET principles (Mean = 3.89) indicates that trainers believe AI is compatible with Kenya's competency-based education framework, which places a strong emphasis on skill demonstration.

### **Theoretical Implications**

The results provide compelling evidence in favor of Rogers' (2003) Diffusion of Innovation Theory, which describes how innovations spread throughout social systems. The knowledge and persuasion phases of the innovation-decision process are reflected in the moderate use of AI technologies in assessment: trainers have positive attitudes toward AI (persuasion) and are aware of its potential (knowledge), but full implementation is still restricted. Trainers view AI assessment tools as complicated and challenging to integrate without sufficient training and infrastructure support, which is consistent with DOI's concept of complexity (Rogers, 2003).

The low implementation of DOI's trialability concept indicates that trainers have few opportunities to test out AI assessment tools. According to CQASOs, trialability is restricted by the lack of official discussions and pilot projects. The observability concept of DOI is also pertinent because, due to limited implementation, trainers might not yet be able to observe tangible proof of AI's advantages. Although noteworthy, the moderate positive correlation ( $R^2 = 0.368$ ) between AI technologies and performance indicates that the benefits are still not fully apparent. The lack of national guidelines and institutional policies reflects DOI's focus on social networks and communication channels in promoting adoption (Rogers, 2003; Kim et al. in 2023).

### **Practical Implications**

The results have a number of useful ramifications for TVET organizations and decision-makers. First, investing in AI assessment tools may result in quantifiable benefits given the strong positive correlation between AI technologies and performance. The moderate utilization level, however, suggests that institutions require more than just tool acquisition—they also require structured implementation strategies. Second, the discrepancy between favorable opinions and low usage implies that training for trainers should emphasize pedagogical integration and ethical issues in addition to technical proficiency (Adamu et al. 2020; Adebayo, 2021).

Third, institutional and national guidelines on AI assessment are desperately needed, according to the policy gaps found by CQASOs and internal quality assurance officers. These rules ought to cover algorithmic fairness, quality assurance standards, and data privacy (in accordance with the Kenya Data Protection Act, 2019). Fourth, given the 46–48% internet connectivity in Western and Nyanza regions, infrastructure investment is essential (Kenya National Bureau of Statistics, 2022; Communications Authority of Kenya, 2023).

## Limitations

It's important to recognize a few limitations. First, rather than objective student achievement data, trainer-perceived performance served as the dependent variable. Although studies show a correlation between trainer-reported performance and objective measurements (Smith and Anderson, 2022; Kunter et al. 2013), objective records should be used in future research to confirm findings. Second, because the study was cross-sectional, conclusions about causality were limited. Third, institutions outside of Kenya's Western and Nyanza regions might not be able to apply the findings. Fourth, the study used self-reported data, which could have been skewed by responses; however, this issue was lessened by the use of qualitative data. Fifth, the study aggregated multiple AI tool categories into a composite 'use of AI technologies' variable. While this captured overall adoption patterns, it may obscure differential effects across tool types. For example, the observed correlation ( $R = .606$ ) might be driven primarily by plagiarism detection while other tools show weaker associations. Future research should disaggregate AI tools to identify which specific applications yield the greatest improvements

## CONCLUSIONS AND RECOMMENDATIONS

### Conclusion

This study looked at how trainer-perceived performance in computer courses at eight national polytechnics in Kenya's Nyanza and Western regions was affected by AI technologies used in assessment. The results showed a moderate use of AI technologies in assessment, with trainers expressing strong positive opinions about AI's potential to enhance assessment efficacy, offer prompt feedback, facilitate personalized learning, and evaluate technical and practical skills. The null hypothesis was rejected because the regression analysis showed a significant moderately positive relationship ( $R = 0.606$ ,  $R^2 = 0.368$ ,  $p < 0.001$ ) between AI technologies and trainer-perceived performance. The implementation of AI assessment tools is hampered by insufficient infrastructure, limited technical capacity, a lack of institutional policies, ethical issues, and a lack of national guidelines, according to qualitative findings. According to the study's findings, AI technologies have a positive association on assessment.

### Recommendations

The following suggestions are made in light of the findings: creating thorough AI evaluation guidelines for national polytechnics, guaranteeing adherence to data privacy regulations, algorithmic fairness, academic integrity, and quality control. With an emphasis on AI tools and ethical issues, institutions should improve the professional development of trainers. Investing in infrastructure is essential, giving rural campuses top priority for dependable internet, appropriate hardware, and power backups. According to the DOI's trialability concept, institutions should also test AI assessment tools in controlled environments to gauge their efficacy and fairness before implementing them more widely. Last but not least, involving trainers, students, industry, and quality assurance organizations in the planning, execution, and assessment of AI projects promotes ownership and relevance

### Suggestions for Further Research

Conduct long-term studies with an emphasis on student achievement to examine the long-term impacts of AI in assessments. In Kenya's TVET context, compare AI-enhanced and conventional approaches using quasi-experimental designs. To determine how infrastructure and policy impact the effectiveness of AI assessments, conduct cross-regional comparative studies. Find out what the students think about motivation and fairness. Examine ethical frameworks for evaluating AI, with a focus on accountability and bias reduction. Use institutional records, such as test results and employment information, to validate findings.

## REFERENCES

1. Adamu, I., Kanbul, S., Gambo, A., & Zanna, T. (2020). Technical and vocational education trainers' computer competencies using artificial intelligence. *Journal of Advanced Research in Social Sciences and Humanities*, 5(6), 256-269.

2. Adebayo, T. O. (2021). Challenges of implementing artificial intelligence tools in Nigerian polytechnics: A focus on rural institutions. *Journal of Educational Technology and Innovation*, 15(2), 45-59.
3. Adeoye, O., Olaleye, S., & Alabi, A. (2021). Enhancing efficiency in assessment through AI: A case study of a National Polytechnic in Lagos. *Educational Management Review*, 15(2), 80-98.
4. Alzakwani, M., Zabri, S. M., & Ali, M. H. (2025). Artificial Intelligence integrated ICT in higher education: An analysis of benefits and challenges. *Learning-Gate Journal*.
5. Baker, T., Smith, L., & Johnson, R. (2023). Integrating AI in education: Technological, organizational, and environmental perspectives. *Educational Technology Research and Development*, 71(3), 457-475.
6. Chanda, K. Z. (2023). The role of artificial intelligence in fostering workplace integrated learning at a South African TVET College during COVID-19 (Doctoral dissertation, University of Johannesburg).
7. Communications Authority of Kenya. (2023). First quarter sector statistics report for the financial year 2022/2023. Nairobi, Kenya: CA.
8. Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications.
9. Dintwe, M., Sebege, R., & Molefe, T. (2021). Enhancing efficiency in assessment through AI: A case study of a National Polytechnic in Gaborone. *Educational Management Review*, 15(2), 80-98.
10. Fischer, T., Müller, S., & Schmidt, K. (2020). AI in Technical and Vocational Education and Training: A comprehensive study in Germany. *Journal of Vocational Education and Training*, 72(3), 340-357.
11. García, A., & López, J. (2020). Adaptive assessment in TVET institutions in Spain: The role of AI. *Journal of Vocational Education and Training*, 38(2), 112-128.
12. Gardner, J., O'Leary, M., & Yuan, L. (2021). Artificial intelligence in educational assessment: 'Breakthrough? Or buncombe and ballyhoo?' *Journal of Computer Assisted Learning*, 37(3), 789-804.
13. Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
14. Kamau, J. M., Otieno, R. A., & Mwangi, D. N. (2021). Application of machine learning algorithms in code assessment: A case study of Kenyan polytechnics. *Journal of Educational Technology and Innovation*, 10(2), 34-45.
15. Kariuki, J., & Njoroge, P. (2021). The impact of AI-driven student support systems on student engagement in TVET education in Mombasa. *Journal of Educational Technology*, 25(2), 237-252.
16. Kenya National Bureau of Statistics. (2022). *Kenya population and housing census 2019: Volume IV – Distribution of population by socio-economic characteristics*. Nairobi, Kenya: KNBS.
17. Kenya. (2019). *Data Protection Act, No. 24 of 2019*. Kenya Law.
18. Kim, S., Brown, C., & Johnson, T. (2023). Communication strategies for AI adoption in education: A diffusion of innovation perspective. *Educational Communication and Technology Journal*, 45(2), 123-137.
19. Kunter, M., Klusmann, U., Baumert, J., Richter, D., Voss, T., & Hachfeld, A. (2013). Professional competence of teachers: Effects on instructional quality and student development. *Journal of Educational Psychology*, 105(3), 805-820.
20. Li, J., Zhao, H., & Wang, Y. (2021). Enhancing efficiency in assessment through AI: A case study of a National Polytechnic in Beijing. *Educational Management Review*, 14(2), 75-91.
21. Mboya, S. O. (2024). Impact of Artificial Intelligence on Technical and Vocational Education and Training: A case study of The Kisumu National Polytechnic, Kenya. *The Kenya Journal of Technical and Vocational Education and Training*, 7, 51.
22. Ministry of Education, Kenya. (2025). *TVET a key enabler of the government's Vision 2030 actualization*. Ministry of Education, Kenya.
23. Mukkala, A. (2024). Integrating AI with ICT for transformative education. *JISEM Journal*.
24. Müller, R., Schmidt, H., & Weber, K. (2021). Enhancing efficiency in assessment through AI: A case study of a National Polytechnic in Germany. *Educational Management Review*, 14(2), 75-91.
25. Mutua, L. K., & Kihoro, J. M. (2021). Perceptions of lecturers on AI-driven grading systems in Kenyan national polytechnics. *International Journal of Technology in Education and Learning*, 6(3), 112-121.
26. Ndaba, S., & Mthethwa, N. (2020). Automating grading and feedback using AI: A case study of a National Polytechnic in Johannesburg. *Educational Management Review*, 14(3), 150-168.
27. Ndungu, J., Wanjiku, M., & Okoth, P. (2021). Project-based learning with AI-integrated curricula in Kenyan polytechnics. *Journal of Educational Technology in Higher Education*, 18(3), 45-62.

28. Okoro, C. A., & Nwankwo, U. O. (2023). Effectiveness of AI-driven adaptive feedback in computer science education: A quasi-experimental study. *Nigerian Journal of Educational Research and Development*, 18(1), 22-37.
29. Oluwole, B., & Adebayo, T. (2020). Adaptive assessment in TVET institutions in Ibadan: The role of AI. *Journal of Vocational Education and Training*, 39(2), 118-135.
30. Onyango, E., & Kelonye, C. (2022). Artificial intelligence (AI) driven interventions in technical and vocational education and training. *Commonwealth of Learning*.
31. Owolabi, O. A., & Aladejana, F. O. (2022). Artificial intelligence and assessment efficiency in Nigerian polytechnics. *African Journal of ICT in Education*, 9(1), 67-79.
32. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
33. Shepherd, S. M., & Willis-Esqueda, C. (2018). Indigenous perspectives on violence risk assessment: a thematic analysis. *Punishment and Society*, 20, 599-627.
34. Smith, T., & Anderson, P. (2022). AI in Apprenticeship Matching: Enhancing Industry-Education Collaboration. *Journal of Vocational Education Research*, 55(3), 289-305.
35. Stryker, C., & Kavlakoglu, E. (2026, June 15). What is artificial intelligence (AI)? IBM. <https://www.ibm.com/think/topics/artificial-intelligence>
36. Walkington, C., & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. *Journal of Research on Technology in Education*, 52(3), 235-252.
37. Wanjiru, P. N., Musyoka, D. K., & Cheruiyot, S. M. (2022). Artificial intelligence in assessment: Enhancing academic integrity and fairness in Kenyan polytechnics. *East African Journal of Educational Research*, 11(4), 90-104.
38. Wekesa, J., & Omollo, D. (2023). Challenges affecting AI content integration into college curricula in Kenya. *Journal of African Educational Research*, 17(3), 67-84.
39. Williams, K., Martinez, L., & Thompson, R. (2023). Understanding AI adoption in education through innovation characteristics. *Journal of Artificial Intelligence in Education*, 33(1), 45-62.
40. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education--where are the trainers? *International Journal of Educational Technology in Higher Education*, 16(1), 1-27.
41. Zhang, H., & Li, L. (2023). Research status and prospects of artificial intelligence technology applied to education and teaching. *Journal of Education, Humanities and Social Sciences*, 14, 199-206.
42. Zhang, T., & Wang, L. (2020). Adaptive assessment in TVET institutions in Shanghai: The role of AI. *Journal of Vocational Education and Training*, 38(2), 112-128.
43. Zouhaier, S. (2023). The impact of artificial intelligence on higher education: An empirical study. *European Journal of Educational Sciences*, 10(1), 17-33