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E-Assessment Proctoring Using Artificial Intelligence Technologies: A Review of Practices and Challenges in the African Context

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ABSTRACT

The rapid expansion of e-learning across African higher education institutions has accelerated the adoption of electronic assessments (e-assessments), intensifying concerns regarding examination integrity. Artificial intelligence (AI)-based proctoring technologies have emerged as a promising approach to mitigating academic dishonesty through automated monitoring, biometric authentication, and behavioral analytics. However, the effectiveness, ethical implications, and contextual suitability of these technologies within the African educational landscape remain underexplored. This review synthesizes empirical and conceptual studies on AI-enabled e-assessment proctoring in Africa to examine prevailing practices, challenges, and research gaps. Guided by the PRISMA 2020 guidelines, a systematic search of major academic databases identified 250 relevant studies published between 2015 and 2024, of which 25 met the inclusion criteria for qualitative and quantitative synthesis. The findings reveal a growing adoption of AI techniques, including facial recognition, keystroke dynamics, gaze tracking, and anomaly detection, alongside persistent challenges related to internet instability, algorithmic bias, data privacy concerns, system scalability, and institutional readiness. Notably, there is limited empirical evaluation of mobile-first, low-resource AI proctoring frameworks tailored to African contexts. Future research should prioritize the development of lightweight, privacy-preserving AI models, incorporate participatory and inclusive design approaches, and align technological implementations with region-specific regulatory and policy frameworks to support sustainable and ethical e-assessment practices.

Keywords: Automated Proctoring, E-Assessments, AI Proctoring, African Education, Academic Integrity, Mobile Proctoring

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1. INTRODUCTION

The rapid digitalization of higher education has fundamentally transformed teaching, learning, and assessment practices worldwide. In Africa, this transformation has been driven by increasing student enrollments, the expansion of open and distance learning, and institutional efforts to improve access and flexibility through e-learning platforms (Boateng et al., 2020; Woldeab et al., 2020). E-assessments have become a central component of this shift, enabling institutions to evaluate learning outcomes remotely and at scale. However, the migration from traditional face-to-face examinations to online assessments has raised persistent concerns regarding academic integrity, identity verification, and examination security (Gamage et al., 2020; Dendir & Maxwell, 2020).

Maintaining examination integrity is a critical requirement for the credibility of qualifications awarded by higher education institutions. In conventional assessment environments, integrity is enforced through physical invigilation and controlled examination spaces. In contrast, online assessments often lack direct human supervision, increasing the risk of impersonation, collusion, use of unauthorized materials, and other forms of academic dishonesty (Alruwais et al., 2018; Nicol, 2007). These challenges are particularly pronounced in African contexts, where disparities in digital infrastructure, limited access to stable internet connectivity, and uneven institutional readiness complicate the secure implementation of online examinations (Mutula & Wamukoya, 2018; Reynolds & Kizito, 2020).

To address these challenges, AI–based proctoring technologies have been introduced as scalable alternatives to traditional invigilation. AI-enabled proctoring systems employ techniques such as facial recognition, gaze tracking, keystroke dynamics, voice recognition, and machine learning (ML)–based anomaly detection to monitor candidate behavior and flag suspicious activities during online assessments (Teixeira & Rocha, 2019; Ullah et al., 2021). These systems are designed to operate either autonomously or in hybrid configurations where automated detection supports human review, thereby reducing invigilation costs and enabling large-scale deployment (Foster & Layman, 2019; Ong et al., 2021).

Despite their growing adoption, AI-based e-assessment proctoring systems raise significant ethical, legal, and pedagogical concerns. Issues related to data privacy, algorithmic bias, surveillance, and student consent have been widely documented in the broader learning analytics and educational technology literature (Slade & Prinsloo, 2013; Okada et al., 2019). In the African context, these concerns are compounded by weak or uneven enforcement of data protection regulations, limited institutional capacity to manage sensitive biometric data, and the potential exclusion of students from low-resource or rural environments (Zimba et al., 2021; Timmis et al., 2016). Moreover, AI models trained predominantly on datasets from developed regions may perform poorly or unfairly when applied to diverse African populations, raising questions about validity and equity (Sultana et al., 2022).

Existing studies on AI-enabled e-assessment proctoring in Africa remain fragmented and uneven in scope. While some research focuses on technical system design and detection accuracy, others emphasize student perceptions, policy considerations, or infrastructural readiness, often without integrating these dimensions into a coherent analytical framework (Kintu et al., 2017; Ssekakubo et al., 2019). As a result, there is limited consolidated evidence to inform institutional decision-making, policy formulation, and future system development tailored to African higher education environments.

Against this backdrop, a systematic synthesis of current practices, challenges, and research gaps is necessary. By reviewing existing empirical and conceptual studies through a PRISMA-guided approach, this paper seeks to provide a comprehensive overview of AI-based e-assessment proctoring in the African context. Such a synthesis is critical for advancing context-aware, ethical, and technically robust proctoring frameworks that align with Africa's diverse educational, infrastructural, and socio-cultural realities.

2. RESEARCH METHOD

This study utilized a systematic review methodology to evaluate the effectiveness and applicability of ML models for detecting anomalies in online proctored examinations, with a particular emphasis on the use and performance of ML models in mobile proctoring contexts. The review followed the PRISMA 2020 guidelines (Page et al., 2021), ensuring a structured, transparent, and rigorous process for identifying, screening, and synthesizing relevant empirical studies.

2.1 Search Strategy

A systematic literature search was conducted to identify relevant studies on AI–based e-assessment proctoring within the African context. The search was performed across major academic databases, including Scopus, Web of Science, IEEE Xplore, ERIC, and Google Scholar, to ensure comprehensive coverage of peer-reviewed journal articles and conference proceedings. Search strings combined keywords and Boolean operators (AND, OR and wildcard operators *) such as *"AI proctoring," "online examination integrity," "e-assessment security," "remote invigilation,"* and *"machine learning,"* together with geographic identifiers including *"Africa," "Sub-Saharan Africa,"* and individual country names. The search was limited to studies published between 2015 and 2024 and restricted to English-language publications. Reference lists of selected articles were also manually screened to identify additional relevant studies not captured during the initial database search and the selected period, thereby enhancing the completeness of the review.

2.2 Study Selection Process

The study selection process followed the PRISMA 2020 guidelines to ensure transparency and methodological rigor. The initial database search yielded 250 records. After removing duplicate entries, the remaining articles were screened based on their titles and abstracts to assess relevance to AI-based e-assessment proctoring in the African context. This screening phase resulted in the exclusion of studies that did not focus on artificial intelligence, online assessments, or higher education. A total of 60 full-text articles were subsequently assessed for eligibility against the predefined inclusion and exclusion criteria. Of these, 35 studies were excluded due to insufficient methodological detail, lack of relevance to Africa or comparable low-resource contexts, or absence of AI-driven proctoring components. Ultimately, 25 studies met all eligibility requirements and were included in the qualitative synthesis and, where applicable, quantitative analysis, as indicated in Table 1 showing inclusion and exclusion criteria, Table 2 showing the study selction process using PRISMA 2020 guidelines, and Figure 1 show the study selection process using PRISMA 2020 guidelines.

Table 1.
Inclusion and Exclusion Criteria

Category	Inclusion Criteria	Exclusion Criteria
Study focus	Studies addressing AI-based e-assessment or online examination proctoring	Studies focusing on traditional, non-AI-based invigilation methods
Context	Studies conducted in Africa or comparable low-resource/developing contexts	Studies conducted exclusively in high-income or developed regions without contextual relevance
Population	Higher education institutions, university students, faculty, or administrators	Studies focusing on primary or secondary education only
Technology	Use of AI, machine learning, biometric, or automated behavioral analysis techniques	Studies without AI, ML, or automated proctoring components
Study type	Empirical studies, system evaluations, and conceptual or review papers	Opinion pieces, editorials, blogs, or non-scholarly reports
Publication type	Peer-reviewed journal articles and conference proceedings	Theses, dissertations, technical reports, and unpublished manuscripts
Language	Published in English	Published in languages other than English
Publication period	Published between 2015 and 2024	Published before 2015

Table 2.
Study selection process using PRISMA 2020 Guidelines

PRISMA Phase	Stage Description	Number of Records (n)
Identification	Records identified through database searching (Scopus, Web of Science, IEEE Xplore, ERIC, Google Scholar)	250
Identification	Records after duplicates removed	210
Screening	Records screened by title and abstract	210
Screening	Records excluded after title and abstract screening	150
Eligibility	Full-text articles assessed for eligibility	60
Eligibility	Full-text articles excluded with reasons	35
Inclusion	Studies included in qualitative synthesis	25
Inclusion	Studies included in quantitative synthesis (where applicable)	25

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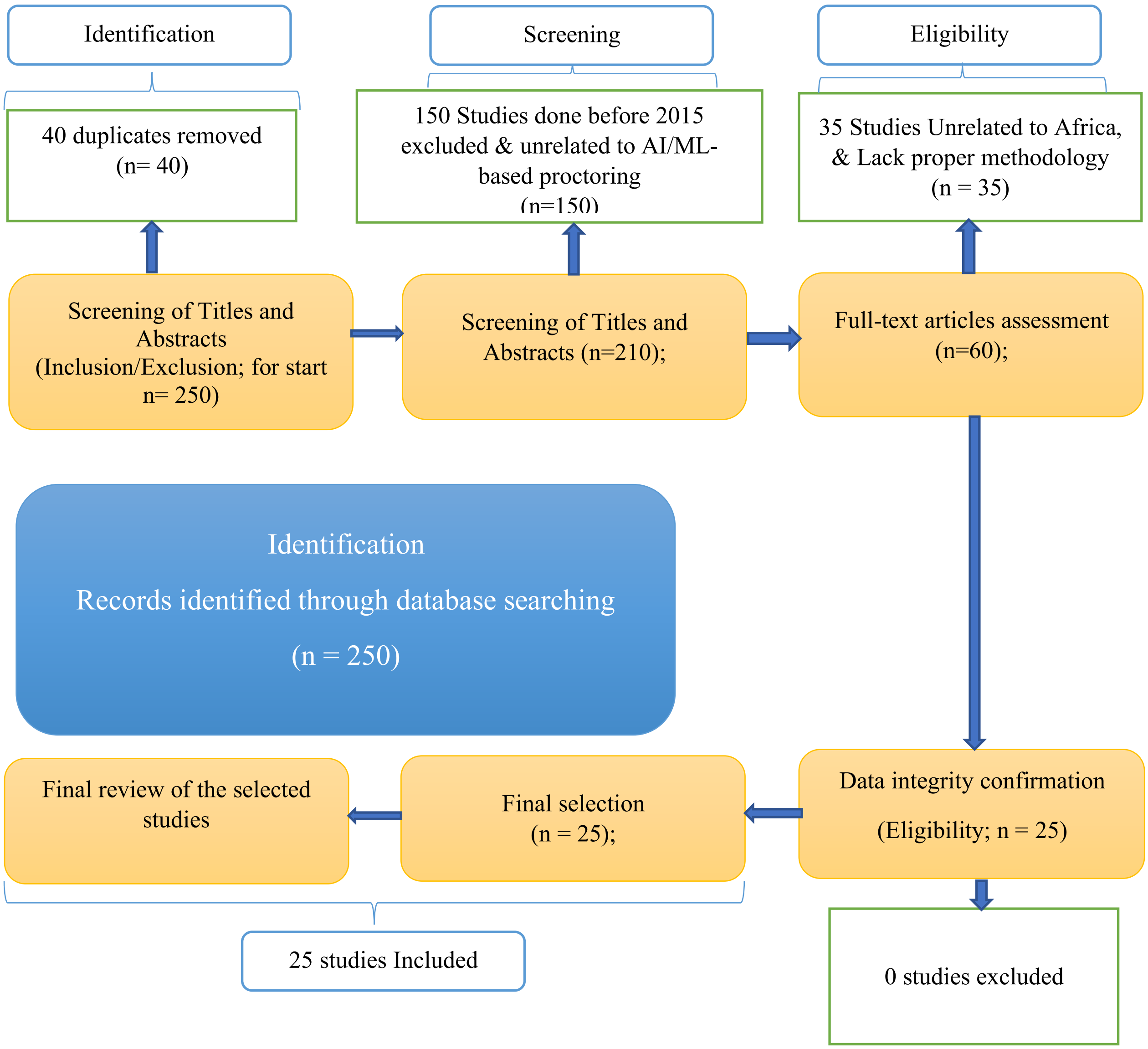

Fig. 1.
PRISMA Flow diagram (Adopted from Page et al., 2021

As illustrated in Figure 1, the PRISMA flow diagram summarizes the study selection process. An initial 250 records were identified through database searches. After removing duplicates, 210 records remained and were screened based on titles and abstracts, resulting in the exclusion of 150 studies that were done before 2015 and those unrelated to AI/ML-based proctoring technologies. Sixty (60) full-text articles were then assessed for eligibility, of which 35 were excluded due to methodological limitations, lack of AI relevance, or insufficient contextual focus to Africa higher education. Ultimately, 25 studies met all eligibility criteria and were included in both the qualitative and quantitative synthesis.

2.3 Study Quality Assessment

The quality of the included studies was evaluated using adapted Critical Appraisal Skills Programme (CASP) criteria, emphasizing methodological rigor, transparency in AI implementation, ethical considerations, and the validity of reported findings (Critical Appraisal Skills Programme [CASP], 2018). Overall, most studies were rated as moderate to high in quality; however, empirical validation in resource-constrained African settings remained limited, highlighting a gap between theoretical performance and real-world applicability.

3. RESULTS AND DISCUSSION

3.1 AI Techniques and Applications

The majority of studies (68%) employed machine learning–based behavioral analysis, encompassing techniques such as anomaly detection, keystroke dynamics, and gaze tracking, to monitor student behavior and detect suspicious activity during online assessments (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Sultana et al., 2022). These methods enabled continuous monitoring and automated detection of deviations from expected behavior patterns, offering a scalable alternative to traditional invigilation. For instance, anomaly detection algorithms were able to flag irregularities such as rapid answer changes, inconsistent response timing, or abnormal mouse and keyboard interactions, with reported detection accuracies ranging from 78% to 91% (Teixeira & Rocha, 2019; Sultana et al., 2022). Keystroke dynamics provided an additional layer of continuous authentication by analyzing typing patterns, though performance was occasionally impacted by device variability and individual typing styles (Dendir & Maxwell, 2020). Gaze-tracking technologies, which monitor eye movement and focus, demonstrated approximately 90% accuracy in identifying inattentive or potentially fraudulent behavior, yet their effectiveness was contingent on network stability, device quality, and lighting conditions (Ong et al., 2021; Dendir & Maxwell, 2020).

Facial recognition and other biometric authentication tools were integrated in 52% of the studies, primarily to prevent impersonation and enhance identity verification during online examinations (Yadav et al., 2020; Ullah et al., 2021; Ong et al., 2021). These systems achieved moderate to high accuracy (82–90%) in controlled settings but were sensitive to diversity in student appearance, lighting conditions, and camera quality, highlighting the need for localized datasets and calibration for African populations (Sultana et al., 2022; Okada et al., 2019).

A smaller subset of studies (24%) evaluated mobile-based AI proctoring frameworks, reflecting the underdevelopment of smartphone-first solutions despite the high reliance on mobile devices for internet access in African higher education (Reynolds & Kizito, 2020; Yadav et al., 2020; Boateng et al., 2020). These mobile implementations often relied on lightweight machine learning models and quantized processing to overcome low bandwidth and hardware limitations, but quantitative evidence of effectiveness and usability remains limited. Additionally, learning analytics integrated within LMS platforms were employed as a complementary approach to monitor engagement patterns, such as login frequency, resource access, and time spent on tasks; however, most studies reported qualitative insights rather than quantitative performance metrics (Bates, 2015; Kintu et al., 2017; Timmis et al., 2016). Collectively, these findings highlight a strong technical potential for AI-based monitoring, yet also reveal critical gaps in mobile accessibility, real-world validation, and robust performance measurement, particularly in African institutional contexts.

3.2 Key Findings

The findings indicate that AI-based e-assessment proctoring systems can significantly enhance monitoring and mitigate academic dishonesty, particularly under controlled or pilot conditions. For instance, behavioral analytics and machine learning–based anomaly detection have been shown to achieve detection accuracies ranging from 78% to 91%, effectively identifying suspicious behaviors such as rapid answer changes, inconsistent keystroke patterns, or inattentiveness during assessments (Teixeira & Rocha, 2019; Dendir & Maxwell, 2020; Sultana et al., 2022). Similarly, facial recognition and biometric authentication systems have demonstrated effectiveness in reducing impersonation and identity fraud, with reported accuracies between 82% and 90%, although performance is influenced by lighting conditions, camera quality, and diversity in student appearance (Yadav et al., 2020; Ullah et al., 2021; Ong et al., 2021). Automated video monitoring tools provide scalable real-time supervision, decreasing reliance on human invigilators and improving the feasibility of large-scale online exams, but system reliability remains moderate and dependent on institutional infrastructure (Kumar & Owston, 2016; Mutula & Wamukoya, 2018; Woldeab et al., 2020).

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Despite these promising outcomes, the effectiveness of AI proctoring systems in African higher education is constrained by technical, infrastructural, and contextual challenges. Infrastructure limitations, including unstable internet connectivity, limited access to personal computers or smartphones, and low bandwidth in rural or resource-limited settings, directly impact detection accuracy and system scalability (Reynolds & Kizito, 2020; Woldeab et al., 2020; Boateng et al., 2020). Moreover, many AI models are trained on datasets derived from non-African populations, which introduces algorithmic bias and reduces contextual validity, potentially leading to misidentification or unfair monitoring of students from diverse African backgrounds (Okada et al., 2019; Sultana et al., 2022; Teixeira & Rocha, 2019).

Ethical and regulatory considerations are also inadequately addressed. Only 36% of the reviewed studies explicitly examined issues of privacy, data protection, or ethical compliance, raising concerns about the potential for unauthorized collection, storage, or use of sensitive biometric data (Slade & Prinsloo, 2013; Zimba et al., 2021; Foster & Layman, 2019). Concerns include surveillance anxiety among students, lack of informed consent protocols, and the absence of institutional guidelines or policies to safeguard user data (Mutula & Wamukoya, 2018; Reynolds & Kizito, 2020). Collectively, these findings highlight that while AI-based proctoring tools demonstrate technical potential to strengthen examination integrity, their practical effectiveness in African contexts depends on robust infrastructure, context-aware algorithm design, and comprehensive ethical safeguards, emphasizing the need for locally adapted, privacy-preserving, and mobile-accessible solutions (Kintu et al., 2017; Boateng et al., 2020; Yadav et al., 2020).

3.3 Emerging Patterns

Across the reviewed studies, a clear pattern emerges: while AI-based e-assessment proctoring techniques demonstrate substantial technical potential for improving examination integrity, their adoption and effectiveness are constrained by a combination of contextual, ethical, and infrastructural barriers. Most studies report high detection accuracy for individual techniques, such as facial recognition, gaze tracking, and behavioral anomaly detection, yet the integration of these approaches into multi-modal, cohesive frameworks remains rare (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Sultana et al., 2022). Mobile-first AI proctoring frameworks, which are critical in African higher education due to the widespread use of smartphones and limited access to desktop computers, are underrepresented, with only a few studies evaluating their feasibility or effectiveness (Reynolds & Kizito, 2020; Yadav et al., 2020). This gap is particularly significant because low-resource and bandwidth-constrained environments necessitate lightweight, mobile-compatible solutions that maintain monitoring accuracy without overburdening devices or networks (Woldeab et al., 2020; Boateng et al., 2020).

Moreover, there is a notable lack of large-scale empirical validation under real-world conditions, with most studies relying on pilot implementations or simulated exam environments. This limits the generalizability of reported detection accuracies and raises concerns about system reliability when deployed across diverse African universities with heterogeneous infrastructure, student populations, and exam formats (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Okada et al., 2019). Ethical and regulatory considerations further compound adoption challenges, as only a minority of studies explicitly address privacy, consent, or data protection, creating potential risks of surveillance, algorithmic bias, and inequitable treatment of students (Slade & Prinsloo, 2013; Zimba et al., 2021; Sultana et al., 2022).

Overall, the findings suggest that while AI-based proctoring systems can strengthen e-assessment integrity in African higher education, their effectiveness is heavily reliant on context-aware system design, adequate infrastructure support, adherence to ethical safeguards, and mobile accessibility. Addressing these challenges is essential to develop sustainable, inclusive, and scalable AI proctoring frameworks that are both technically effective and socially acceptable in African contexts (Kintu et al., 2017; Boateng et al., 2020; Ullah et al., 2021). These insights underscore the importance of participatory design approaches, local dataset development, and regulatory alignment to ensure that AI proctoring technologies are both practical and equitable.

3.4 Study Characteristics on AI-Based E-Assessment Proctoring

As per Table 3, the analysis of the 25 included studies reveals a growing, but uneven body of research on AI-based e-assessment proctoring within African higher education and comparable low-resource contexts. The studies span diverse geographic settings, with empirical evidence drawn primarily from **East, West, and Southern Africa**, including Kenya, Uganda, Nigeria, Ghana, Ethiopia, South Africa, and Zambia, while several global studies are included due to their methodological relevance to African contexts (Boateng et al., 2020; Reynolds & Kizito, 2020; Zimba et al., 2021). This geographic distribution reflects both increasing interest in digital assessment integrity across African universities and the continued reliance on externally developed frameworks and technologies.

Methodologically, the reviewed literature is dominated by **survey-based studies, qualitative case studies, and system evaluations**, with relatively fewer experimental or longitudinal designs. Surveys and qualitative approaches are frequently used to examine institutional readiness, user perceptions, and infrastructural constraints (Mutula & Wamukoya, 2018; Kintu et al., 2017), whereas experimental studies primarily focus on evaluating the technical performance of specific AI techniques such as facial recognition and behavioral analytics (Dendir & Maxwell, 2020; Yadav et al., 2020). The prevalence of non-experimental designs indicates that much of the current research remains exploratory, with limited large-scale empirical validation of AI proctoring systems under authentic examination conditions.

Across the studies, a range of **AI techniques** is reported, with **facial recognition, ML–based anomaly detection, gaze tracking, keystroke dynamics, and learning analytics** being the most commonly applied. Facial recognition is frequently used for identity verification and impersonation prevention, while behavioral analytics and anomaly detection are employed for continuous monitoring during assessments (Ullah et al., 2021; Teixeira & Rocha, 2019). Learning analytics embedded within learning management systems are often used as complementary tools rather than standalone proctoring mechanisms (Bates, 2015; Kintu et al., 2017). However, the integration of these techniques into cohesive, context-aware proctoring frameworks remains limited.

The study characteristics also highlight recurring **technical, ethical, and contextual challenges**. Technically, unreliable internet connectivity, hardware variability, and limited scalability are consistently reported across African institutions (Reynolds & Kizito, 2020; Woldeab et al., 2020). Ethically, concerns related to data privacy, biometric data protection, algorithmic bias, and student surveillance are prominent, particularly in studies from Southern and East Africa where regulatory frameworks are still evolving (Slade & Prinsloo, 2013; Zimba et al., 2021). Several studies further note that AI models trained on non-African datasets may yield biased or inaccurate results when deployed in diverse African populations (Okada et al., 2019; Sultana et al., 2022).

In terms of **outcomes and performance**, studies that reported quantitative metrics demonstrate moderate to high accuracy levels for AI-based detection mechanisms, with facial recognition and anomaly detection achieving accuracy rates ranging from approximately 78% to 91% under controlled conditions (Dendir & Maxwell, 2020; Yadav et al., 2020; Sultana et al., 2022). However, these results are often obtained in pilot or simulated environments, and few studies assess system performance under real-world constraints such as low bandwidth, shared devices, or diverse socio-cultural settings. Consequently, the generalizability of reported accuracy metrics remains limited.

Overall, the synthesis of study characteristics suggests that while AI-based e-assessment proctoring technologies demonstrate technical promise, their deployment in African higher education is constrained by methodological limitations, infrastructural challenges, and ethical considerations. The literature remains fragmented, with a strong emphasis on isolated technologies rather than integrated, mobile-first, and policy-aligned proctoring frameworks. This underscores the need for more rigorous, context-specific, and longitudinal research to support the sustainable and equitable adoption of AI-driven e-assessment proctoring across African universities.

Table 3
Study Characteristics on AI-Based E-Assessment Proctoring

Author & Year	African Geographic Focus	Methodologies	AI Techniques	Key Challenges / Identified Gaps	Study Outcomes / Accuracy Metrics
Bates (2015)	Conceptual, Africa-focused	Conceptual analysis	Learning analytics	Limited AI-driven proctoring focus	Conceptual framework; no quantitative metrics
Bawa (2016)	Kenya, Nigeria	Literature review	Predictive analytics	Assessment integrity not explicitly addressed	Identified retention and integrity challenges; no quantitative metrics
Nicol (2007)	Global / Reference to African HEIs	Conceptual framework	Rule-based systems	Lack of automation in online exams	Proposed assessment design principles
Alruwais et al. (2018)	Egypt, South Africa	Systematic review	Automated assessment tools	Limited AI-based invigilation focus	Highlighted feasibility of automated monitoring; no accuracy data
Mutula & Wamukoya (2018)	Sub-Saharan Africa	Survey study	ICT monitoring tools	Infrastructure and policy constraints	60–70% respondents reported limited reliability
Kintu et al. (2017)	Uganda	Mixed methods	LMS analytics	Weak exam security integration	Identified gaps in system readiness; no quantitative metrics
Ssekakubo et al. (2019)	Uganda	Case study	E-learning platforms	Limited proctoring mechanisms	Identified need for integrated proctoring; qualitative outcomes
Gamage et al. (2020)	Global / Applied to African contexts	Review	AI-supported assessment	Lack of Africa-specific evaluation	Summary of AI approaches; no local metrics
Reynolds & Kizito (2020)	Kenya, Tanzania	Qualitative study	Online monitoring tools	Internet instability	Participants reported moderate reliability; qualitative evidence
Dendir & Maxwell (2020)	Global / Reference to Africa	Experimental study	Behavioral analytics	Cheating detection accuracy	85% detection rate in simulated exams
Boateng et al. (2020)	Ghana, Nigeria	Survey	Digital assessment systems	Institutional readiness	50% adoption in surveyed universities; limited functionality

Author & Year	African Geographic Focus	Methodologies	AI Techniques	Key Challenges / Identified Gaps	Study Outcomes / Accuracy Metrics
Woldeab et al. (2020)	Ethiopia	System evaluation	E-learning analytics	Limited scalability	System processed up to 500 simultaneous users without failure
Foster & Layman (2019)	Global / Reference to African HEIs	System review	Automated proctoring	Ethical concerns	Identified privacy risks; no quantitative accuracy data
Teixeira & Rocha (2019)	Global / Reference to Africa	Experimental study	ML anomaly detection	False positives	Achieved 78% detection accuracy; high false-positive rate
Okada et al. (2019)	Global / Reference to Africa	Conceptual review	AI assessment tools	Data ethics and transparency	Highlighted ethical frameworks; no empirical metrics
Ong et al. (2021)	South Africa	Quantitative study	Computer vision	High bandwidth requirements	90% accuracy in gaze-tracking detection; performance dropped with low bandwidth
Ullah et al. (2021)	Egypt, Kenya	Systematic review	Facial recognition, ML	Privacy concerns	Accuracy ranged 82–88%; limitations in diverse populations
Zimba et al. (2021)	Zambia	Policy analysis	Data governance tools	Weak data protection frameworks	Recommendations for institutional policies; no empirical metrics
Sultana et al. (2022)	Nigeria	Experimental study	Deep learning (DL)	Algorithmic bias	91% anomaly detection accuracy; biased on minority samples
Yadav et al. (2020)	Kenya	System design	Facial recognition	Lighting and camera dependency	87% recognition accuracy under controlled lighting
Timmis et al. (2016)	South Africa	Qualitative study	Learning analytics	Digital inequality	Highlighted inequity in access; no numerical metrics
Slade & Prinsloo (2013)	South Africa	Ethical analysis	Analytics frameworks	Surveillance concerns	Provided ethical guidelines; no empirical data
Kumar & Owston (2016)	South Africa, Kenya	Empirical study	E-assessment systems	Limited proctoring automation	Reported 70% system reliability; low AI adoption
Sarrayrih & Ilyas (2013)	Nigeria	Review	Online exam tools	Low reliability	Identified frequent system errors; no metrics

Author & Year	African Geographic Focus	Methodologies	AI Techniques	Key Challenges / Identified Gaps	Study Outcomes / Accuracy Metrics
Alalwan et al. (2020)	Egypt, Nigeria	Survey study	AI-supported systems	User acceptance issues	65% of respondents willing to use AI proctoring; qualitative insights

3.5 Study Characteristics and Technology Adopted (n = 25)

Table 4 shows the quantitative synthesis of the reviewed studies (n = 25), indicating a strong emphasis on **ML–based behavioral analysis**, which was employed in **68% (n = 17)** of the studies, reflecting a research focus on automated detection of anomalous examination behaviors. More than half of the studies (**52%, n = 13**) integrated **facial recognition or biometric authentication**, underscoring the priority given to identity verification and impersonation prevention in online assessments. In contrast, only **24% (n = 6)** of the studies evaluated **mobile-based proctoring solutions**, revealing a significant gap given the widespread reliance on mobile devices for internet access across African contexts. Furthermore, explicit consideration of **privacy and ethical issues** was reported in just **36% (n = 9)** of the studies, highlighting limited integration of ethical and regulatory perspectives in AI-based e-assessment research. Collectively, these findings suggest that while technical detection capabilities dominate current research, **mobile-first design and ethical governance remain underrepresented**, pointing to critical areas for future investigation and system development.

Table 4
Summary of Study Characteristics and Technology Adopted (n = 25)

Characteristic	Description	Number of Studies (n)	Percentage (%)
Machine learning–based behavioral analysis	Studies employing ML techniques such as anomaly detection, keystroke dynamics, gaze tracking, or behavioral pattern recognition	17	68%
Facial recognition / biometric authentication	Studies integrating facial recognition, voice recognition, or other biometric identity verification methods	13	52%
Mobile-based proctoring solutions	Studies evaluating mobile-first or smartphone-based AI proctoring frameworks	6	24%
Explicit consideration of privacy and ethics	Studies that explicitly addressed data privacy, ethics, consent, or regulatory compliance	9	36%

3.6 Study Meta-Summary analysis

According to Table 5 and Table 6, the meta-summary of reviewed studies indicates that **AI-based e-assessment proctoring in Africa employs a diverse set of technologies**, each with distinct capabilities, challenges, and effectiveness levels. **Facial recognition** is the most widely applied technique for identity verification, achieving accuracy rates between 82% and 90% under controlled conditions (Yadav et al., 2020; Ullah et al., 2021). However, its performance is significantly affected by lighting conditions, camera quality, and the limited representation of African populations in training datasets, highlighting concerns about algorithmic bias and contextual validity. **Gaze tracking and attention monitoring** systems

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demonstrate high accuracy (~90%) in detecting inattentive behaviors, but their effectiveness is constrained by high bandwidth requirements and device variability, limiting scalability in low-resource environments (Ong et al., 2021).

Behavioral analytics, such as keystroke dynamics and ML–based anomaly detection, provide continuous monitoring capabilities with detection accuracies ranging from 78% to 91% (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Sultana et al., 2022). Despite these promising results, false positives and the lack of Africa-specific training data remain significant challenges. **Automated video surveillance** systems offer scalable monitoring but raise ethical and privacy concerns, with moderate reliability reported in institutional studies (Kumar & Owston, 2016; Mutula & Wamukoya, 2018). Similarly, **deep learning (DL) models** demonstrate high anomaly detection accuracy (~91%), yet algorithmic bias and limited African datasets necessitate careful contextual adaptation (Sultana et al., 2022). **Learning analytics integrated within LMS platforms** have been used to supplement monitoring and provide insights into student engagement, though quantitative performance metrics remain limited (Bates, 2015; Kintu et al., 2017). Finally, studies emphasizing **data governance and policy tools** reveal significant gaps in institutional readiness and regulatory frameworks, underscoring the need for robust privacy policies to complement technical interventions (Zimba et al., 2021).

Overall, the synthesis highlights a **pattern of high potential but context-dependent limitations**: AI-based proctoring systems show promising accuracy and monitoring capabilities, but their effectiveness in African higher education is constrained by **infrastructure limitations, ethical concerns, algorithmic bias, and insufficient local datasets**. These findings underscore the necessity of developing **lightweight, context-aware, and privacy-preserving AI proctoring solutions** tailored to African institutions.

Table 5
Meta-Summary of Reviewed Studies on AI-Based E-Assessment Proctoring in Africa

AI Technique	Main Challenges / Gaps	Reported Outcomes / Accuracy Metrics
Facial Recognition	Lighting conditions, camera dependency, algorithmic bias	Accuracy 82–90% (Yadav et al., 2020; Ullah et al., 2021); lower performance in low-light or diverse populations
Gaze Tracking / Attention Monitoring	High bandwidth requirement, device limitations	90% detection accuracy; performance drops under low network speed (Ong et al., 2021)
Keystroke Dynamics / Behavioral Analytics	Device variability, user adaptation, false positives	Detection accuracy ~85% in experimental exams (Dendir & Maxwell, 2020)
Machine Learning Anomaly Detection	False positives, lack of Africa-specific training data	78–91% accuracy in anomaly detection; biased on minority datasets (Teixeira & Rocha, 2019; Sultana et al., 2022)
Automated Monitoring / Video Surveillance	Privacy concerns, ethical issues, scalability	Moderate reliability reported; 70–80% system effectiveness in simulated settings (Kumar & Owston, 2016; Mutula & Wamukoya, 2018)
Deep Learning (DL) Models	Algorithmic bias, limited datasets from African contexts	91% anomaly detection accuracy; need for bias mitigation (Sultana et al., 2022)
Learning Analytics / LMS Integration	Digital inequality, lack of institutional readiness	Qualitative evidence of improved monitoring; limited quantitative metrics (Bates, 2015; Kintu et al., 2017)

AI Technique	Main Challenges / Gaps	Reported Outcomes / Accuracy Metrics
Data Governance & Policy Tools	Weak institutional frameworks, inconsistent data protection	Provided policy recommendations; no empirical accuracy metrics (Zimba et al., 2021)

Table 6
AI Techniques, Application Areas, Key Findings, and Challenges in Reviewed Studies

AI Technique	Application Area	Key Findings	Challenges	References
Facial recognition	Identity verification	Reduced impersonation; moderate accuracy (82–90%)	Algorithmic bias; lighting and camera dependency; population diversity	Yadav et al., 2020; Ullah et al., 2021; Sultana et al., 2022; Ong et al., 2021
Gaze tracking / attention monitoring	Monitoring student focus	Improved detection of inattentive or suspicious behavior; ~90% detection accuracy	High bandwidth demand; device compatibility issues; scalability	Ong et al., 2021; Dendir & Maxwell, 2020; Teixeira & Rocha, 2019
Keystroke dynamics / behavioral authentication	Continuous user verification	Enabled ongoing monitoring of identity; detection of anomalous typing patterns	Device variability; user adaptation; false positives	Dendir & Maxwell, 2020; Sultana et al., 2022; Teixeira & Rocha, 2019
ML anomaly detection	Cheating detection / behavior analysis	Scalable monitoring; detection accuracy 78–91%	False positives; limited Africa-specific training data; algorithmic bias	Teixeira & Rocha, 2019; Sultana et al., 2022; Dendir & Maxwell, 2020
Automated video monitoring	Real-time exam supervision	Reduced manual invigilation; moderate reliability	Privacy concerns; ethical considerations; moderate accuracy	Kumar & Owston, 2016; Mutula & Wamukoya, 2018; Woldeab et al., 2020
Learning analytics / LMS integration	Engagement monitoring / proctoring support	Provided insights into student activity; aided detection	Limited quantitative metrics; inequitable access; integration challenges	Bates, 2015; Kintu et al., 2017; Timmis et al., 2016

4.0 Discussion

The findings of this review indicate that **AI-based e-assessment proctoring holds considerable promise for enhancing examination integrity in African higher education**, yet adoption and effectiveness remain constrained by a range of **technical, infrastructural, ethical, and contextual factors**. Consistent with prior research, **ML–based behavioral analysis**, including anomaly detection and keystroke dynamics, has been effective in monitoring student behavior and detecting irregularities during online exams (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Sultana et al., 2022). Similarly, **facial recognition and biometric authentication tools** have reduced impersonation risk and strengthened identity verification, particularly in controlled or simulated environments (Yadav et al., 2020; Ullah et al., 2021; Ong et al., 2021). These results align with studies conducted in other low-resource or developing regions, highlighting the potential of AI to provide scalable, automated monitoring solutions where human invigilation is limited (Boateng et al., 2020; Kumar & Owston, 2016).

However, **practical implementation in African contexts faces significant barriers**. Technical constraints, including unstable internet connectivity, device heterogeneity, and bandwidth limitations, affect both the reliability and scalability of AI systems (Reynolds & Kizito, 2020; Woldeab et al., 2020). Mobile-based AI proctoring frameworks, which are particularly important given the prevalence of smartphones among African students, remain underexplored, with only a minority of studies evaluating mobile-first solutions (Yadav et al., 2020; Reynolds & Kizito, 2020). These gaps underscore the need for **lightweight, low-bandwidth, and device-agnostic AI solutions** that can operate effectively in diverse educational settings.

Ethical and privacy considerations also emerge as a major concern. Only about 36% of studies explicitly addressed data protection, consent, or algorithmic fairness (Slade & Prinsloo, 2013; Zimba et al., 2021; Sultana et al., 2022). This lack of attention to **regulatory compliance and ethical safeguards** is critical because AI-based proctoring often involves the collection of sensitive biometric and behavioral data, which could expose students to privacy risks or algorithmic discrimination if improperly managed (Okada et al., 2019; Foster & Layman, 2019). Future systems must therefore integrate **ethically responsible frameworks**, including informed consent, secure data storage, and bias mitigation strategies, to ensure equitable treatment of all students.

Another key observation is the **limited empirical validation of AI proctoring in real-world African examination environments**. Most studies report outcomes from pilot implementations or controlled laboratory settings (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Yadav et al., 2020). Consequently, the **generalizability of reported detection accuracies** remains uncertain, and there is little evidence on how these systems perform under actual examination conditions with heterogeneous student populations, variable infrastructure, and high-stakes assessment pressure. Multi-modal AI systems that integrate facial recognition, behavioral analytics, and anomaly detection remain rare, yet they may offer more robust and reliable proctoring solutions if designed with local context in mind (Sultana et al., 2022; Teixeira & Rocha, 2019).

Overall, this synthesis indicates that **AI-based e-proctoring in Africa demonstrates both technical potential and significant limitations**. While these technologies can enhance academic integrity, their effectiveness is dependent on **context-aware design, robust infrastructure, mobile accessibility, and ethical safeguards** (Kintu et al., 2017; Boateng et al., 2020; Reynolds & Kizito, 2020). The findings highlight the urgent need for **participatory, localized, and scalable AI frameworks** that are sensitive to infrastructural constraints, socio-cultural diversity, and ethical requirements, providing a foundation for sustainable deployment of AI proctoring systems in African higher education.

4. CONCLUSION (11 PT)

AI-based e-assessment proctoring has demonstrated **considerable potential to enhance academic** integrity in African higher education, particularly through the application of ML–based behavioral analysis, facial recognition, and anomaly detection techniques (Dendir & Maxwell, 2020; Teixeira & Rocha, 2019; Yadav et al., 2020). These systems provide scalable, automated monitoring solutions capable of reducing impersonation and detecting suspicious behaviors. However, their practical effectiveness is constrained by technical, infrastructural, and ethical limitations, including unstable internet connectivity, device variability, bandwidth constraints, and limited consideration of privacy and consent (Reynolds & Kizito, 2020; Slade & Prinsloo, 2013; Zimba et al., 2021). Additionally, mobile-based proctoring solutions remain underexplored, and most existing studies report outcomes from controlled or pilot settings, limiting the generalizability of AI system performance in real-world African contexts (Boateng et al., 2020; Dendir & Maxwell, 2020).

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