

Behavioral Analysis Using Machine Learning Algorithms in Online Proctored Assessments; The Potential of Mobile Proctoring in E-Assessments: A Review

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ABSTRACT

The rapid expansion of online learning has intensified the need for secure and reliable examination systems. While artificial intelligence (AI) and machine learning (ML) are increasingly employed to safeguard integrity through behavioral analysis, current proctoring solutions remain largely desktop-centric and poorly adapted to mobile environments, where smartphones dominate access. These limitations—spanning heterogeneous hardware, unstable lighting and connectivity, algorithmic bias, privacy concerns, and limited explainability—undermine fairness and trust in misconduct detection. This study reviews the potential of mobile-based proctoring systems that leverage ML for real-time behavioral analysis in e-assessments. A systematic search across Scopus, IEEE Xplore, SpringerLink, and Google Scholar identified 200 publications from 2015–2025. After applying inclusion and exclusion criteria, 30 peer-reviewed empirical studies were analyzed in depth. Findings reveal that ML-driven behavioral analytics enhance accuracy and fairness by detecting anomalies such as gaze aversion, facial emotion changes, and environmental inconsistencies. However, research gaps persist in mobile optimization, ethical safeguards, privacy protection, and bias mitigation. The review concludes that hybrid mobile frameworks integrating multimodal behavioral features and adaptive ML models are essential to strengthen proctoring accuracy while ensuring accessibility and privacy. Future research should prioritize context-aware and explainable AI to foster equitable and trustworthy online assessment environments.



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1. INTRODUCTION

This paper entails a systematic review on behavioral analysis using ML algorithms in online proctored assessments, focusing on the potential of mobile proctoring in e-assessments. This review employs PRISMA 2020 guidelines. The digital transformation of higher education has significantly accelerated in the past decade, particularly due to increased demand for flexible and remote learning options [1], [2]. As online learning ecosystems expand, educational institutions increasingly rely on digital platforms not only for content delivery but also for high-stakes assessments [3]. This rise in e-assessment has amplified concerns over academic integrity, highlighting the limitations of traditional invigilation methods in virtual environments [4].

Artificial intelligence and machine learning technologies have emerged as promising solutions for automating and strengthening examination monitoring processes. These AI-powered systems can track various behavioral cues; such as facial expressions, gaze direction, posture changes, audio anomalies, and keystroke patterns, to infer potential cheating attempts during online examinations [5], [6]. The integration of ML algorithms with computer vision has particularly revolutionized how proctoring platforms analyze real-time behavioral signals [7].

Although many AI-proctoring systems are computer-based, recent trends indicate a growing adoption of mobile proctoring modalities. Mobile devices provide unique advantages: affordability, portability, multiple embedded sensors, and widespread accessibility; especially across developing regions like East Africa [8], [9]. The use of smartphone cameras, gyroscopes, accelerometers, and microphones can significantly enrich behavioral data streams, making mobile devices ideal for low-cost proctoring solutions [10], [11].

Despite advancements, the integration of ML-based behavioral analytics into mobile proctoring systems remains under-explored. Several studies point to challenges relating to model accuracy, environmental variability, cultural bias, network instability, privacy restrictions, and ethical considerations [12], [13]. Moreover, concerns regarding transparency, fairness, and data protection have slowed large-scale adoption [14], [15].

This review synthesizes findings from 30 selected studies to examine behavioral analysis models used in online proctoring, with a special emphasis on the potential and limitations of mobile platforms. The review identifies methodological trends, research gaps, and future opportunities for enhancing mobile-based ML proctoring systems.

The rapid adoption of online assessments has intensified reliance on AI-based behavioral analysis to safeguard examination integrity. Although conventional desktop-based proctoring systems demonstrate strong performance in detecting behavior indicative of academic misconduct, they remain resource-intensive, infrastructure-dependent, and largely inaccessible in low-resource settings where smartphones are the primary digital access devices [5], [6]. Mobile-based behavioral analysis offers a promising alternative; however, existing solutions are insufficiently optimized for mobile environments characterized by heterogeneous hardware capabilities, unstable network connectivity, limited processing power, and variable lighting conditions, all of which adversely affect the reliability of behavior detection models [25].

Moreover, current machine learning approaches for behavioral analysis in online proctoring exhibit notable limitations, including algorithmic bias, restricted transparency, and heightened privacy risks, particularly in contexts that depend on continuous biometric, audio, and sensor-based monitoring [2], [23]. The absence of African-centered behavioral datasets and context-aware model training further compromises the fairness and generalizability of behavioral inference in developing regions [1]. In addition, the opaque nature of automated behavioral flagging mechanisms diminishes student and instructor trust and raises ethical concerns regarding unjustified or erroneous misconduct detection [30].

Consequently, there is a critical need for a mobile-first, ethically grounded, and context-aware behavioral analysis framework that integrates lightweight and explainable machine learning models, reduces privacy intrusion, mitigates bias, and supports equitable and trustworthy online assessment across diverse educational environments.

2. RESEARCH METHOD

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to promote transparency, methodological rigor, and reproducibility throughout the review process [16]. The PRISMA framework facilitated a systematic approach to identifying, screening, assessing eligibility, and ultimately selecting studies focused on behavioral analysis using machine learning algorithms, with particular attention to the potential of mobile proctoring in online assessments.

A total of 200 articles were initially identified through database searches. After removing duplicates and applying inclusion and exclusion criteria during the screening and eligibility phases, 30 studies were ultimately selected for inclusion in the final review using the inclusion and exclusion criteria given (Refer to Table 1). The selection process is summarized in the PRISMA flow chart (Refer to Figure 2) and the article screening process (Refer to Figure 1).

2.1 Search Strategy

A systematic literature search was conducted across four major databases which include Scopus, IEEE Xplore, SpringerLink, and Google Scholar. The search includes key terms and Boolean operators to expand the scope of the search. The following keywords were used: ("machine learning" OR "artificial intelligence" OR "deep learning") AND ("behavioral analysis" OR "student behavior") AND ("online proctoring" OR "remote invigilation") AND ("mobile proctoring" OR "mobile assessment") AND ("e-assessment" OR "academic integrity").

The search covered publications from 2015 to 2025 to capture both pre- and post-pandemic developments in e-assessment technologies.

2.2 Study Selection Process

An initial pool of 200 studies was identified. The selection followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. After screening titles and abstracts, duplicates were removed, and full-text reviews were conducted to determine eligibility [16], which are shown in Table 1.

Table 1. Inclusion and exclusion Criteria.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journals or reputable conference papers	Editorials, blogs, or non-peer-reviewed work
Studies using ML/AI for behavioral or anomaly detection during e-assessments	Papers unrelated to behavioral or ML-based proctoring
Research focusing on online or mobile proctoring systems	Studies exclusively on plagiarism, cybersecurity, or LMS analytics
Papers between 2015–2025	Papers outside the pre-pandemic unrelated to Proctoring
Empirical, experimental, or system-design studies	Articles lacking methodological clarity
Studies written in clear English	Non-English publications

After applying these criteria, 30 articles were included in the final analysis, which are shown in Figure 1.

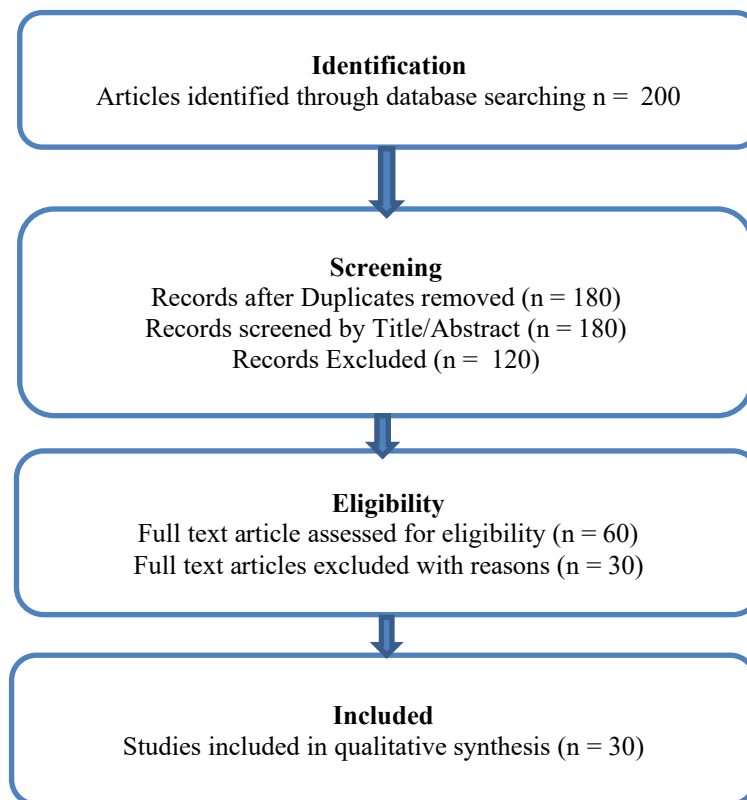


Figure 1. PRISMA Article selection process (Source: Self, Adopted from [16])

The article selection process follows the key steps as below as per [16] (Figure 2):

1. **Identification:** 200 articles were initially retrieved from databases (Scopus, IEEE Xplore, SpringerLink, and Google Scholar).
2. **Screening:** After removing duplicates, 180 unique studies remained. Titles and abstracts were screened, and 120 were excluded for irrelevance or lack of ML/AI focus.
3. **Eligibility:** 60 full-text articles were reviewed for detailed inclusion. Thirty-five (30) were excluded for reasons such as insufficient methodology, lack of behavioral analysis, or non-peer-reviewed status.
4. **Included:** 30 articles met all inclusion criteria and were finally selected for the systematic review.

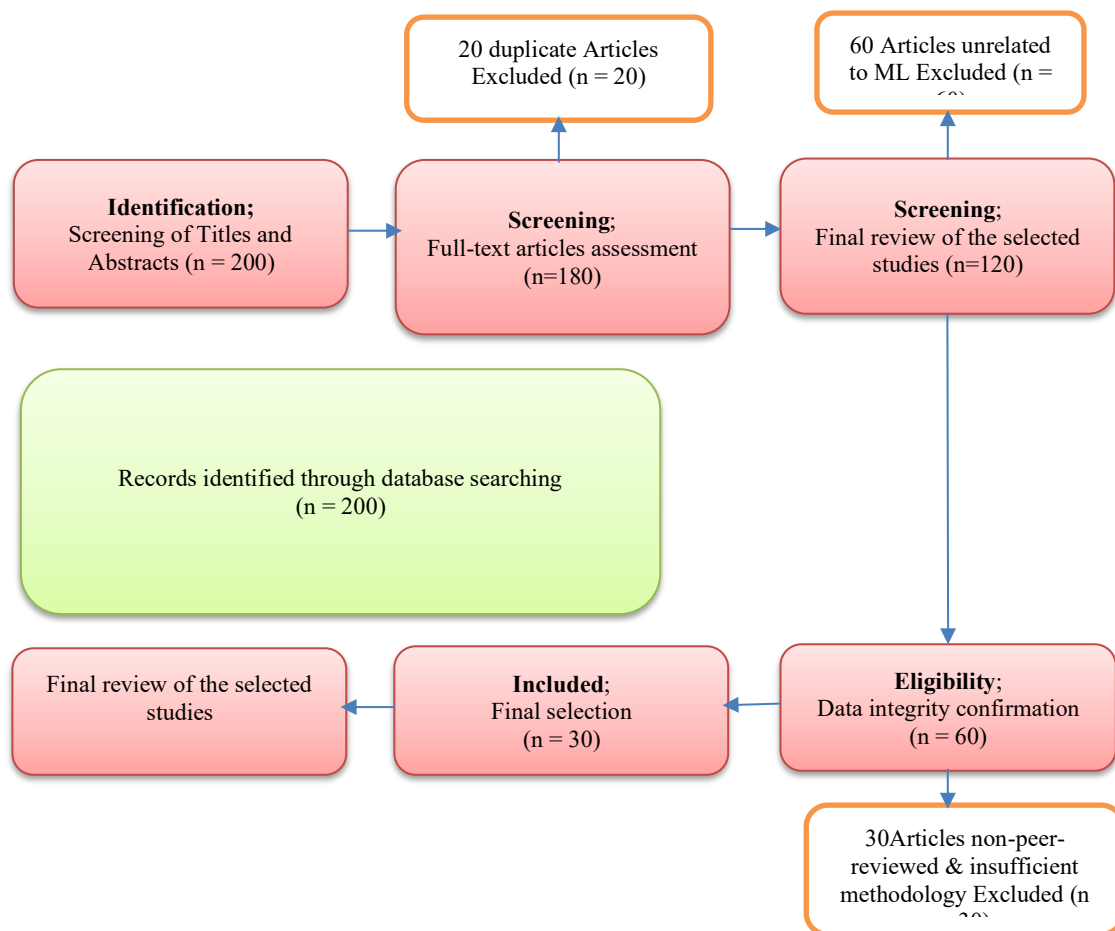


Figure 2. PRISMA flowchart showing the selection process (*Adopted from [16]*)

This process ensured methodological rigor, transparency, and adherence to PRISMA guidelines [16].

2.3 Study Quality Assessment

The methodological quality of the selected studies was systematically evaluated to ensure the reliability and validity of the findings synthesized in this review. Each of the 30 included articles was assessed using adapted criteria commonly applied in systematic reviews of educational technology and artificial intelligence research. The assessment focused on research design clarity, data source adequacy, machine learning model transparency, evaluation metrics, and ethical considerations.

Studies employing well-defined experimental or quasi-experimental designs, clearly described datasets, and validated performance metrics such as accuracy, precision, recall, and F1-score were rated as high quality. Particular emphasis was placed on whether the studies reported model training procedures, validation strategies, and limitations, as these factors directly influence reproducibility and generalizability. Articles that integrated cross-validation, multimodal data sources, and comparative algorithm analysis demonstrated stronger methodological rigor.

Additionally, ethical dimensions, such as informed consent, data privacy protection, and bias mitigation, were considered key quality indicators. Studies that explicitly addressed biometric data handling and fairness concerns were regarded as more robust, especially in the context of online and mobile proctoring. Conversely, articles lacking transparency in data collection or algorithmic decision-making were assessed as having moderate methodological strength.

Overall, the quality assessment revealed that while most studies demonstrated strong technical contributions, fewer adequately addressed ethical safeguards, explainability, and context-specific validation. This underscores the need for future research to adopt standardized quality assessment frameworks that balance technical performance with ethical and contextual considerations in AI-driven e-assessment systems.

3. RESULTS AND ANALYSIS

3.1 Finding

The 30 selected studies reveal substantial technological progress and ongoing challenges in ML-driven behavioral analytics within online and proctoring systems. Findings are organized into five major themes as subsequently discussed.

1. Machine Learning Algorithms Used in Behavioral Detection

Machine learning (ML) algorithms play a central role in detecting and analyzing student behaviors during online and mobile proctored examinations. Among these, Convolutional Neural Networks (CNNs) are the most widely used due to their high accuracy (87–96%) in facial recognition, gaze tracking, and head pose estimation [5], [17]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are applied for sequential behavior and audio analysis, effectively identifying suspicious temporal patterns [18]. Traditional algorithms such as Support Vector Machines (SVMs) and Random Forests (RFs) remain valuable for classifying normal versus suspicious activities with lower computational demands [13], [19]. Recent advances emphasize multimodal fusion models, which combine visual, audio, and interaction data to create more reliable and context-aware behavioral profiles [14]. Overall, deep learning; especially CNN-based and multimodal approaches, offers superior performance and robustness, though optimization for mobile devices and diverse testing conditions remains a key challenge.

2. Behavioral Indicators Monitored

AI-powered proctoring systems monitor a range of behavioral indicators to ensure exam integrity. Facial expression analysis is widely used to detect multiple faces, eye closure, or masked faces, helping identify identity fraud or inattentiveness [17]. Head movements and gaze tracking use geometric and ML-driven pose estimation to detect gaze aversion or frequent off-screen glances that may signal cheating [17]. Voice analysis employs Mel Frequency Cepstral Coefficients (MFCCs) and neural networks to detect irregularities such as multiple voices or background conversations [20]. Environmental object detection identifies unauthorized items like phones, books, or additional persons within the test environment [6]. Finally, mobile-specific behavioral analytics use built-in sensors to monitor device tilting, app switching, and microphone consistency; key indicators of possible misconduct during e-assessments [21]. Collectively, these multimodal indicators enable accurate, real-time detection of suspicious behavior, enhancing fairness and reliability in online and mobile proctoring systems.

3. Mobile Proctoring Technologies

Mobile proctoring technologies have become vital for ensuring exam integrity, especially in regions with limited laptop access such as Africa and Asia [8]. Smartphone-based systems utilize the front camera, gyroscope, and accelerometer to monitor facial cues, gaze direction, and device movement, providing a comprehensive behavioral profile of the examinee [9]. Recent innovations in sensor fusion and ML models enhance accuracy by integrating multiple data streams; video, audio, and motion; allowing reliable monitoring even under diverse environmental conditions [22]. Although mobile proctoring achieves 75–90% accuracy, performance can decline in poor lighting or with unstable internet. Despite these challenges, it offers a flexible, low-cost, and scalable solution for upholding examination integrity in mobile-based e-assessments.

4. Ethical, Privacy, and Bias Concerns

AI-based proctoring systems raise significant ethical and privacy concerns. The collection of biometric data such as facial images and voice recordings poses risks of misuse and inadequate data protection [23]. Algorithmic bias has also been observed, where facial recognition models perform less accurately for individuals with darker skin tones or in low-light conditions, leading to unfair flagging [2]. Moreover, constant monitoring can heighten student anxiety and create feelings of intrusive surveillance that undermine trust and performance [24]. A further issue is the lack of transparency in automated decision-making, as most systems provide little explanation for flagged behaviors [14]. Addressing these challenges requires improved data protection, fairness checks, and the adoption of explainable AI models to promote ethical and equitable e-assessment practices.

The reviewed studies demonstrate that ML algorithms such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests (RFs), and Recurrent Neural Networks (RNNs) are widely used for detecting anomalous student behavior. Commonly monitored behavioral features include Facial expressions (using CNNs and deep learning), Eye and head movements (via gaze tracking), Voice tone variations (using audio-based ML models), Environmental noise and object detection (via computer vision). Mobile proctoring applications utilize smartphone cameras and sensors to capture behavioral data, while cloud-based ML models process real-time inputs for integrity checks. Studies by [5] and [10] indicate that ML-driven

mobile proctoring can achieve accuracy rates above 90% in detecting cheating behaviors when combined with multimodal data.

However, technical and ethical limitations persist. Challenges include inconsistent lighting conditions, unstable internet connectivity, limited device processing power, and privacy concerns associated with biometric data collection [7]. Moreover, most existing models are trained on Western datasets, creating biases that limit generalization to diverse learning contexts such as African universities.

5. Comparative Analysis

A critical distinction between mobile proctoring and general (desktop-based) online proctoring lies in both their technical architectures and their ethical–privacy implications, which are deeply interconnected rather than separable concerns. While conventional online proctoring systems are typically designed for laptops or desktops with relatively stable hardware configurations, mobile proctoring systems operate within a far more heterogeneous and constrained technological ecosystem. This fundamental difference has significant consequences for system accuracy, fairness, privacy, and user trust.

From a technical perspective, desktop-based online proctoring benefits from larger screens, higher-resolution webcams, stable power supply, and relatively consistent sensor behavior. As a result, computer-vision models, particularly CNNs used for facial recognition and gaze tracking, tend to perform with higher and more stable accuracy in desktop environments [5], [6]. Mobile proctoring, by contrast, must contend with variable camera quality, fluctuating lighting conditions, limited processing power, and battery constraints. These factors necessitate lightweight and adaptive ML models, often employing sensor fusion techniques that combine camera input with accelerometer and gyroscope data to compensate for visual uncertainty [22], [9]. While such multimodal approaches enhance robustness, they also increase system complexity and data sensitivity.

This technical distinction directly amplifies ethical and privacy challenges in mobile proctoring. Unlike desktop systems that primarily rely on webcam and microphone data, mobile proctoring expands surveillance to include motion sensors, orientation data, and application-level monitoring. Although this richer data stream improves anomaly detection, it simultaneously intensifies concerns about over-surveillance and proportionality. Studies indicate that students perceive mobile-based monitoring as more intrusive because smartphones are personal, always-on devices closely associated with private life [24]. Thus, technical reliance on additional sensors inherently raises the ethical burden of justification, consent, and data minimization.

Algorithmic bias further illustrates the tight coupling between technical design and ethical risk. Desktop proctoring systems already exhibit demographic bias in facial detection under non-ideal lighting conditions [2]. Mobile environments exacerbate this issue due to inconsistent lighting and lower camera fidelity, increasing false positives for students with darker skin tones or those in low-resource settings. This challenge is not merely a model performance issue but an ethical one, as biased detection outcomes can lead to systematic disadvantage and academic injustice. Without locally trained datasets and fairness-aware learning strategies, mobile proctoring risks reinforcing structural inequities, particularly in developing regions [1].

Privacy-preserving strategies also diverge between the two proctoring modalities. Desktop systems often rely on cloud-based processing, transmitting large volumes of biometric data to centralized servers. While mobile systems initially followed similar architectures, recent research increasingly advocates for on-device inference and federated learning as technically feasible and ethically preferable alternatives [22], [15]. These approaches reduce data exposure by keeping raw biometric data on the user's device, thereby aligning technical efficiency with privacy-by-design principles. This convergence demonstrates that ethical compliance in mobile proctoring is not an external constraint, but a design requirement embedded in system architecture.

Explainability further differentiates mobile and general online proctoring. Desktop systems often provide post-exam review dashboards due to greater computational resources and storage capacity. Mobile proctoring systems, however, frequently operate as real-time flagging mechanisms with minimal explanation provided to users. This lack of transparency undermines trust, particularly when combined with the heightened surveillance associated with smartphones. Integrating Explainable AI (XAI) into mobile proctoring is therefore not optional but essential to balance technical automation with ethical accountability [30].

In summary, while general online proctoring prioritizes accuracy and scalability, mobile proctoring demands a more delicate balance between technical adaptability and ethical responsibility. The mobile context magnifies privacy risks, bias sensitivity, and trust deficits, making it imperative that technical innovations, such as sensor fusion, lightweight models, and edge computing, are explicitly aligned with ethical principles such as fairness, transparency, and data minimization. Failure to integrate these dimensions risks not only reduced system effectiveness but also the erosion of legitimacy and acceptance of AI-driven assessment technologies.

The reviewed literature identifies several key research gaps in the development and implementation of AI-powered mobile proctoring systems. First, there is a limited emphasis on mobile-first frameworks, as most existing solutions are desktop adaptations that do not fully utilize smartphone capabilities such as sensors and mobility [25], [26]. Secondly, a major limitation is the lack of African-centered datasets, which restricts

model generalizability and often results in biased or inaccurate detection outcomes when applied in African contexts [1], [27].

Another significant gap is the minimal integration of explainable AI (XAI) approaches, which could enhance transparency, interpretability, and user confidence in automated flagging systems [14]. Similarly, multimodal behavioral fusion on smartphones; the integration of video, audio, and motion sensor data for holistic behavioral analysis; remains underexplored despite its potential to reduce false positives and improve detection reliability [11], [10]. Finally, user trust and acceptance of AI-driven monitoring systems have received little empirical attention, even though these factors strongly influence the sustainability and ethical acceptance of mobile proctoring [24], [15]. Addressing these research gaps through mobile-optimized, contextually inclusive, and transparent approaches will be crucial for advancing equitable and effective e-assessment practices globally.

3.2 Discussion

The findings from the reviewed literature reveal a strong and growing potential for machine learning (ML) algorithms to enhance behavioral analysis and uphold academic integrity in online assessments. ML-based systems, especially those integrating computer vision and multimodal sensor analytics, have shown impressive accuracy in detecting irregular behaviors such as gaze aversion, multiple-person detection, and unauthorized device usage. However, despite this promise, several critical limitations continue to hinder large-scale and equitable implementation, particularly within mobile-based e-assessment environments.

To begin with, while numerous studies report high accuracy rates for desktop-based proctoring systems, there remains a limited number of mobile-optimized frameworks capable of operating effectively across diverse devices and environmental conditions. Mobile devices, though widely accessible, introduce significant variability in hardware performance, camera quality, lighting conditions, and sensor calibration. These inconsistencies can affect detection accuracy and user experience. As highlighted by [21] and [22], achieving robust mobile proctoring requires adaptive ML architectures that can dynamically adjust to such environmental differences, potentially through lightweight models, context-aware algorithms, or transfer learning techniques that optimize performance on varied devices.

A second critical limitation relates to algorithmic fairness and demographic bias. Studies by [2] and [23] show that facial recognition and behavioral analysis systems often underperform when applied to individuals with darker skin tones or those in poorly lit environments. This problem stems from the lack of diversity in training datasets, which are often dominated by lighter-skinned subjects from Western or East Asian populations. As a result, certain students may be unfairly flagged as suspicious, raising serious ethical and equity concerns in educational contexts. Addressing these biases requires developing inclusive datasets, conducting algorithmic audits, and implementing fairness-aware learning techniques to ensure consistent performance across demographic groups.

A third prominent issue involves privacy and data protection. Many students report discomfort and anxiety associated with continuous camera surveillance, voice recording, and the storage of biometric data [28], [29]. The recording and central storage of sensitive personal information not only **pose** ethical and psychological risks but also create potential vulnerabilities to data breaches and misuse. To mitigate these risks, researchers have begun exploring privacy-preserving ML approaches such as federated learning, which enables local model training without transferring raw data, and on-device inference, which allows data processing directly on users' smartphones. These methods could maintain system performance while safeguarding student privacy.

Another major concern is the lack of explainability in AI-driven proctoring systems. Current models often operate as "black boxes," offering no insight into why certain behaviors are flagged as suspicious. This opacity undermines user confidence and can lead to disputes between students and institutions. As [30] emphasize, integrating Explainable AI (XAI) mechanisms would significantly improve transparency, allowing educators and examinees to understand model decisions. XAI could also enhance accountability, reduce false accusations, and promote ethical adoption of automated proctoring tools.

Finally, research from African and other developing regions highlights persistent infrastructural and contextual challenges. Studies by [1], and [12] reveal that factors such as unstable internet connectivity, inconsistent lighting, and limited access to high-end devices impede the reliability of AI-based mobile proctoring systems. Furthermore, the lack of locally developed datasets means that algorithms trained in foreign contexts often perform poorly when deployed in African universities. These findings underscore the importance of designing context-aware ML models that reflect local realities; both technical and socio-cultural, and of investing in regional data collection to ensure inclusivity and fairness.

Ultimately, the findings highlight the growing sophistication of ML algorithms in online behavioral analysis but also expose the potential of mobile-based applications. While ML enhances detection precision, there is insufficient emphasis on contextual adaptability and fairness. In developing regions, mobile proctoring offers a practical alternative due to the ubiquity of smartphones and lower deployment costs [1]. However, privacy regulations and data storage policies must evolve to support ethical AI adoption.

Future research on mobile AI-powered proctoring systems should place strong emphasis on the development of context-aware and culturally sensitive behavioral analysis models trained on diverse, real-world datasets [35]. Existing studies consistently show that model performance degrades when deployed outside the environments in which they were trained, particularly in settings characterized by variable lighting conditions, diverse skin tones, heterogeneous device capabilities, and fluctuating environmental noise [5], [6]. These limitations underscore the need for geographically inclusive datasets that better reflect authentic examination contexts, especially in underrepresented regions such as Africa and parts of Asia, where mobile devices dominate access to digital assessments [1], [36]. Another critical research challenge lies in the limited interpretability of machine learning models used in behavioral proctoring systems. Many current approaches operate as opaque “black boxes,” offering little insight into why certain behaviors are classified as anomalous [30]. The integration of Explainable Artificial Intelligence (XAI) techniques—such as attention visualization, feature attribution, and rule-based explanations—has the potential to significantly enhance transparency, user trust, and institutional acceptance of automated proctoring systems [14]. Explainability is particularly crucial in mobile examination environments, where constrained environmental control increases the risk of false positives and may lead to disproportionate academic consequences for learners [37]. From a systems and deployment perspective, future research should further explore edge computing and on-device inference paradigms tailored to mobile proctoring. Cloud-based behavioral analysis increases bandwidth consumption and heightens privacy risks associated with transmitting sensitive biometric data [23]. In contrast, edge-based architectures enable real-time behavioral inference directly on smartphones, reducing latency while preserving privacy by ensuring that raw data remains on-device [32]. This shift aligns computational efficiency with ethical principles such as data minimization and privacy-by-design.

In addition, greater emphasis should be placed on multimodal behavioral fusion frameworks capable of integrating video, audio, motion sensors, and interaction logs into a unified inference model. Single-modality approaches remain vulnerable to noise and ambiguity in mobile environments, whereas multimodal fusion has been shown to improve robustness and reduce false-positive rates by contextualizing behavioral signals across multiple modalities [2], [33]. Consequently, lightweight multimodal fusion architectures optimized for mobile hardware represent a key research priority. Ethical and regulatory considerations must remain central to the advancement of mobile proctoring technologies. Ongoing collaboration between researchers, policymakers, educators, and legal experts is necessary to establish clear frameworks governing biometric data collection, informed consent, data storage, and algorithmic accountability [24]. Furthermore, cross-institutional and cross-regional collaboration is essential for developing standardized evaluation benchmarks, open-access datasets, and interoperable mobile proctoring platforms that can be adapted to diverse educational contexts while maintaining fairness and academic integrity [34], [38]. To strengthen the technical rigor of future mobile AI-powered proctoring research, several methodological improvements are required. These include the adoption of standardized evaluation metrics beyond accuracy, such as fairness indicators, false-positive rates, and energy efficiency to better reflect mobile deployment constraints [5], [30], [39]; detailed reporting of datasets, preprocessing pipelines, and training procedures to enhance reproducibility [6], [14], [40]; and increased focus on lightweight model architectures optimized for mobile hardware [23], [32], [41]. Additionally, systematic stress testing under adverse conditions and the integration of privacy-preserving techniques—such as federated learning and differential privacy—should be treated as core design requirements rather than optional enhancements [2], [24], [34], [42]–[44].

4. CONCLUSION

This review highlights the transformative potential of machine learning–based behavioral analysis in online proctored assessments, particularly within mobile-first contexts where smartphones provide broader accessibility than traditional computing devices. Mobile proctoring offers a flexible and scalable pathway for expanding e-assessment access; however, its effective deployment remains constrained by challenges related to generalizability, fairness, privacy protection, interpretability, and mobile optimization. The study contributes to the existing literature by synthesizing recent advances in machine learning techniques for behavioral analysis, with a focused examination of mobile proctoring systems that remain underrepresented in prior research. It systematically organizes behavioral indicators, technological approaches, and ethical considerations, providing a structured reference for researchers, practitioners, and system developers. Furthermore, the review extends current discourse by emphasizing context-specific challenges, including the need for mobile-first design principles, culturally inclusive datasets, and transparent AI mechanisms suited to diverse educational environments. Overall, advancing mobile AI-powered proctoring systems requires a research agenda that is context-aware, ethically grounded, and technologically adaptive. Emphasizing transparency, fairness, privacy preservation, and practical deployment constraints will be essential for ensuring that future e-assessment technologies are not only technically effective but also socially equitable and globally scalable.

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