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Beyond the Flag: Preliminary Learner-Centered Design Considerations for AI-Supported Assessment in ODeL Physics Education

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***Abstract*—Artificial intelligence (AI)-supported online proctoring is increasingly used in online and distance education, although its implementation continues to raise questions about anxiety, privacy, fairness, and technical reliability. This exploratory mixed-method case study examined learners' experiences during the first implementation of an AI-supported online proctored examination in a doctoral physics education course offered through Open and Distance e-Learning (ODeL). The examination included ten PhD in Education students to interpret frontier physics concepts, communicate them for a specific Grade 7-12 audience, identify prerequisite knowledge, and design a classroom activity. Quantitative ratings and written responses were collected concurrently through an anonymous post-examination survey and integrated during interpretation. Eight of the ten learners perceived the system as useful in discouraging academic dishonesty, while six indicated that they would be comfortable using it again. Their responses also showed concerns about monitoring anxiety, technical interruptions, privacy, and the interpretation of AI-generated flags. The findings suggested that learners' acceptance depended not only on the perceived usefulness of proctoring but also on how the assessment was explained, prepared for, supported and reviewed. Four preliminary design considerations were developed from the integrated findings: Purposeful Assessment, Transparent Procedures, Learner Preparation, and Technical Resilience. These principles offer preliminary guidance for designing AI-supported assessment in ODeL while keeping academic decisions under informed human judgment.**

Keywords—ai-supported assessment; online proctoring; learner-centered assessment; physics education; Open and Distance e-Learning

I. INTRODUCTION

Maintaining academic integrity in remote examinations remains a practical concern for institutions offering Open and Distance e-Learning (ODeL). Live online invigilation can provide direct human supervision, but it also requires sustained staffing, stable connectivity, and simultaneous participation. AI-supported examination systems have been developed to automate selected monitoring and administrative functions while seeking to preserve assessment integrity and reduce the burden of administering online examinations [1, 2]. Despite these advantages, AI-supported proctoring has also generated concerns regarding privacy, fairness, transparency, and the psychological impact of being monitored during high-stakes examinations [3].

Research on online proctoring has generally focused on academic integrity, technology acceptance, privacy, and learner anxiety [2, 4, 5]. Learners may recognize its potential to discourage dishonest behavior while remaining uneasy about continuous monitoring, technical failure, or the possibility that ordinary actions will be interpreted as suspicious [5]. However, these studies primarily evaluate learners' perceptions of the technology itself rather than examining how the overall assessment experience can be intentionally designed to better support learners.

From a learner-centered assessment perspective, the question is not limited to whether an AI-supported proctoring system functions as intended. Academic integrity can also be supported through the design of learning environments and assessment tasks that encourage original engagement and make cheating less compatible with the intended learning process [6]. When AI-supported proctoring is used, it should therefore be treated as one component of the wider assessment design rather than as the principal means of ensuring integrity. This broader design includes transparent procedures, clear expectations, appropriate learner preparation, technical support, and fair review of AI-generated reports. These provisions are particularly important because AI-driven proctoring requires institutions to balance academic integrity with privacy and learner experience [5].

The disciplinary setting formed part of the assessment context. Learners completed constructed-response tasks that required them to interpret advanced physics concepts and apply pedagogical and instructional-design judgment. The study did not directly measure whether online proctoring affected these disciplinary forms of reasoning. Nevertheless, the nature of the task remains relevant because learners experienced the monitoring system while completing extended, discipline-based responses rather than a generic objective examination.

Although previous studies have documented learner perceptions of online proctoring, fewer have translated those experiences into practical design considerations for an ODeL assessment process. This study addresses that need by examining the first implementation of an AI-supported online proctored examination in a doctoral physics education course at the University of the Philippines Open University. It does not evaluate the technical accuracy of the proctoring system or determine whether it prevented academic dishonesty. Instead, it examines how learners experienced the implementation and identifies design features that may support a fairer, clearer, and more manageable assessment experience.

Specifically, this study investigates: (1) how learners perceived and experienced the first implementation of an AI-supported online proctored assessment in an ODeL physics education course; (2) which features of the assessment experience facilitated or hindered a learner-centered assessment experience; and (3) what preliminary learner-centered design considerations could be derived to inform subsequent implementations of AI-supported assessment in ODeL.

II. Conceptual and Analytical Orientation

This study adopts a learner-centered view of assessment, recognizing assessment not only as a means of evaluating learning outcomes but also as a designed experience that should provide learners with fair, transparent, and practicable conditions for demonstrating what they know and can do. This position is consistent with approaches that locate academic integrity within learning and assessment design [6] and with recent calls to balance integrity, privacy, and learner experience when implementing AI-driven proctoring [5].

In ODeL environments, maintaining academic integrity must be balanced with learners' cognitive, emotional, and technological experiences during assessment. Consequently, the quality of AI-supported assessment should be evaluated not only by its ability to deter academic dishonesty but also by how effectively it supports learners throughout the assessment process.

Selected constructs from the Technology Acceptance Model (TAM) informed the analysis [7]. Perceived usefulness was relevant to whether learners considered AI-supported proctoring helpful in discouraging academic dishonesty. Perceived ease of use helped interpret their experiences of operating within the proctored environment, while willingness to use the system again provided an indication of behavioral intention. The study did not attempt to test or validate TAM. Nor were all survey items treated as TAM measures. Questions concerning anxiety, privacy, fairness, procedural clarity, and technical reliability addressed additional issues identified in online-proctoring literature and in the institutional implementation.

The two perspectives served different but complementary purposes. TAM-related constructs were used to describe learners' responses to the technology, while learner-centered assessment guided the interpretation of what their experiences implied for assessment design. The quantitative ratings identified descriptive patterns within the cohort. The written responses provided context for these ratings and surfaced concerns that could not be understood through measures of perceived usefulness and willingness to use the system again alone. The four preliminary design considerations were derived by integrating the quantitative and qualitative findings and relating them to aspects of the assessment process that educators and institutions could reasonably modify.

III. Methodology

A. Research Design

This study employed an exploratory mixed-methods case-study design. The bounded case was the first implementation of an AI-supported online proctored examination in one doctoral physics education course offered through an ODeL institution. The case-study design allowed the implementation to be examined within its actual course and assessment context. Quantitative ratings were used to describe patterns in learners' perceptions, while written responses were used to examine the experiences and concerns underlying those patterns.

Quantitative and qualitative data were collected concurrently though on post-examination survey. The two forms of data were analyzed separately and brought together during interpretation. The study was exploratory rather than confirmatory: it did not test causal relationships, validate a technology-acceptance model, or evaluate the detection accuracy of Proctoring Pro. Its purpose was to identify learner-experience issues that could inform the design of subsequent implementations.

B. Participants and Assessment Context

The participants were ten ((n=10)) in-service teachers enrolled in a doctoral physics education course at an ODeL university in the Philippines. They came from multiple admission cohorts and had substantial prior experience with ODeL, having completed several online courses through the university's learning management system. This background allowed the study to focus on their experiences with AI-supported assessment rather than on their initial adjustment to the ODeL environment.

The two-hour, closed-book examination consisted of constructed-response tasks situated in physics education. An assigned article on frontier physics concepts was provided within the examination as the common source material. Learners interpreted selected concepts from the article and explained them for an audience of physics teachers handling a specified Grade 7–12 level. They also identified prerequisite physics concepts that could help connect the frontier topics with learners' existing knowledge and designed a grade-appropriate classroom activity or experiment. Access to external websites and course modules was not permitted during the examination.

The implementation followed four phases: (1) a pre-examination orientation supported by an AI-proctoring examination toolkit; (2) a non-graded mock examination intended to familiarize learners with the proctored environment and verify their technical readiness; (3) the AI-supported online proctored examination; and (4) a post-examination evaluation survey. Fig. 1. summarizes this sequence.

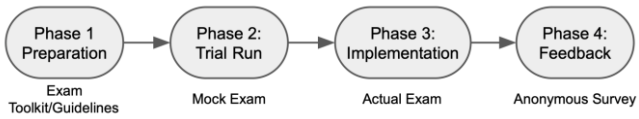


Fig. 1. AI-supported assessment implementation flow showing the sequence of activities: Toolkit/Guidelines → Mock Exam → Final Exam → Post-exam Survey. Both mock and final examinations were administered using Proctoring Pro.

C. AI-Supported Assessment Procedure

The actual examinations were conducted using Proctoring Pro integrated with the university's LMS. Before the examination, learners completed an orientation and a mock examination using the same proctoring configuration to familiarize themselves with the examination procedures and technical requirements.

The learners were informed that the AI-supported proctoring system would generate reports of potential examination irregularities as part of the academic integrity procedure. These AI-generated reports served only as preliminary evidence and were not used for automated academic decisions. All flagged events were manually reviewed by the faculty-in-charge (FIC). When an AI-generated report suggests a potential examination violation or academic dishonesty and it was verified by the faculty-in-charge, the learner was invited to provide a written explanation before any academic decision such as score deductions or examination forfeiture was made. Final academic decisions therefore remained under FIC judgment rather than AI automation.

D. Data Collection

Immediately after completing the examination, learners were invited to voluntarily complete an anonymous online survey administered within the LMS. The survey consists of seven Likert-scale items and three open-ended questions. The Likert-scale items measured learners' perceptions of the clarity of the examination procedures, fairness of the AI-supported assessment, monitoring anxiety, technical reliability, privacy, perceived effectiveness in discouraging academic dishonesty, and willingness to use the AI-supported assessment system again. Selected survey items were informed by the Technology Acceptance Model [7] to capture learners' perceptions of usefulness, ease of use, and behavioral intention toward AI-supported assessment while incorporating assessment-specific constructs relevant to online proctoring.

The open-ended questions explored the learner's perceived challenges, sources of distraction during the examination and recommendations for improving future AI-supported assessments. Together, the quantitative and qualitative data provided complementary evidence for understanding learners' assessment experiences and identifying learner-centered assessment design considerations.

E. Data Analysis

Responses to the Likert-scale item were summarized using descriptive statistics, including frequencies, means, medians, modes, and standard deviations. Response distributions were visualized using bar charts to identify overall patterns of learners' perceptions. Given the exploratory nature of the study and the limited sample size, the analysis focused on descriptive rather than inferential statistics.

The qualitative responses were analyzed using inductive thematic analysis following Braun and Clarke's six-phase approach [8]: familiarization with the data, generation of initial codes, development of candidate themes, review of themes, definition and naming of themes, and production of the analysis. The researchers first read the responses repeatedly to become familiar with the data. Meaningful statements were then assigned initial codes reflecting learners' experiences and recommendations, including monitoring anxiety, concern about inaccurate flagging, technical disruption, procedural uncertainty, need for faculty validation, and need for technical support. Related codes were grouped into broader themes and reviewed against the original responses. Non-substantive responses, such as "NA," "None," and blank entries, were not used as evidence for theme development.

The resulting themes were then compared with corresponding quantitative patterns through a joint-display approach. The four preliminary design considerations were developed by translating the integrated findings into practical learner-centered AI-supported assessment-design implications; therefore, they represent context-specific interpretative outputs rather than predetermined categories or validated dimensions.

F. Ethical Considerations

Participation in the post-exam survey task was voluntary and anonymous. Participants were informed that choosing to participate or decline would not affect their course standing, performance, or grades. Because the participants were educators who were also enrolled as students, the researcher accessed the survey data only after the semester had ended and final grades had been submitted.

IV. Results and Discussion

A. Learners Demonstrated Cautious Acceptance of AI-supported Assessment

The quantitative findings indicate that learners generally recognized the educational purpose of AI-supported online proctoring despite expressing reservations about some aspects of its implementation. As shown in Fig. 2-D and Table I, a strong majority of learners (80%) agreed that the AI-supported proctoring system discouraged dishonest behaviour during the examination (M = 4.30, SD = 1.34). Similarly, 60% indicated that they would be comfortable using the system again in future high-stakes examinations (M = 3.70, SD = 1.25), although nearly one-third remained neutral and one participant expressed strong disagreement.

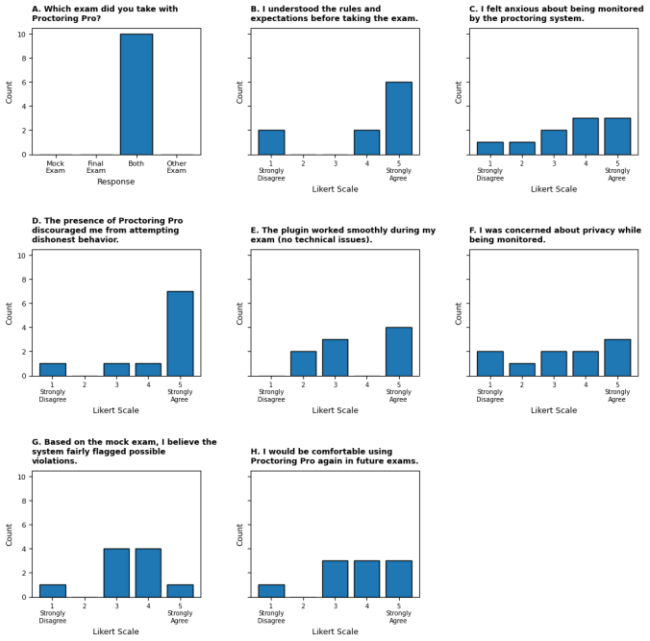


Fig. 2. Student responses to Proctoring Pro survey items: exam usage (A) and perceptions of rules, anxiety, technical issues, fairness, and comfort (B-H).

The qualitative findings helped contextualize the quantitative results. Participant codes (P1–P10) are used to distinguish the anonymous responses quoted in the findings. Learners' concerns centered on monitoring-related anxiety, uncertainty about AI-generated flagging, technical interruptions, and the need for human review. For example, one learner reported becoming *"so cautious while having the exam"* because of concern that the AI might misinterpret ordinary movements (P2). Another described how the *"constant awareness of being monitored"* created *"an added layer of stress and pressure,"* making it more difficult to focus on the examination questions (P9). Technical disruptions also affected the assessment experience. One learner explained that the webcam monitor disappeared while the examination was in progress, requiring troubleshooting during an already time-limited assessment (P8).

However, these concerns were not reported uniformly. Some learners responded with *"Nothing so far," "I think it is all good,"* or *"None"* when asked about distractions or recommendations. The concerns should therefore be understood as significant experiences reported by some learners rather than as views shared by every participant.

TABLE I
DESCRIPTIVE STATISTICS OF TEN STUDENTS (N = 10). LIKERT-SCALE RESPONSES (B-H) ON THEIR EXPERIENCE WITH PROCTORING PRO DURING THE EXAM.

Prompt	*Mean (M)*	*Median*	*Mode*	*Standard Deviation (SD)*	*% Agree/ Strongly Agree*
B. Understood rules	4.0	5	5	1.63	80%
C. Felt anxious	4.0	5	5	1.63	60%
D. Discouraged dishonesty	4.3	5	5	1.34	80%
E. Worked smoothly	3.8	4	5	1.32	50%
F. Privacy concern	3.3	3.5	5	1.57	50%
G. Flagging fair (mock)	3.4	3.5	3,4	1.07	50%
H. Comfortable to reuse	3.7	4	3,4,5	1.25	60%

Taken together, the quantitative and qualitative findings suggest that learners did not uniformly reject AI-supported online proctoring. While learners recognized its potential contribution to discouraging academic dishonesty, they simultaneously emphasized the importance of transparent procedures, technical reliability, and human oversight in shaping a positive assessment experience. Thus, acceptance of AI-supported assessment appeared to be conditional on how the assessment was designed and implemented.

From a learner-centered assessment perspective, AI should therefore be used to support fair, trustworthy and meaningful assessment rather than being treated as the primary goal of the assessment process. Learners appear more willing to engage with AI-supported assessment when its educational purpose is clearly communicated and aligned with principles of fairness. Consequently, the integrated quantitative and qualitative findings informed the first characteristic of learner-centered AI-supported assessment: *purposeful assessment.* This characteristic emphasizes that learners should understand why AI is incorporated into the assessment process and perceive it as supporting rather than replacing, fair assessment practices.

Table II summarizes how the qualitative evidence and related quantitative patterns were integrated to derive the four preliminary learner-centered design considerations.

B. Transparent Procedures Support Perceptions of Fairness

While learners generally understood the examination procedures, their confidence in the assessment depended on how transparently the AI-supported monitoring process was communicated. Table I showed that 80% of the learners agreed that they understood the exam rules and procedures (M = 4.00, SD = 1.63). However, only half agreed that the AI-generated flagging during the mock examination was fair (M = 3.40, SD = 1.07), while responses regarding privacy were similarly divided (M = 3.30, SD = 1.57). This difference suggests that understanding the exam rules alone was not enough to establish confidence in the AI-supported assessment process.

Learners expressed uncertainty about whether ordinary examination behavior might be treated as suspicious. One learner identified *"the unintentional movement of my eye from the screen to the keyboard"* as particularly challenging because it could be recognized by the system as a violation (P1). This learner further requested that *"a human would still check the report and not solely rely on the AI"* (P2). Similarly, another recommended that the *"FIC may validate behaviors flagged by the system"* to support fair judgment (P7). Learner also suggested providing clearer explanations of the purpose

of AI-supported monitoring, the behaviors that could trigger flags, and how learner data would be handled.

In this implementation, AI-generated flags should be treated as indicators for faculty review rather than as determinations of academic misconduct. The FIC remains responsible for examining the flagged event, considering contextual explanations such as connectivity loss, power interruption, ordinary eye or body movement, and environmental noise, and determining whether further inquiry is warranted. No academic penalty should be imposed solely on the basis of an automated flag. Where a flag may affect an academic decision, the learner should be informed and given an opportunity to provide an explanation.

These findings indicate that transparency extends beyond providing examination instructions. Learners also wanted to understand how AI-supported monitoring worked, what information was collected, and how FIC judgment would be used during the review process. Transparent procedures help learners develop confidence that the assessment process is fair, understandable and accountable. Therefore, *transparent procedures* emerged as the second design principle for future learner-centered AI-supported assessment.

C. Learner Preparation Reduced Uncertainty

Although learners received a proctoring guide and participated in a mock examination, 60% still reported anxiety, as shown in Table I. This anxiety should also be interpreted in light of the high-stakes nature of the examination and the assessment-integrity procedure, in which learners understood that AI-generated reports could initiate FIC review when potential examination violations were identified.

The open-ended responses suggest that preparation may have improved familiarity with the platform without fully addressing learners' fear of being incorrectly flagged or penalized. One learner stated, *"I became conscious with my behavior during examinations"* (P3), while another described the *"constant awareness of being monitored"* as an additional source of stress that made it harder to focus on the questions (P9). A learner also reported uncertainty about the camera requirements: *"I didn't know that the camera requires me to always show my face. Maybe, that should be mentioned ahead of time"* (P5). Preparation may also need to explain allowable behavior, possible flagging events, how technical disruptions are treated, and how faculty review protects learners from automatic penalties.

The findings suggest that learner preparation should be considered an integral part of AI-supported assessment rather than an optional activity before the examination. Structured preparation can help learners develop confidence, clarify expectations, and reduce unnecessary uncertainty before participating in high-stakes assessments. Accordingly, *Learner Preparation* emerged as the third preliminary learner-centered design consideration, emphasizing structured orientation. Authentic practice opportunities, and timely support before the assessment.

D. Technical Resilience

Another important result is the mixed perception regarding the technical performance of the AI-supported assessment. Half of the learners agreed that the system worked smoothly during examination (M = 3.8, SD = 1.32), whereas the remaining learners either expressed neutral responses or disagreed. This result is more varied as compared to the more generally positive perceptions on the purpose of the Ai-supported assessment.

Technical difficulties redirected learners' attention from answering the examination questions to managing the assessment environment. One learner reported that when the webcam monitor disappeared, *"I had no choice but to troubleshoot the problem,"* adding pressure to an already time-limited examination (P8). The same learner described a power interruption that restarted the internet connection and created concern that recurring power interruptions could prevent completion of the examination despite having Wi-Fi access (P10). These accounts underscore the importance of recovery procedures and context-sensitive contingency measures in ODeL assessment.

For learners in an ODeL environment, technical disruptions cannot always be prevented. Rather than assuming a flawless assessment environment, AI-supported assessment should be designed to anticipate and accommodate foreseeable technical interruptions. Clear recovery procedures, visible examination timers, standby technical support, and contingency measures for connectivity or power disruptions can help learners resume the assessment with minimal interruption and maintain their focus on demonstrating learning. These findings suggest that *technical resilience* - the capacity of the assessment process to respond fairly and effectively to technical disruptions - is an important learner-centered assessment consideration because it directly shapes learners' assessment experience.

E. Preliminary Learner-Centered Design Considerations

The integrated findings suggest that learners' responses to AI-supported proctoring depended not only on its perceived usefulness for discouraging academic dishonesty but also on the assessment procedures surrounding its use. Learners identified concerns involving the purpose of monitoring, clarity of procedures, preparation before the examination, human review of flagged events, and responses to technical disruption.

Four preliminary learner-centered design considerations were identified from the case: (1) **Purposeful Assessment**, which requires a clear and proportionate reason for using AI-supported proctoring; (2) **Transparent Procedures**, which includes clear communication of examination rules, monitoring practices, permitted behavior, and faculty review; (3) **Learner Preparation**, which involves structured orientation and practice under conditions similar to the actual examination; and (4) **Technical Resilience**, which requires contingency measures, recovery procedures, and timely support when technical problems occur. Table II summarizes how the qualitative interpretations and corresponding quantitative patterns informed these four preliminary considerations.

TABLE II
SUMMARY OF THE QUALITATIVE THEMES, INTERPRETATIVE FINDINGS AND THE DERIVED LEARNER-CENTERED ASSESSMENT DESIGN IMPLICATIONS

Qualitative evidence or interpretative finding	Final qualitative theme	Related quantitative pattern	Preliminary design consideration

Learners' acceptance was qualified by concerns about how monitoring was communicated and implemented	Acceptance depended on the perceived purpose and implementation of proctoring	8/10 perceived deterrent value; 6/10 were comfortable with reuse	**Purposeful Assessment**
Learners feared false flagging, were uncertain about permitted behavior, and requested FIC validation	Trust depended on transparent procedures and human judgment	8/10 understood the rules, but only 5/10 perceived flagging as fair and 5/10 expressed privacy concerns	Transparent Procedures
Learners described anxiety, behavioral self-consciousness, and fear of accidental violations	Monitoring created hypervigilance and divided learners' attention	6/10 reported anxiety despite prior guidance and a mock examination	Learner Preparation
Learners experienced webcam loss, connectivity and power interruptions, delayed access, and troubleshooting demands	Technical and environmental instability intensified time pressure	Only 5/10 agreed that the system operated smoothly	Technical Resilience

These considerations are presented as context-informed guidance derived from one exploratory implementation. They do not constitute a validated framework, a required sequence, or an exhaustive set of principles. Instead, they identify aspects of the assessment experience that educators may examine when planning future AI-supported assessments in ODeL. Further research involving larger and more diverse learner groups, courses, assessment contexts, and proctoring platforms is needed to examine the applicability and refinement of these considerations.

V. Conclusion

This study examined the first use of AI-supported online proctoring in a doctoral physics education course offered through ODeL. The ten learners did not respond to the system in a uniform way. Most saw a reason for using it: eight perceived it as capable of discouraging dishonest behavior. That recognition did not remove their concerns. Only six indicated that they would be comfortable using it again, and their written responses repeatedly returned to monitoring anxiety, technical interruptions, privacy, flagging, and the importance of faculty review.

The results suggest that acceptance cannot be understood from perceived usefulness alone. Learners also evaluated the assessment through the procedures surrounding the technology. They wanted to know what was expected, how reports would be interpreted, where human judgment entered the process, and what protection they had when technical problems occurred. These concerns led to four design considerations for subsequent implementations: Purposeful Assessment, Transparent Procedures, Learner Preparation, and Technical Resilience.

The physics education setting identifies the kind of performance learners were expected to demonstrate. The examination required them to interpret frontier physics concepts, explain them for a specified school-level audience, identify prerequisite knowledge, and design a classroom activity. These were extended tasks involving disciplinary understanding and pedagogical judgment. The present survey did not directly examine whether monitoring affected those forms of reasoning. It would therefore be premature to claim a distinct physics-specific effect. The context nevertheless matters when designing the mock examination, defining permitted resources, setting the available time, and deciding how technical interruptions will be handled.

Future implementations should retain human review of AI-generated reports and make that review process visible to learners. The orientation should explain permitted behavior and resources in terms of the actual assessment, while the mock examination should reproduce its main procedural demands. Institutions should also establish clear responses to disconnection, equipment failure, lost time, and disputed reports before the high-stakes examination begins. These measures do not eliminate every concern surrounding online proctoring, but they reduce the number of consequential decisions left unclear during the examination itself.

Several limitations restrict the conclusions that can be drawn. The study involved one class, ten respondents, one platform, and the first implementation of the assessment process. It relied on self-reported experiences collected after the examination and did not independently measure anxiety, proctoring accuracy, academic dishonesty, or effects on examination performance. The design considerations should therefore be treated as preliminary design guidance. Further research could examine their relevance across larger cohorts, other disciplinary settings, and different forms of assessment. A future physics education study could also investigate whether continuous monitoring affects the extended conceptual and pedagogical reasoning required by constructed-response tasks.

AI-supported proctoring may contribute to academic-integrity procedures, but it cannot carry the fairness of an assessment by itself. That responsibility remains with the people who design the tasks, explain the rules, prepare the learners, respond to technical failure, and interpret the resulting evidence. A learner-centered implementation begins there.

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