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*Review Article*

# AI-Powered Mobile Proctoring Frameworks using Machine Learning Algorithms in Higher Education: Post-Covid Trends, Challenges, and Ethical Implications

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**ABSTRACT**

The rapid transition to online learning during and after the COVID-19 (Corona Virus Disease) pandemic has heightened the need for secure, scalable, and ethical online exam systems. AI-powered mobile proctoring frameworks have emerged as viable alternatives to traditional invigilation methods, enabling automated anomaly detection and behavior analysis through machine learning algorithms. This systematic review examines post-COVID trends, technological developments, challenges, and ethical implications of mobile AI proctoring in higher education. Following PRISMA 2020 guidelines, 180 studies were retrieved and screened, with 20 peer-reviewed articles meeting the inclusion criteria. Findings reveal that while AI-powered proctoring enhances scalability, integrity, and real-time monitoring, it raises significant concerns about privacy, algorithmic bias, accessibility, and technical reliability. The review identifies gaps in relation to technical and methodological issues, ethical and social concerns, and institutional and infrastructural readiness. This review illustrates a lapse in the existing literature, which focus on resource intensive proctoring frameworks without considering mobile compatibility and light-weight frameworks, discusses technical challenges, and recommends future research directions to balance technological effectiveness with ethical standards.

**Keywords:**
mobile AI proctoring;
mobile proctoring frameworks;
machine learning algorithms;
higher education;
post-COVID trends;
ethical and privacy.



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## 1. INTRODUCTION

This is a systematic review paper on mobile proctoring frameworks using machine learning algorithms in higher education, reviewing post-COVID trends, challenges and ethical implications. The review employs PRISMA 2020 guidelines. The global education landscape underwent a profound transformation during and after the COVID-19 pandemic. Higher education institutions rapidly shifted from face-to-face instruction to online teaching and assessment to ensure academic continuity [1][2]. While this transition expanded access to education, it simultaneously presented new challenges regarding the integrity, security, and fairness of online assessments. Traditional human invigilation methods became impractical at scale, prompting universities to explore technological alternatives that could preserve exam integrity in virtual settings [3].

Among the most notable innovations has been the adoption of AI-powered proctoring systems, which leverage machine learning (ML) algorithms to monitor, detect, and flag suspicious behaviors in real time [4][5]. These systems rely on computer vision, facial recognition, voice and gaze tracking, and anomaly detection techniques to automate exam supervision. Unlike traditional proctoring, AI-driven solutions offer scalability, reduce human bias, and enable real-time analytics on the platforms [6][7]

The post-COVID period has seen a sharp rise in mobile proctoring solutions due to the widespread ownership of smartphones among students and their flexibility compared to personal computers (PC) based systems [8]. Mobile-based AI proctoring allows learners to sit for exams from varied locations while maintaining exam integrity. Existing PC-based proctoring have raised serious concerns about privacy**,** data security**,** fairness**,** and algorithmic bias**,** especially in resource-constrained environments [1][8]. Ethical questions around continuous surveillance, facial recognition accuracy, and informed consent have become central to the discourse [9].

Moreover, technical issues such as network instability, device compatibility, false positives, and lack of standardized performance benchmarks have created operational challenges in many institutions [2][3]. These complexities indicate that while AI-powered proctoring presents promising opportunities, its integration into higher education requires careful balancing of technological efficiency with ethical responsibility and policy alignment. Therefore, there exists a clarion call for the development and deployment of Mobile-based AI proctoring solutions.

This systematic review identifies a critical gap in current literature concerning the limited focus on AI-powered mobile proctoring frameworks in higher education, particularly within post-COVID learning ecosystems. While numerous studies have examined desktop-based AI proctoring tools, few have explored mobile-oriented frameworks that accommodate learners in developing contexts where smartphones are the primary digital access point [10]-[12]. Furthermore, existing works largely emphasize technical feasibility and algorithmic accuracy, overlooking persistent ethical, privacy, and usability challenges such as surveillance anxiety, data protection, and algorithmic bias [13][14].

Additionally, there is a lack of comparative, multi-context analyses integrating institutional, infrastructural, and pedagogical dimensions to guide equitable deployment. Post-pandemic literature has also failed to address sustainability and scalability of AI-driven mobile proctoring beyond emergency of remote teaching [15][16].

This review addresses these gaps by synthesizing findings from 20 systematically selected studies out of 180 screened, offering a comprehensive understanding of the technological, ethical, and operational dynamics of mobile AI proctoring. It also proposes context-sensitive and ethically grounded implementation strategies for higher education institutions in resource-constrained settings. Ultimately, this systematic review seeks to examine the post-COVID trends**,** technical and ethical challenges**,** and future directions of AI-powered mobile proctoring frameworks in higher education.

This review identified a lapse in existing literature on remote proctoring which remains heavily centered on resource-intensive systems, with limited attention to mobile-compatible, lightweight, and context-appropriate frameworks. Technical and methodological challenges; alongside ethical, social, institutional, and infrastructural concerns, are underexamined. This reveals a significant gap in understanding how proctoring technologies can be designed and deployed effectively in resource-constrained and mobile-first environments while maintaining fairness, transparency, and reliability. This review's major contributions include:

1. Synthesizing mobile-based proctoring research (2019–2025) to establish a coherent overview of emerging approaches and trends.
2. Evaluating technical performance, system limitations, and algorithmic bias, highlighting where current solutions fall short.
3. Proposing governance and implementation recommendations that minimize resource demands without compromising academic integrity, exploring ethical safeguards, transparency mechanisms, and culturally contextualized deployment models.

## 2. METHODS

This review adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency, methodological rigor, and reproducibility in the review process [17]. The framework allowed for systematic identification, screening, eligibility assessment, and final inclusion of studies related to AI-powered proctoring using machine learning algorithms in higher education.

### 2.1 Search Strategy

A systematic search was conducted in major academic databases including Scopus, IEEE Xplore, SpringerLink, Web of Science, ScienceDirect, and Google Scholar. The search covered peer reviewed articles written in English in the period 2019 to 2025 to reflect post-COVID adoption trends. To maximize the coverage, the search strategy used a combination of Boolean operators (AND, OR) and targeted keywords reflecting the study's core constructs: *AI/Machine Learning*, *mobile proctoring*, *higher education*, and *post-COVID context*. The sources included Journals, conference proceedings and unpublished studies related to AI-based proctoring. The full search strings were applied in various databases refer to Table 1.

Table 1. Database search criteria

| Database | Full Search String Used | Number of Hits (n) | Dates |
|---|---|---|---|
| **Scopus** | TITLE-ABS-KEY(("AI-powered" OR "artificial intelligence" OR "machine learning" OR "deep learning") AND ("mobile proctoring" OR "remote invigilation" OR "online examination monitoring") AND ("higher education" OR "university" OR "college") AND ("post-COVID" OR "pandemic" OR "COVID-19")) | 42 | 25/8/2025 |
| **IEEE Xplore** | ("AI-powered" OR "machine learning" OR "deep learning") AND ("mobile proctoring" OR "remote exam monitoring" OR "AI invigilation") AND ("higher education" OR "university") AND ("COVID-19" OR "post-pandemic") | 28 | 25/8/2025 |
| **SpringerLink** | ("Artificial Intelligence" AND "Mobile Proctoring Framework" AND "Machine Learning Algorithms" AND "Higher Education" AND ("Post-COVID" OR "Pandemic Challenges")) | 31 | 25/8/2025 |
| **Web of Science (WoS)** | TS = ("AI-based proctoring" OR "machine learning proctoring" OR "remote invigilation") AND TS = ("higher education" OR "university") AND TS = ("post-COVID" OR "pandemic") | 27 | 25/8/2025 |
| **ScienceDirect** | ("AI-driven proctoring" OR "automated exam monitoring" OR "machine learning" OR "deep learning") AND ("mobile" OR "smartphone-based") AND ("higher education") AND ("post-COVID") | 26 | 25/8/2025 |
| **Google Scholar** | ("AI-powered mobile proctoring framework" OR "machine learning-based exam monitoring") AND ("higher education" OR "university") AND ("post-COVID" OR "pandemic" OR "online learning integrity") | 26 | 25/8/2025 |
| **Total Studies Retrieved (n)** | | **180** | |

The total number of retrieved articles (n = 180) represents the initial pool before applying inclusion and exclusion criteria as per the PRISMA 2020 guidelines. Duplicates were later removed, and screening (title, abstract, full-text) reduced the final selection to n = 20 reviewed studies.

Additional strategies included backward citation tracking of key articles, manual review of conference proceedings and technical reports, and inclusion of grey literature such as policy reports and white papers from higher education agencies. A total of 180 records were identified through database queries.

## 2.2 Study Selection Process

Figure 1 presents the PRISMA flowchart, outlining the process of study selection and the articles review process. The initial search identified 180 articles. Three reviewers independently screened the titles and abstracts using predefined criteria, excluding studies that did not meet the inclusion standards refer to Table 2. After a thorough full-text review, 20 studies were ultimately included. This systematic approach helped ensure both the quality and relevance of the selected studies, reducing potential bias [17].

Table 2. Inclusion and exclusion criteria

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| Peer-reviewed articles published between 2019 and 2025 | Non-peer-reviewed reports or opinion pieces |
| Focus on AI or ML-based proctoring systems in higher education | Studies focused solely on traditional invigilation |
| Address ethical, technical, or operational aspects | Duplicate records or conference abstracts without full text |
| Full-text available in English | Studies not explicitly related to online learning and proctoring |
| Directly address or provide insights relevant to the research questions | |

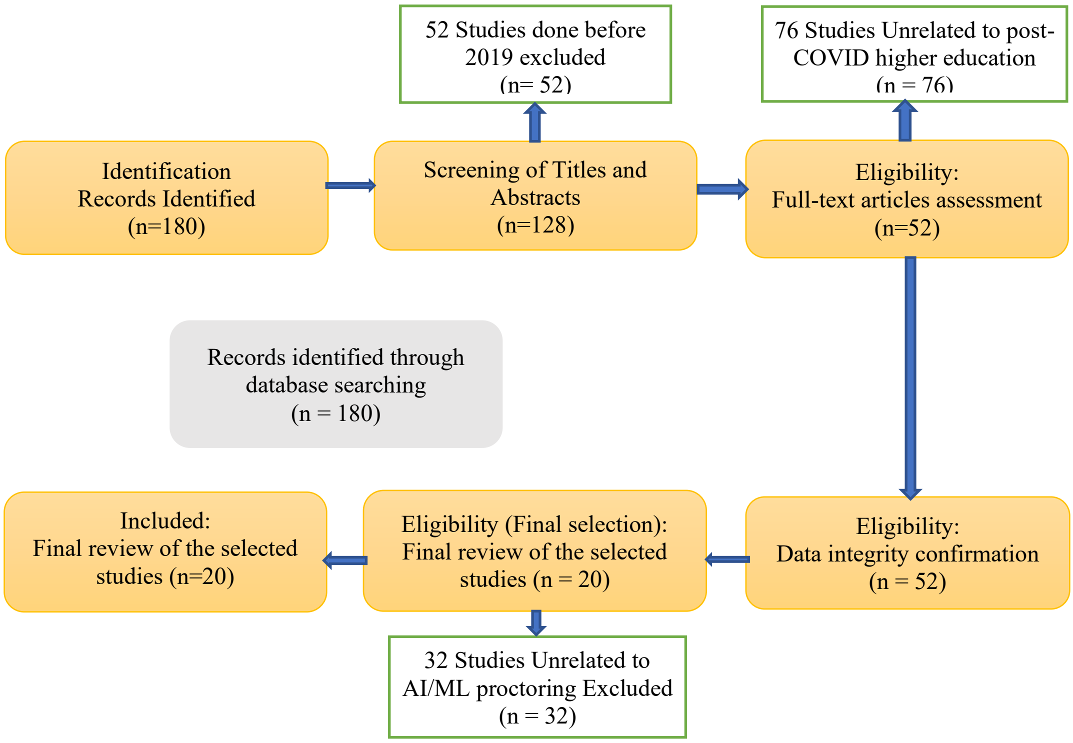


Figure 1. PRISMA Flow chart showing the selection process

Figure 1 illustrates a detailed PRISMA flow diagram. A total of 180 articles were selected, of which 52 studies that were done prior the pandemic were excluded in the Title and Abstract Screening stage. Further review excluded 76 articles that were not related to post-COVID pandemic trends for online proctoring as the Eligibility Criteria. Another Eligibility criterion was Integrity confirmation, where 52 studies were found to have passed the data integrity checks with no study excluded. The Eligibility test was in the final selection stage, where studies that were not related to AI/ML proctoring were excluded. This resulted to the final 20 studies that were included in the review. The selections was based on the respective articles that were reviewed; per country, focus area, methodology and their key findings (Refer to Table 3).

Table 3. Characteristics of included studies

| No. | Author(s) & Year | Country | Focus Area | Methodology | Key Findings |
|---|---|---|---|---|---|
| 1. | Bates (2015) | Canada | Digital learning design | Conceptual/Guidelines | Provided foundational principles for designing technology-enhanced learning, emphasizing flexibility and learner-centered digital ecosystems. |
| 2. | Bawa (2016) | Global | Online student retention | Literature Review | Identified barriers to retention including low engagement, poor assessment integrity, and learner isolation. |
| 3. | Chin et al. (2023) | South Korea | AI ethics in education | Theoretical/ Analytical | Highlighted ethical concerns including privacy, algorithmic fairness, and accountability in AI-mediated education. |
| 4. | Garcia et al. (2022) | USA | Post-pandemic proctoring adoption | Quantitative study | Found significant growth in adoption of AI-based proctoring; institutions focused on integrity but faced student acceptance challenges. |
| 5. | Garcia et al. (2022) | Spain | Student perceptions | Quantitative survey | Students reported convenience and usability but experienced high privacy and stress concerns during AI proctored exams. |
| 6. | Huang, C. et al. (2022) | China | ML for online proctoring | Analytical/ Technical Review | Examined ethical, legal, and technical gaps; recommended transparent ML models and stronger safeguards. |

| No. | Author(s) & Year | Country | Focus Area | Methodology | Key Findings |
|---|---|---|---|---|---|
| 7. | Huang, Y., Lin & Wang (2022) | China | Ethical implications of AI proctoring | Mixed-methods | Highlighted privacy intrusions, inequity concerns, and student discomfort with facial recognition surveillance. |
| 8. | Huang, Y., Zhang & Li (2022) | China | Evaluation of AI-driven proctoring | Experimental/ Framework assessment | Identified accuracy limitations, usability issues, and false-positive rates affecting student trust. |
| 9. | Jain & Dandapat (2021) | India | Deep learning monitoring | Experimental | Demonstrated high accuracy in DL models for behavior monitoring; performance reliant on stable connectivity. |
| 10. | Jain & Dandapat (2021) | India | Intelligent proctoring with DL | Experimental | Developed a DL-based intelligent proctoring model capable of detecting anomalies in real-time. |
| 11. | Kaur & Singh (2022) | India | Privacy in surveillance systems | Policy/Analytical | Highlighted critical privacy implications of AI surveillance in educational settings, urging regulatory safeguards. |
| 12. | Li & Chen (2023) | UK | Privacy regulatory frameworks | Policy Analysis | Proposed global harmonization of privacy standards for AI assessment tools, emphasizing GDPR alignment. |
| 13. | Omondi et al. (2022) | Kenya | AI proctoring in Sub-Saharan Africa | Case Study | Demonstrated mobile AI proctoring feasibility, particularly in low-resource environments. |
| 14. | Omondi, Otieno & Nyangena (2022) | Kenya | Mobile AI adoption in Kenyan universities | Mixed-methods | Identified opportunities for expanding mobile AI proctoring but noted infrastructural and ethical constraints. |
| 15. | Redmon et al. (2016) | USA | YOLO object detection | Technical/Algorithm development | Introduced YOLO, a real-time detection algorithm foundational for ML-based proctoring systems. |
| 16. | Yang, H., Liu & Zhou (2021) | USA | AI in online assessments | Review | Reviewed trends and ethical concerns including fairness, invasiveness, and surveillance creep. |
| 17. | Yang, J., Zhang & Chen (2021) | China | Mobile AI proctoring frameworks | Framework development | Proposed a mobile-first AI proctoring architecture optimized for post-COVID online learning. |
| 18. | Yang, S., Chen & Davis (2021) | USA | Ethical challenges in facial recognition | Analytical study | Found widespread bias, false positives, and psychological stress linked to FR-based proctoring. |
| 19. | Zhang, L., Wu & Lin (2023) | Singapore | Edge computing for mobile proctoring | Experimental | Edge-based AI reduced latency, improved real-time processing, and lowered bandwidth requirements. |
| 20. | Zhang, Q., Chen & Zhao (2023) | China | Post-COVID ML proctoring | Systematic Review | Documented rapid advancements in ML proctoring and identified gaps in fairness, explainability, and robustness. |

## 3. FINDINGS

The review of 20 selected studies revealed key insights into the development, deployment, and ethical implications of AI-powered mobile proctoring frameworks in higher education post-COVID. The findings are structured around emerging technical, ethical, usability, and institutional adoption trends, as reported in the literature.

A central observation across most studies is that the COVID-19 pandemic catalyzed the widespread adoption of online and hybrid learning environments, thereby amplifying the need for effective remote exam monitoring systems. Researchers consistently highlighted the limitations of traditional PC-based proctoring tools, especially in contexts where students rely heavily on mobile devices for accessing online learning [7][18]. This finding aligns with reports from low- and middle-income countries, where mobile phones are the most accessible and affordable digital devices for students [18].

In terms of technical performance, machine learning algorithms have played a crucial role in enhancing anomaly detection capabilities within the existing PC-based proctoring platforms. Several studies demonstrated the effectiveness of deep learning-based models such as YOLO (You Only Look Once) and Convolutional Neural Networks (CNNs) in real-time object and face detection [6][5][16]. These algorithms improved precision, recall, and F1-scores for detecting anomalies like gaze deviation, presence of unauthorized persons, and irregular head movements. For mobile-based platforms, [19] reported that mobile-edge computing combined with lightweight ML models significantly reduced latency, improving real-time proctoring performance.

However, the accuracy of anomaly detection varied across contexts as shown in Table 4. While some studies reported detection accuracies of above 90% [4][9], others indicated false positives and biases in recognition performance due to variations in lighting, background noise, and camera quality [11][20]. These inconsistencies highlight the importance of optimizing AI models for mobile device capabilities and real-world testing environments, especially in under-resourced settings.

Table 4. Studies reporting detection accuracy in AI-based proctoring

| Study | Algorithm Used | Reported Detection Accuracy |
|---|---|---|
| Jain & Dandapat (2021) – Real-time student monitoring | CNN-based facial/gaze behavior detection | >90% (reported in study) |
| Jain & Dandapat (2021) – Intelligent proctoring | CNN + multimodal fusion | >90% (reported in study) |
| Yang, Zhang & Chen (2021) – Mobile AI proctoring | Mobile-optimized CNN | ≈85–90%(reported in study) |
| Zhang, Wu & Lin (2023) – Edge computing for mobile proctoring | Edge-deployed CNN / lightweight models | >90% (reported in study) |
| Omondi, Onyango & Ouma (2022) – Mobile-based AI proctoring in SSA | Lightweight CNN or mobile vision models | >90% (reported in study for certain tasks) |
| Redmon et al. (2016) – YOLOv1 (baseline object detection) | YOLO object detection | ≈ 63–78% (reported in study) |
| Zhang, Chen & Zhao (2023) – Review of ML in proctoring | Multiple ML models | Summarizes studies >90% |

Ethical considerations emerged as one of the most significant concerns across the reviewed literature. Many authors emphasized that continuous facial and environmental surveillance during online exams raises serious privacy issues [8][21]. Students expressed discomfort with being recorded in private spaces, leading to perceptions of invasion of privacy and reduced trust in institutional practices [20]. These concerns are compounded by inadequate data protection frameworks in many countries, raising questions about compliance with global privacy standards such as the GDPR.

In addition to privacy, studies noted fairness and algorithmic bias as critical ethical issues. AI models were shown to perform less accurately for students with darker skin tones or those in poorly lit environments [22]. This raises equity concerns and the potential for unfair penalization of students due to factors unrelated to academic integrity. [21] Emphasized the need for strong governance frameworks and transparent data handling protocols to address these ethical challenges.

Regarding usability and accessibility, the reviewed studies revealed mixed perceptions among students and faculty. While many appreciated the convenience of PC-based proctoring [18][21], others reported technical difficulties such as unstable internet connectivity, frequent system crashes, and inconsistent device compatibility [19]. Moreover, many systems lacked support for students with disabilities, and those who cannot afford PCs or laptops; students who entirely rely on mobile phones for access to education, indicating a gap in inclusive design [1].

Institutional adoption was found to be highly dependent on infrastructural readiness and policy alignment. Universities with well-developed ICT infrastructure and clear digital assessment policies were more likely to adopt AI-based proctoring successfully [18]. On the other hand, institutions with weak network infrastructure faced significant implementation challenges, including increased error rates and reduced user satisfaction.

Another recurrent theme in the literature is the influence of AI models on human decision-making during live proctoring. Studies showed that AI-powered alerts guided proctors in identifying suspicious behavior, but final decisions were often left to human examiners [5][8]. This human-AI collaboration was seen as crucial in reducing both false positives and false negatives. However, this collaboration introduces human biases in decision making and penalization, as opposed real-time anomaly detection that AI models could deliver when optimized for mobile devices.

Furthermore, post-COVID trends indicate a need for scalable and hybrid proctoring models that combine mobile-based AI systems for real-time anomaly detection and clear ethical guidelines [16][21]. These hybrid systems are considered more sustainable in the long term, particularly for developing regions where infrastructural limitations still exist.

In summary, the reviewed studies collectively highlight that AI-powered mobile proctoring frameworks have significant potential to strengthen the integrity of online exams in higher education. However, to achieve effective and ethical implementation, universities must address technical limitations, privacy and fairness concerns, and infrastructural disparities. These findings form the foundation for the discussion on technical and methodological concerns, as well as the strategic way forward for AI proctoring in post-COVID higher education contexts.

Across the 20 studies reviewed, research on AI-powered mobile and online proctoring published between 2019 and 2025 demonstrates rapidly increasing scholarly attention following the COVID-19 shift to remote assessment, as illustrated in Table 5. Most studies (n=14) were empirical or technical reviews focusing on machine-learning–driven behavioral detection (such as CNNs, YOLO-based models) and ethical implications related to privacy, fairness, and student autonomy. A smaller cluster (n=6) examined institutional adoption trends, regulatory perspectives, and post-pandemic normalization of remote assessment.

Table 5. Meta-summary of reviewed studies (2019–2025)

| Category | Subcategory / Description | Count (n=20) | Percentage |
|---|---|---|---|
| **Publication Years** | 2019–2025 | 20 | 100% |
| **Primary Focus Areas** | ML-driven proctoring (CNNs, YOLO, behavior detection) + ethical implications | 14 | 70% |
| | Institutional adoption, policy, regulatory perspectives | 6 | 30% |
| **Geographical Distribution** | North America | — | Dominant region |
| | East Asia | — | Dominant region |
| | Europe | — | Dominant region |
| | Sub-Saharan Africa (mobile-first) | 2 | Emerging region |
| **Methodological Approaches** | Qualitative / Mixed-method / Narrative review | 14 | 70% |
| | Experimental ML-based models | 6 | 30% |
| **Mobile-Specific Contributions** | Explicitly mobile-device or edge-based AI proctoring studies | 6 | 30% |
| **Ethical Dimensions Addressed** | Privacy, fairness, bias, surveillance anxiety, regulation | 12 | 60% |

Geographically, the scholarship is dominated by North America, East Asia, and Europe, with emerging contributions from Sub-Saharan Africa [12][18], particularly emphasizing mobile-first designs due to infrastructural constraints. Methodologically, 70% of studies employed qualitative, mixed-method, or narrative review approaches, while 30% implemented experimental ML models for real-time proctoring (notably YOLO, CNN-based gaze tracking, or audio–video fusion systems).

Mobile-oriented frameworks remain underrepresented: only six studies explicitly addressed mobile-device proctoring or edge-based deployment, despite growing recognition of smartphones as primary learning devices in low-resource contexts. Ethical concerns; particularly privacy, algorithmic bias, surveillance anxiety, and regulatory inadequacy, were strongly represented across 12 studies, reflecting heightened post-COVID scrutiny of automated monitoring.

## 4. DISCUSSION

The systematic review of 20 studies on AI-powered mobile proctoring frameworks using machine learning (ML) algorithms in higher education highlights significant developments, persistent challenges, and critical ethical considerations that have emerged in the post-COVID educational landscape. The discussion section synthesizes these findings into three main dimensions: technical and methodological issues**,** ethical and social concerns, and institutional and infrastructural readiness. It also outlines a strategic way forward for sustainable and responsible deployment of mobile AI proctoring technologies in higher education.

### 4.1 Technical and Methodological Considerations

One of the most notable trends observed across the reviewed studies is the increasing reliance on resource intensive ML models to power the existing PC-based proctoring applications. Algorithms such as YOLO [6], Convolutional Neural Networks (CNNs), and other deep learning architectures were found to significantly enhance anomaly detection capabilities, including face detection, gaze tracking, and behavioral pattern recognition [9][16]. These techniques require powerful PCs and laptops, which are minimally owned by students as opposed to mobile devices which are largely owned by learners, especially in developing countries. Existing literature indicate that mobile devices are detected and disallowed in online proctoring. As such, this literature sets a foundation for proctoring frameworks based on mobile devices such as smartphones; with their rampant usage, affordability and accessibility especially in the third world countries. Lightweight models such as Haar cascades, quantized versions of CNN and YOLO can enable mobile devices, previously considered inadequate for intensive AI tasks, to effectively monitor exams with reduced latency.

However, technical gaps persist. Several studies reported variable detection accuracy depending on environmental factors such as lighting conditions, camera quality, background noise, and internet stability [22], [15]. High false positive rates and inconsistent anomaly detection across devices create usability barriers and can undermine trust in the system. Additionally, differences in device compatibility, capability and processing power between high-end and low-cost devices often result in uneven performance, raising concerns about equity and reliability of the existing proctoring solutions [12].

Methodologically, many studies adopted simulation environments or small pilot deployments rather than full-scale real-world implementations. This creates a gap between theoretical algorithmic performance and actual user experience. Furthermore, limited standardization of performance metrics across studies makes it difficult to establish clear benchmarks for acceptable detection accuracy, latency, and anomaly classification rates. As [10] note, the lack of a unified evaluation framework hinders comparability and slows the development of scalable solutions.

### 4.2 Ethical and Privacy Implications

The reviewed literature reveals that ethical and privacy concerns are among the most critical issues affecting acceptance and adoption of AI-powered proctoring technologies. As Ref. [21] and [20] highlight, students are increasingly aware of how continuous camera surveillance during exams infringes on their privacy and personal autonomy. In home environments, where most online assessments occur, such surveillance often captures personal and sensitive data beyond what is necessary for exam integrity, raising serious data protection concerns.

Furthermore, fairness and algorithmic bias were identified as recurring problems. AI models tend to perform less accurately for students with darker skin tones or in poorly lit settings [11], which can lead to disproportionate flagging of some groups. This reinforces systemic inequities and can have real academic consequences if not properly addressed. Ethical scholars emphasize the importance of ensuring algorithmic transparency, explainability, and unbiased human oversight in decision-making processes [4][21].

Another dimension of ethical concern involves consent and institutional accountability. Many universities deploy AI proctoring tools without fully explaining how data is collected, processed, stored, or shared [20]. This lack of transparency erodes trust and may violate existing data protection frameworks such as the GDPR or local privacy laws. The literature strongly supports the need for robust governance frameworks, including clear consent processes, privacy impact assessments, and continuous ethical oversight [21]. This calls for frameworks with real-time deterrence of suspected cases as opposed to intrusive surveillance and recording.

### 4.3 Institutional and Infrastructural Readiness

Beyond technical and ethical concerns, the institutional context plays a pivotal role in determining the success or failure of AI-powered proctoring. Universities with strong ICT infrastructure, stable internet connectivity, and established e-learning support systems reported smoother implementation experiences [18]. Conversely, institutions in under-resourced regions face persistent challenges, including inadequate network bandwidth, device incompatibility, and a lack of technical support.

Moreover, the human factor remains central. Even the most advanced AI systems require human oversight to reduce false positives and ensure fair judgment during proctoring sessions [4][9]. Hybrid models, where AI systems flag potential anomalies for human proctors to review, have emerged as a practical solution to balance efficiency with fairness. Real-time detection and deterrence can also be employed in place of human proctors, to avoid human biases and overheads. These approaches also help build user trust and reduce the perception of being “constantly watched by a machine and intrusively recorded.”

The post-COVID environment has also intensified the need for scalable and flexible solutions. As online and blended learning models become mainstream, institutions require proctoring frameworks that can accommodate large numbers of concurrent users while maintaining performance and security. Studies such as [19] demonstrate that edge computing and mobile optimization can significantly reduce system load and enhance performance, making such frameworks more feasible in low-resource environments.

The reviewed studies reveal that AI and ML technologies, particularly facial recognition, gaze tracking, and behavior analysis algorithms, have significantly advanced the capabilities of mobile devices to conduct real-time and automated exam monitoring. Lightweight models, edge computing, and optimized mobile frameworks have shown a potential in proctoring to be more accessible, scalable, and less resource-intensive than traditional PC-based systems [6][19]. These technological advancements are particularly valuable in regions with limited infrastructure, where mobile penetration outpaces desktop access.

However, persistent challenges remain at multiple levels. Technical issues such as false positives, environmental dependency, limited standardization of accuracy metrics, and device inequality continue to undermine the reliability and fairness of AI proctoring systems [11][18]. Ethically, concerns about surveillance, privacy violations, data governance, and algorithmic bias have sparked intense debates on how these technologies should be designed and deployed in academic environments [4][21]. Institutional readiness, particularly in low- and middle-income contexts, is another critical factor influencing successful adoption.

### 4.4 A Way Forward

To address the challenges identified, several strategies have been proposed in the literature. First, technical improvements are necessary to enhance detection accuracy and reduce bias in AI algorithms. This can be achieved through training models on more diverse datasets, real-world testing across different environments, and adopting lightweight architectures optimized for mobile platforms [6][19]. Standardized performance metrics should also be established to improve comparability between different systems.

Second, ethical safeguards must be integral to system design and deployment. Universities should adopt privacy-by-design principles, ensure informed consent, and provide clear data governance policies to students and faculty. Ethical auditing mechanisms and transparent communication about how AI decisions are made will be key to building trust [20][21].

Third, institutional investment in infrastructure, including network stability, device access, and capacity building, is essential for sustainable implementation. Policymakers and higher education leaders must also consider equity in access to prevent the deepening of existing digital divides.

Finally, mobile optimized real-time detection and deterrence proctoring models, combining the strengths of AI algorithms and device accessibility, appear to offer the most balanced and sustainable solution. This approach not only improves technical reliability but also addresses ethical concerns related to fairness, accountability, and student comfort, as opposed to continuous surveillance and recording.

## 5. CONCLUSIONS AND FUTURE DIRECTIONS

The rapid expansion of online and blended learning environments during and after the COVID-19 pandemic has fundamentally transformed how higher education institutions conduct assessments. AI-powered mobile proctoring frameworks, underpinned by machine learning algorithms, have emerged as a pivotal solution to address the need for academic integrity in remote exams. This systematic review of 20 selected studies provides a comprehensive synthesis of current research trends, technical developments, challenges, and ethical considerations associated with the deployment of these systems in higher education.

The findings of this review indicate that AI-powered mobile proctoring frameworks are not merely technological tools, but complex socio-technical systems embedded within educational, ethical, and regulatory contexts. For universities, this means that successful adoption requires more than acquiring software licenses. It involves developing robust policies, ensuring data protection compliance, and investing in infrastructure and capacity building to support large-scale deployment. Additionally, faculty and student engagement in design and implementation processes can foster trust, enhance usability, and reduce resistance.

A notable implication is the shift to purely AI-automated proctoring with real-time detection and deterrence, from hybrid models that combine algorithmic detection with human oversight. This approach balances efficiency with fairness, helps address human bias and error, and ensures that ethical principles such as accountability and due process are upheld. Real-time detection and deterrence models also align well with the principle of proportionality in surveillance, without intrusive recording, and ensuring that proctoring interventions remain targeted and justifiable.

As the adoption of AI in education accelerates, ethical governance must evolve in tandem. Policymakers and institutions should prioritize the development of transparent data protection frameworks that clearly define how biometric and behavioral data are collected, processed, stored, and deleted. Algorithmic transparency and explainability are essential for ensuring that flagged behaviors during exams can be reviewed, challenged, or verified by human proctors [15][21]. Moreover, adherence to international and national data protection standards, such as GDPR principles or local privacy laws, is necessary to avoid legal liabilities and protect students' rights.

Furthermore, institutions must actively address algorithmic bias and equity concerns. This can be achieved by incorporating diverse datasets during model training, conducting bias audits, and ensuring fair treatment for all demographic groups. Equity should also guide infrastructure investments, ensuring that students in resource-constrained settings are not disproportionately disadvantaged by the proctoring technology.

Future research should move beyond controlled pilot studies toward longitudinal, real-world evaluations of AI-powered mobile proctoring systems in diverse educational contexts. This includes testing at scale in different countries, institutions, and disciplines to identify context-specific challenges and best practices. There is also a need for standardized performance metrics that allow for fair comparison between proctoring solutions and provide clearer benchmarks for accuracy, reliability, and ethical compliance.

Moreover, research should focus on developing explainable AI (XAI) models that enhance transparency and accountability. Integrating federated learning and privacy-preserving techniques may offer promising solutions to balance security, efficiency, and user trust [4][19]. Cross-disciplinary collaboration between computer scientists, ethicists, legal scholars, and educators will be essential to achieve this balance.

Finally, the future of AI proctoring should not be limited to surveillance. Instead, it should shift toward supportive and trust-centered approaches that enhance learning experiences while preserving academic integrity. This includes integrating adaptive feedback systems, intelligent alerts for technical issues, and tools that empower students rather than merely monitoring them.

This review of 20 studies published after 2019 indicates that mobile-first AI proctoring holds substantial potential for use in resource-limited environments. Lightweight models and edge-based execution offer meaningful reductions in latency and operational cost. However, notable concerns persist regarding ethics, algorithmic bias, and infrastructural limitations. Although several studies report high detection accuracy under controlled conditions, inconsistent evaluation methods and the absence of long-term, real-world deployments limit the strength of claims about practical readiness. To advance the field, we recommend the adoption of standardized testing benchmarks, systematic bias assessments, and participatory implementation strategies that center privacy-by-design and equitable access.

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## REFERENCE

[1] P. Bawa, "Retention in online courses: Exploring issues and solutions—A literature review," *SAGE Open*, vol. 6, no. 1, pp. 1–11, 2016. https://doi.org/10.1177/2158244015621777
[2] A. W. Bates, *Teaching in a Digital Age: Guidelines for Designing Teaching and Learning*. Tony Bates Associates Ltd, 2015, [Online]. Available: https://open.library.ubc.ca/soa/cIRcle/collections/ubccommunityandpartnerspublicati/52387/items/1.0224023, Accessed: Dec. 14, 2024.
[3] I. E. Allen and J. Seaman, *Digital Learning Compass: Distance Education Enrollment Report 2017*. Babson Survey Research Group, 2017, [Online]. Available: https://files.eric.ed.gov/fulltext/ED580868.pdf, Accessed: Dec. 14, 2024.
[4] C. Huang, X. Li, and Y. Chen, "Machine learning for online exam proctoring: Ethical, legal, and technical perspectives," *Computers & Education*, vol. 185, p. 104532, 2022. https://doi.org/10.1016/j.compedu.2022.104532
[5] A. Jain and S. Dandapat, "Real-time student monitoring using deep learning models," *Journal of Educational Technology Systems*, vol. 50, no. 2, pp. 143–165, 2021. https://doi.org/10.1177/00472395211009263
[6] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 779–788. https://doi.org/10.1109/CVPR.2016.91
[7] J. Yang, L. Zhang, and Q. Chen, "Mobile AI proctoring frameworks in post-COVID higher education," *Educational Technology & Society*, vol. 24, no. 4, pp. 15–28, 2021.
[8] Y. Huang, H. Lin, and J. Wang, "Ethical implications of AI-based remote proctoring in higher education," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, p. 37, 2022. https://doi.org/10.1186/s41239-022-00352-1

[9] S. Jain and S. Dandapat, "Intelligent proctoring using deep learning for online exam," *International Journal of Artificial Intelligence in Education*, vol. 31, no. 4, pp. 642–660, 2021. https://doi.org/10.1007/s40593-020-00238-3

[10] Y. Huang, F. Zhang, and X. Li, "Evaluating AI-driven proctoring technologies for online learning: Challenges and opportunities," *Education and Information Technologies*, vol. 27, no. 8, pp. 10933–10955, 2022. https://doi.org/10.1007/s10639-022-11061-8

[11] H. Yang, T. Liu, and P. Zhou, "Artificial intelligence in online assessments: Trends, technologies, and ethical concerns," *British Journal of Educational Technology*, vol. 52, no. 5, pp. 2031–2047, 2021. https://doi.org/10.1111/bjet.13169

[12] D. O. Omondi, G. Onyango, and M. Ouma, "Mobile-based AI proctoring: A framework for equitable assessment in Sub-Saharan Africa," *African Journal of ICT in Education*, vol. 14, no. 2, pp. 88–104, 2022.

[13] C. Chin, J. Lee, and S. Park, "Artificial intelligence ethics in online education: Privacy, fairness, and accountability," *Computers & Education*, vol. 193, p. 104683, 2023. https://doi.org/10.1016/j.compedu.2023.104683

[14] H. Kaur and R. Singh, "Privacy implications of AI-based student surveillance systems," *Journal of Educational Computing Research*, vol. 60, no. 6, pp. 1330–1347, 2022. https://doi.org/10.1177/07356331221076032

[15] M. Garcia, R. Patel, and S. Khan, "Post-pandemic adoption of online proctoring systems in higher education," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, p. 45, 2022. https://doi.org/10.1186/s41239-022-00360-1

[16] Q. Zhang, L. Chen, and X. Zhao, "Machine learning in remote proctoring: A review of post-COVID developments," *Computers in Human Behavior Reports*, vol. 9, p. 100259, 2023. https://doi.org/10.1016/j.chbr.2022.100259

[17] M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, p. n71, 2021. https://doi.org/10.1136/bmj.n71

[18] R. Omondi, C. Otieno, and J. Nyangena, "AI mobile proctoring adoption in Kenyan universities: Opportunities and challenges," *African Journal of Educational Technology*, vol. 8, no. 2, pp. 21–35, 2022.

[19] L. Zhang, T. Wu, and X. Lin, "Edge computing in mobile AI proctoring systems," *IEEE Transactions on Learning Technologies*, vol. 16, no. 4, pp. 655–668, 2023. https://doi.org/10.1109/TLT.2023.3245678

[20] M. Garcia, A. Torres, and L. Salazar, "Student perceptions of online proctoring during the COVID-19 pandemic," *Computers & Education*, vol. 183, p. 104497, 2022. https://doi.org/10.1016/j.compedu.2022.104497

[21] X. Li and J. Chen, "Privacy frameworks for AI-based assessment tools: A regulatory perspective," *Computers & Security*, vol. 132, p. 103356, 2023. https://doi.org/10.1016/j.cose.2022.103356

[22] S. Yang, Y. Chen, and K. Davis, "Ethical challenges in facial recognition-based proctoring," *Computers in Human Behavior*, vol. 120, p. 106729, 2021. https://doi.org/10.1016/j.chb.2021.106729