

Do Students Embrace AI-Powered Academic Integrity? Examining Students' Technology Acceptance of Security-Enhanced Online Exams

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Abstract: This study examines students' technology acceptance of artificial intelligence (AI)-powered online exams that use AI techniques to detect cheating and ensure academic integrity. Grounded in the Technology Acceptance Model (TAM), this explanatory sequential mixed-methods research (QUAN→qual) investigates the factors that influence student adoption of such systems. An AI-powered online examination system was developed and implemented for eight courses, with 90 students participating in an online survey to assess their acceptance using a five-factor TAM scale (Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Facilitating Conditions, and Computer Anxiety). Additionally, 20 students were interviewed. The findings reveal that while some students appreciate the AI-powered online exam for ensuring fairness and merit-based grading, others are skeptical due to concerns about cheating. Statistical analysis shows significant positive correlations among four TAM factors (Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, and Facilitating Conditions). Furthermore, the qualitative results identify 14 key factors that influence student acceptance of AI-powered secure online exams. Unlike prior studies on general e-learning or conventional proctoring tools, this study applies a five-factor TAM framework to a purpose-built AI-powered secure examination system, combining survey and interview data. This research provides valuable insights for educators and policymakers seeking to understand how AI-powered security features impact student acceptance of online exams.

Keywords: AI-powered online exams, AI-based online assessments, artificial intelligence, academic integrity, academic honesty, technology acceptance model, TAM, security-enhanced online examination systems, measurement and evaluation, students' perspectives

Highlights

What is already known about this topic:

- Online exams face ongoing security concerns; AI-powered proctoring tools (facial recognition, voice analysis, behavior tracking) have emerged to deter and detect cheating.
- TAM is widely applied to educational technology, but mostly to general e-learning or conventional proctoring, not to AI-powered secure exam systems.

What this paper contributes:

- Applies a five-factor TAM (PU, PEU, ATU, FC, CA) to a purpose-built AI-powered secure exam system via an explanatory sequential mixed-methods design (QUAN→qual).
- Identifies 14 qualitative factors shaping acceptance, including desire for academic justice, course type, exam environment, and perception of AI vs. human proctoring.

Implications for theory, practice and/or policy:

- Framing AI-powered exams as fairness tools rather than surveillance, and identifying the proctor as AI rather than human, can boost acceptance and reduce anxiety.
- Practice sessions, multiple-choice formats, lab-based delivery, and a clear right of appeal can lower anxiety and improve acceptance of AI-secured online exams.

Introduction

Measurement and evaluation determine whether the objectives in education have been achieved or not. Developments in information technologies allow the development of online measurement and evaluation tools and exams to be carried out on online platforms. However, the adequacy of validity, reliability, and security of measurement and evaluation conducted in the online environment is still being discussed (Chiang et al., 2022). Security is the leading criticism of online exams in distance learning, and security-enhanced online examination systems are employed to ensure academic integrity in online exams (Topuz & Karaman, 2017). As institutions increasingly adopt online assessment platforms, the challenge of maintaining examination integrity has become a focal point for educational researchers and practitioners alike (Topuz et al., 2022). This growing concern has prompted the integration of artificial intelligence (AI) techniques into online examination systems, offering automated and scalable solutions for cheating prevention and detection.

Building on these developments, security-enhanced online examination systems can detect and prevent cheating with AI-powered analysis (Jia & He, 2022; Noorbehbahani et al., 2022), including but not limited to: facial recognition, voice recognition, and evaluating answer sheets. Thus, machine-based surveillance can complement traditional human proctoring, enabling automated monitoring and supervision of the examination process. For instance, AI-powered proctoring systems utilize facial recognition, gaze tracking, and behavior analysis to monitor students during exams (Padmavathi et al., 2024; Zheng et al., 2024). In addition, Gopane et al. (2024) have introduced an online examination system that integrates the FaceNet Model, Lucas-Kanade Algorithm, and Active Appearance Model to enhance face detection and monitor students' activities. This hybrid approach enables the system to extract semantic indicators effectively, facilitating the evaluation of potential cheating behaviors during online assessments. These kinds of advancements in the integration of AI techniques into online examination systems not only improve the administration of online exams but also foster an environment of trust and fairness. However, students' concerns, such as data privacy and the potential for bias in AI algorithms, underscore the need for responsible implementation of these technologies (Marano et al., 2024). Consequently, understanding how students perceive and accept these AI-powered examination tools is essential for their effective and equitable deployment. Therefore, when organizing online exams, it is important to consider students' acceptance of and views on the AI-powered online exams they will take.

Liu et al. (2015) have pointed out that security issues in online exams can affect students' acceptance of the exams. Focusing on students' acceptance of AI-powered online exams with enhanced security is crucial, as the AI-driven features designed to ensure exam integrity may inadvertently impact students' academic performance or motivation negatively. This effect can be analyzed by gathering students' opinions, providing insights into how the AI-powered secure online exams can be utilized more effectively. Despite the growing adoption of AI-driven security in online exams, prior research has largely focused on general e-learning platforms or commercially available proctoring tools, and has rarely examined how students perceive and accept purpose-built, multi-layered AI-powered secure examination systems. The present study addresses this gap. Therefore, the purpose of this research is to investigate student acceptance of an online examination system that is supported by AI and includes advanced security features to prevent and detect cheating. To systematically investigate this, the study draws upon the Technology Acceptance Model (TAM) and applies a five-factor extension of it, as elaborated in the Theoretical Background subsection of the Literature Review. In line with the stated purpose, answers have been sought to the following three research questions:

RQ1. To what extent do students accept AI-powered secure online exams?

RQ2. Are there statistically significant relationships among the TAM factors related to students' acceptance of AI-powered secure online exams?

RQ3. What are the factors that influence students' acceptance of AI-powered secure online exams?

The rest of this paper is structured as follows. Section 2 presents the theoretical background and a review of the relevant literature. Section 3 describes the methods, including the research design and characteristics of the AI-powered secure online examination system developed for this research. In Section 4, the findings of this research are presented. Section 5 provides a discussion of the findings in light of the existing literature. Finally, Section 6 offers conclusions and recommendations for future studies.

Literature

This section reviews the existing literature on online examination security, AI-powered proctoring, and technology acceptance in educational contexts, establishing the foundation for the current research questions, and then, introduces the theoretical framework that grounds the study.

Online Examination Security and Academic Integrity

The shift toward online assessment has introduced significant challenges to maintaining academic integrity. Noorbehbahani et al. (2022) conducted a systematic review of cheating in online exams from 2010 to 2021, revealing that cheating remains a pervasive concern in digital assessment environments. A systematic review of online examinations similarly concluded that, although digital formats offer flexibility and scalability, the interface and security design of an examination system function as critical enablers of, or barriers to, assessment integrity (Butler-Henderson & Crawford, 2020). Synthesizing 56 studies on online assessment security, Garg and Goel (2022) found that dishonest behavior emerges from the interaction of environmental opportunities, such as unrestricted internet access, with individual characteristics, and they documented a clear movement away from purely rule-based safeguards toward machine learning techniques for the automated detection of misconduct. These findings highlight the multifaceted nature of cheating prevention in online exams, yet the integration of AI for automated detection and deterrence remains an emerging area of inquiry.

AI-Powered Proctoring Systems

Recent advances in AI have enabled the development of sophisticated proctoring systems that go beyond traditional rule-based security measures. Jia and He (2022) described the design and implementation of an intelligent online proctoring system that leverages AI for real-time exam monitoring. In a quasi-experiment comparing unproctored and webcam-proctored high-stakes exams, Dendir and Maxwell (2020) reported that the introduction of online proctoring was associated with a substantial decline in average exam scores, which they interpreted as evidence that monitoring effectively mitigates academic dishonesty. However, the same surveillance features may produce unintended consequences for test-takers; Conijn et al. (2022) found that proctored examinations can intensify students' sense of being watched and elevate test anxiety, raising concerns about the potential negative side-effects of intensive monitoring. Consistent with this tension, Coghlan et al. (2021) raised important ethical considerations regarding online exam supervision technologies, noting the tension between ensuring integrity and respecting student privacy. While these studies have advanced our understanding of AI proctoring, relatively few have examined student acceptance of such systems from a technology adoption perspective.

Technology Acceptance in Educational Assessment

TAM has been widely applied in educational technology research. Sprenger and Schwaninger (2021) used TAM to examine student acceptance of four digital learning technologies, demonstrating its continued relevance in contemporary educational settings. In the specific domain of online assessment, Fink et al. (2023) proposed and empirically validated a technology-based exams acceptance model, finding that Perceived Usefulness was the strongest predictor of the behavioral intention to use e-exams

and confirming the contribution of Computer Anxiety as an external determinant. Jiang et al. (2023) extended TAM to investigate university students' acceptance of online proctoring during COVID-19, confirming significant relationships among TAM constructs, with Perceived Usefulness and social influence emerging as the strongest predictors of acceptance. A systematic mapping of TAM research further indicates that the model remains a robust framework for studying technology acceptance in higher education, with Perceived Ease of Use being the most frequently examined antecedent and extended versions of TAM increasingly dominating the field (García-Murillo et al., 2021).

Despite this growing body of research, studies examining technology acceptance specifically for AI-powered secure online examination systems remain scarce. Most existing work focuses on general e-learning platforms or conventional proctoring tools, leaving a gap in understanding how students perceive and accept AI-driven security features in high-stakes examination contexts. The present study addresses this gap by applying a five-factor TAM framework to examine student acceptance of an AI-powered secure online examination system, combining quantitative survey data with qualitative interview insights to provide a comprehensive understanding of the factors influencing acceptance. Furthermore, this study extends the existing literature by situating TAM within the specific context of AI-driven surveillance in high-stakes assessments, a domain where student perceptions of fairness, privacy, and algorithmic trust intersect with traditional acceptance factors. By examining a purpose-built AI-powered examination system rather than a commercially available proctoring tool, this research offers insights into how system-specific design features shape acceptance, thereby contributing to both the technology acceptance and educational assessment literatures. The three research questions guiding this study were formulated to progressively explore the level of acceptance (RQ1), the interrelationships among acceptance factors (RQ2), and the specific factors that influence acceptance (RQ3).

Theoretical Background

This study is grounded in the Technology Acceptance Model (TAM), originally proposed by Davis (1989) as a theoretical framework for understanding how users come to accept and use new technologies. The purpose of TAM is to explain the factors determining technology acceptance (Davis et al., 1989). Davis (1989) posited that two primary beliefs (namely Perceived Usefulness and Perceived Ease of Use) are fundamental determinants of user attitudes toward technology, which in turn influence intentions to use and actual usage behavior. This framework is particularly relevant to the current study because AI-powered secure online exams represent a novel technological intervention that students must adopt in a high-stakes educational context, making the assessment of acceptance factors critical for successful implementation.

Some of the other technology acceptance models developed based on the TAM model are as follows: Technology Acceptance Model 2 (Venkatesh & Davis, 2000); Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003); Technology Acceptance Model 3 (Venkatesh & Bala, 2008); Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012); and, Technology Acceptance Model for Teachers (Ursavaş et al., 2014). While there are common factors (Perceived Usefulness and Perceived Ease of Use) found in all of these models, there are also factors (e.g., Attitude Toward Use, Facilitating Conditions, and Computer Anxiety) found in only some of these models. In the present study, five factors were selected from across these models to capture a comprehensive picture of student acceptance. Perceived Usefulness (PU) is the degree of personal perception of the person using a system about the increase in job performance (Raman & Don, 2013). Perceived Ease of Use (PEU) is the degree to which a person believes that the system will be easy to use (Davis et al., 1989). Attitude Toward Use (ATU) is a person's positive or negative evaluation of technology use (Ursavaş et al., 2014). Facilitating Conditions (FC) refer to the extent of availability of technical support for using new technology (Venkatesh et al., 2003). Computer Anxiety (CA) is the feeling of fear and anxiety when an individual is likely to use a computer or while using a computer (Venkatesh & Bala, 2008). Therefore,

students' acceptance of online exams can be examined with these five factors, namely: PU, PEU, ATU, FC, and CA.

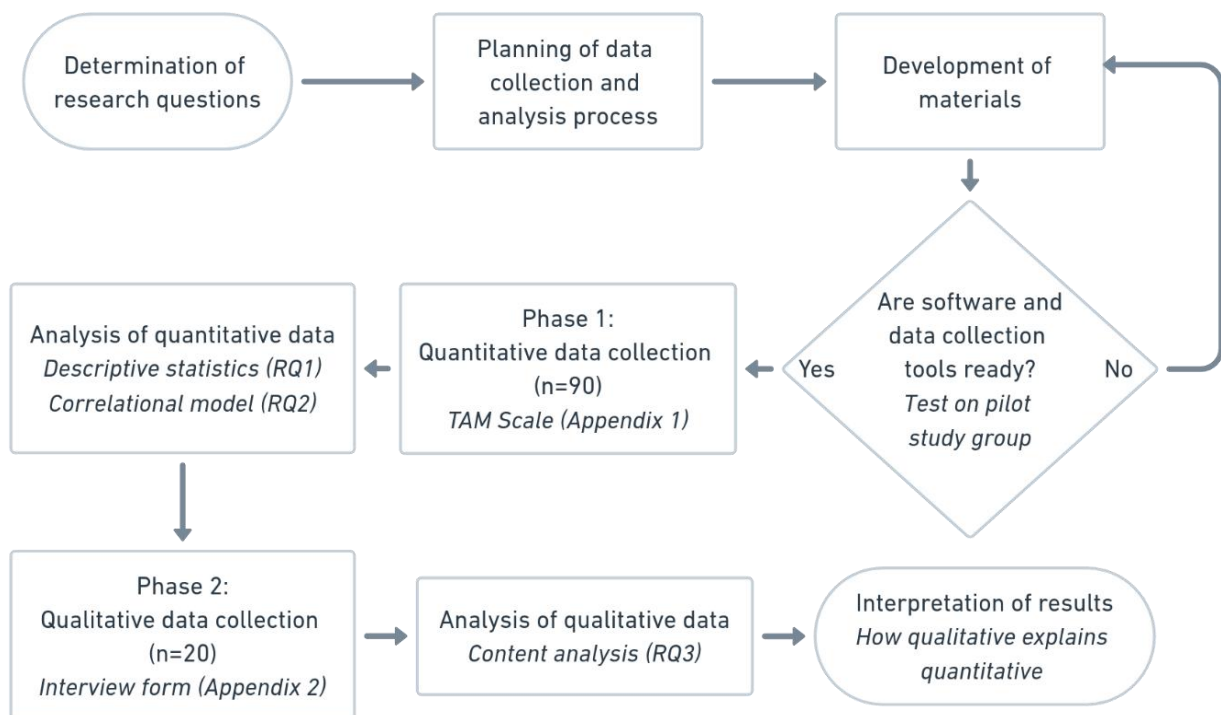
These five factors were selected to give both cognitive (PU, PEU, ATU) and affective (CA) coverage of acceptance, together with external enablers (FC), providing a more holistic assessment than studies relying solely on PU and PEU.

Methodology

Research Design

This research is designed according to the principles of explanatory sequential mixed methods research and uses both quantitative and qualitative research methods (QUAN→qual) to find answers to the research questions, respectively (Creswell & Creswell, 2018). In the literature, some studies using the TAM scale (de la Mora Velasco et al., 2025; Hamkah et al., 2025) are structured within a quantitative research design and primarily aim to test predefined hypotheses. In contrast, other studies (Greer & Abel, 2022; Liu et al., 2019) adopt a mixed-methods design, combining quantitative and qualitative approaches to explore research questions in greater depth. In line with the latter approach, the present study is also based on an explanatory sequential mixed-methods design. Thus, qualitative analysis aims to better explain the quantitative data analysis. Figure 1 illustrates the mixed method research strategy of this research adapted from Creswell and Creswell (2018).

Figure 1. Mixed methods research strategy



The AI-Powered Secure Online Examination System

A central element of this study is the web-based AI-powered secure online examination system that was developed by the researchers to serve as the technological platform for the exams. Unlike conventional online exam platforms that rely primarily on manual proctoring or basic browser lockdown features, this system incorporates multiple layers of AI-driven security designed to both prevent and detect cheating in real time. The following subsections describe the system's architecture and its key security features in detail.

The system operates as a web application accessible through standard browsers. Upon logging in, students are required to grant access to their webcam and microphone before the exam can begin. The system enforces full-screen mode throughout the examination and restricts students from opening new browser tabs, using keyboard shortcuts, or right-clicking. Questions are presented one at a time in randomized order, with answer options also randomized, and students are unable to return to previously answered questions. These rule-based prevention mechanisms form the first layer of security.

The second layer involves AI-powered real-time detection capabilities. Using image processing techniques, the system continuously analyzes the webcam feed to detect multiple faces in the frame, the absence of a face (indicating the student may have left the screen), and the presence of forbidden objects such as mobile phones or books. Voice analysis algorithms monitor the audio feed to detect moments when silence is broken, which may indicate verbal communication with others. Additionally, the system logs and analyzes data on IP addresses, response timing, keyboard usage patterns, and answer-changing behavior to identify anomalous patterns that may indicate dishonesty. For example, the system flags students who answer difficult questions in unusually short times, who switch correct answers after initially selecting incorrect ones, or who take the exam from unauthorized IP addresses. In terms of the underlying AI, these capabilities can be grouped into three categories: computer-vision-based image processing for face and forbidden-object detection, audio-based voice activity detection, and log-based anomaly detection of behavioural data (such as IP, response-timing, answer-changing, and keystroke patterns).

The combination of prevention-oriented restrictions and AI-powered detection mechanisms distinguishes this system from traditional online examination tools. A complete list of the system's security features for cheating prevention is provided in Appendix 1, and the AI-powered detection features are detailed in Appendix 2. Researchers determined these security features by systematically analyzing the existing literature (Topuz & Karaman, 2017).

It is important to note that the system was designed with ethical considerations in mind. Webcam images and audio recordings were processed locally for real-time analysis and stored securely with restricted access limited to authorized instructors and researchers. Students were fully informed about the nature and extent of monitoring prior to each examination, and explicit consent was obtained as part of the ethics protocol. The system did not employ biometric identification beyond the examination session, and all recorded data were used solely for the purposes of exam integrity verification and research analysis. These measures align with the ethical guidelines recommended by Coghlan et al. (2021) for responsible implementation of online exam supervision technologies.

Data Collecting Tools

This research includes two data collection tools, namely (i) five-point Likert-type TAM scale for RQ1 and RQ2, and (ii) the semi-structured interview form for RQ3.

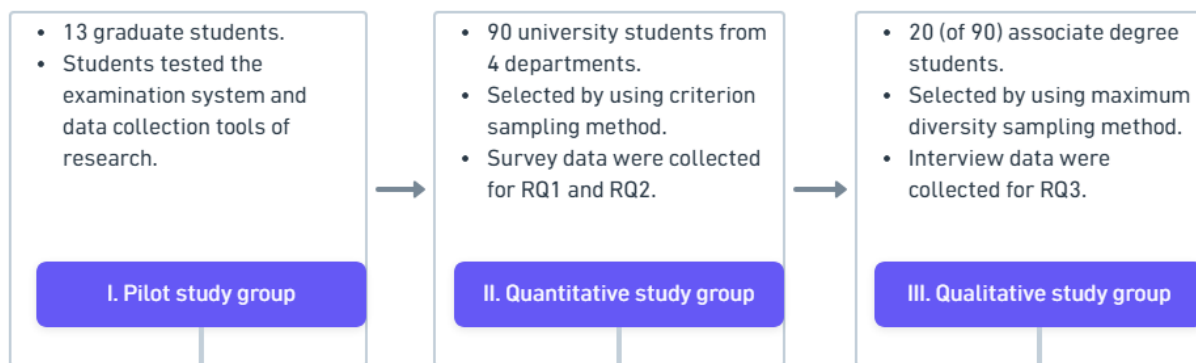
To determine the level of students' acceptance of AI-powered secure online exams (RQ1), the quantitative data have been collected using the three fundamental factors of the TAM (PU, PEU, and ATU). To explore the bilateral relationships among the TAM factors (RQ2), two important variables related to technology acceptance (Ursavaş et al., 2014; Venkatesh & Bala, 2008; Venkatesh et al., 2012) have also been included in the scale, namely CA and FC. In order to avoid the need to translate the statements/items of the selected five factors, this study adopted the items proposed by Ursavaş et al. (2014), as the items were presented in the language of the participants. Although the original instrument was developed for teachers, the constructs it measures (Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Facilitating Conditions, and Computer Anxiety) are not specific to the teaching role but reflect general user beliefs about technology; the items were therefore applicable to students with only minor contextual wording adaptation. The suitability of the instrument for the student sample was further verified empirically through the pilot study and the factor-structure confirmation reported in the Validity and Reliability subsection.

For the third research question (RQ3), a semi-structured interview form was created depending on the guideline proposed by Yıldırım and Şimşek (2008). This interview form includes six open-ended questions to collect qualitative data related to the students' acceptance of AI-powered online exams within the framework of TAM factors.

Study Group

This research has three study groups, namely (i) pilot study group, (ii) quantitative study group, and (iii) qualitative study group. The required informed consent was obtained from participants and ethics approval was obtained from the Ethics Committee of *Ardahan University in Türkiye* (decision no. 46639018/29 and dated 04 May 2015). Figure 2 shows a summary about the study groups.

Figure 2. Study groups



Firstly, participants in pilot study group have consisted of 13 graduate students. They participated in two online exams using the developed examination system. Then, software bugs in the online examination system were detected and fixed. Besides, the data collection tools (survey and interview questions) were also tested.

Secondly, the quantitative study group consisted of 90 university students (female: 34, male: 56, average age: ~24) from four different departments, namely: Computer Programming (CP1), Office Management and Executive Assistant - Formal Education (OM1), Office Management and Executive Assistant - Second Education (OM2), and Medical Documentation and Secretarial (MD1). Due to the difficulty of conducting online exams with all courses, the “criterion sampling” method, one of the “purposive sampling” methods (Yıldırım & Şimşek, 2008), has been used while determining the courses and departments. The criteria used to determine which departments' students will be selected are defined as follows: the number of students enrolled in the course was required to be less than 36, as 40 computers were available in the computer laboratory and four of them needed to be kept as spare. In addition, approval from the course instructors was required, and the instructor teaching the course had to agree to conduct the final exam using the online examination system developed within the scope of this research. Furthermore, the exam questions were required to be prepared in a multiple-choice format, and the use of a keyboard during the exam was not allowed. Finally, students were required to answer the exam questions without using pen or paper, and the use of pen and paper during the exam was strictly prohibited.

Thirdly, participants of the qualitative study group were selected from the quantitative study group using “sequential mixed method sampling” (Teddlie & Yu, 2007). After all students in the quantitative study group participated in two different online exams through the developed online examination system, qualitative study group was selected using the maximum diversity sampling method (Yıldırım & Şimşek, 2008) by taking into account the students' gender and exam passing status. Thus, the qualitative study group consists of 20 students (9 females and 11 males): balanced across gender and exam-passing status, including students who passed both, only one, or neither of the two exams.

Data Analysis

Data analysis was conducted in two stages, namely (i) analysis of quantitative data collected via TAM scale for RQ1 and RQ2, and (ii) analysis of qualitative data collected via interviews for RQ3, following the sequential mixed methods research design proposed by Creswell and Creswell (2018).

Firstly, in order to determine the acceptance level of AI-powered online exams for RQ1, the arithmetic mean of three factors (PU, PEU and ATU) has been calculated. In order to examine the bilateral relationships among the five factors related to students' acceptance of AI-powered online exams (for RQ2), the normal distribution status of the data was questioned. When looking at the kurtosis and skewness values of the five TAM factors, it was understood that all factors met the normality assumption according to Cain et al. (2017), as the kurtosis and skewness values were between -1 and +1. Therefore, the data were analyzed using the Pearson correlation coefficient method in SPSS 22 for RQ2.

Secondly, the qualitative data were analyzed using the content analysis method in order to identify the factors that influence students' acceptance of AI-powered online exams within the framework of TAM factors for RQ3. In order to explain the quantitative findings on students' technology acceptance levels of AI-powered online exams through qualitative insights into the factors influencing their acceptance, the coding process was conducted in two stages: (i) initial coding and (ii) focused coding, following Charmaz (2006). The first author conducted the initial coding of the transcribed interviews using the TAM as a guiding framework. The second author then independently reviewed and refined the coding scheme to enhance content validity and ensure analytical trustworthiness. Thus, codes were derived to capture and explain the five factors of the TAM framework. The coding process was carried out by authors through a software called NVivo 8. To ensure the trustworthiness of the qualitative findings, several strategies were employed. First, the two-stage coding process (initial and focused coding) with independent review by both authors served as a form of investigator triangulation, reducing individual bias in code assignment. Second, the use of maximum diversity sampling for the qualitative study group ensured that a broad range of student perspectives (varying by gender, exam performance, and department) were represented, enhancing the transferability of the findings. Third, the use of direct participant quotations throughout the results section provides an audit trail that allows readers to assess the credibility of the interpretive claims. Finally, the integration of quantitative and qualitative findings through the explanatory sequential design enabled methodological triangulation, where qualitative insights were used to explain and contextualize quantitative patterns, thereby strengthening the overall validity of the conclusions.

Validity and Reliability

Before data analysis, an Exploratory Factor Analysis (EFA) was conducted because the scale was applied to a new sample, even though EFA had already been deemed appropriate in the study in which the TAM scale was developed (Ursavaş et al., 2014). Appendix 3 shows the new Cronbach's alpha values for each factor. The Cronbach's alpha internal consistency reliability coefficient of the data was calculated as 0.893 for 5 factors in the scale. Cronbach's alpha value greater than 0.7 indicates high reliability of the scale (Hair et al., 2017). Thus, all factors were considered reliable and deemed suitable for further analysis. On the other hand, in order to test construct validity, KMO and Bartlett's test of sphericity value was calculated as 0.834 using SPSS 22 with the following parameters for 17 items in the scale: method is "principal component", analysis is "correlation matrix", rotation method is "direct oblimin", and rotation method delta is "0". Besides, factor loadings were calculated and were found to range between 0.550 and 0.806 ($p < .001$). Thus, the data were assumed to be reliable, the measurement model demonstrates acceptable construct validity, and the sample size was sufficient to explain the factors (Büyüköztürk, 2011, p126). Although the sample size of 90 may appear modest, it meets established guidelines for factor analysis (participant-to-item ratio of 5.3:1; Hair et al., 2017). Together with the pilot study, these procedures (EFA and internal-consistency reliability) indicate that the teacher-based TAM scale is appropriate for use in the student context.

Research Procedures

Two courses were selected from each department, and students took the AI-powered online exams twice. The purpose of having students use the system twice is to give them more experience to comment on the AI-powered system from different perspectives.

Quantitative data have been collected through an open-source online survey system called LimeSurvey. The examination system has automatically shown an online survey screen to students who completed the second online exam.

Qualitative data have been collected through interviews. Firstly, each student in the qualitative study group was asked for an appointment. The interviews were then conducted in a suitable classroom and recorded with a voice recorder after obtaining the necessary permission from each participant. Approximately 485 minutes of audio were obtained from interviews with a total of 20 participants.

Limitations

This research has three limitations. Firstly, the sample size is limited to 90 students in four departments. However, as discussed in the Data Analysis section, the sample size satisfies established criteria for exploratory factor analysis (participant-to-item ratio of 5.3:1, KMO = 0.834), and the mixed-methods design compensates for the modest quantitative sample by providing rich qualitative data from 20 in-depth interviews totaling approximately 485 minutes of recorded audio, which enabled detailed thematic saturation across the five TAM factors.

Secondly, students' opinions about AI-powered secure online exams are limited to the system developed within the scope of this research. While this limits generalizability to other AI-powered examination platforms, it also constitutes a methodological strength: by developing and implementing a purpose-built system with documented security features (detailed in Appendices 1 and 2), this study provides a controlled and replicable context for examining technology acceptance, unlike studies that rely on commercially available tools whose features may vary across versions and institutions.

Thirdly, students' secure online exam experience with this system is limited to computer labs, not homes. This limitation was a deliberate methodological choice to ensure standardized testing conditions across all participants. Nonetheless, the qualitative interviews captured extensive student perspectives on hypothetical home-based administration, and these insights (presented in Tables 2 and 4) provide a preliminary basis for understanding how the exam environment may influence acceptance. Future research should empirically test the system in home environments to validate these preliminary qualitative findings. Because the exams were administered in a controlled computer laboratory, the transferability of these findings to home-based open and distance learning (ODL) settings remains an open empirical question. Home-based administration would also raise additional data-protection considerations (such as the processing of webcam and audio data in private living spaces) and equity concerns related to the digital divide, given that students differ in their access to suitable devices, stable internet connections, and private examination environments.

Fourthly, the AI-powered nature of the system raises ethical considerations that may have influenced participants' responses. Continuous monitoring (including webcam and microphone surveillance, response-timing, and keystroke analysis) may in itself elevate computer anxiety; in addition, the possibility of false positives (for example, due to technical problems or the behaviour of neurodivergent students) and the limited transparency and explainability of automated detection (including the absence of a human-in-the-loop mechanism) may have shaped how students responded to the TAM scale and the interviews. These factors should therefore be borne in mind when interpreting the validity, reliability, and interpretation of the findings.

Findings

This section presents the empirical findings organized by the three research questions. The interpretation and contextualization of these findings in relation to the existing literature are presented separately in the Discussion section.

RQ1: Students' Technology Acceptance Level of AI-Powered Secure Online Exams

The first research question aims to determine students' acceptance level of AI-powered secure online exams. Table 1 shows the averages of each TAM factor.

Table 1. Students' technology acceptance level of the AI-powered secure online exams

TAM Factors	n	Min	Max	M	SD
1) Perceived Usefulness	90	1	5	2.61	1.06
2) Perceived Ease of Use	90	1	5	2.96	1.09
3) Attitude Toward Use	90	1	5	2.65	1.05
4) Computer Anxiety	90	1	5	3.10	1.10
5) Facilitating Conditions	90	1	5	3.00	1.10
<i>Level of technology acceptance*</i>	90	1	5	2.74	0.95

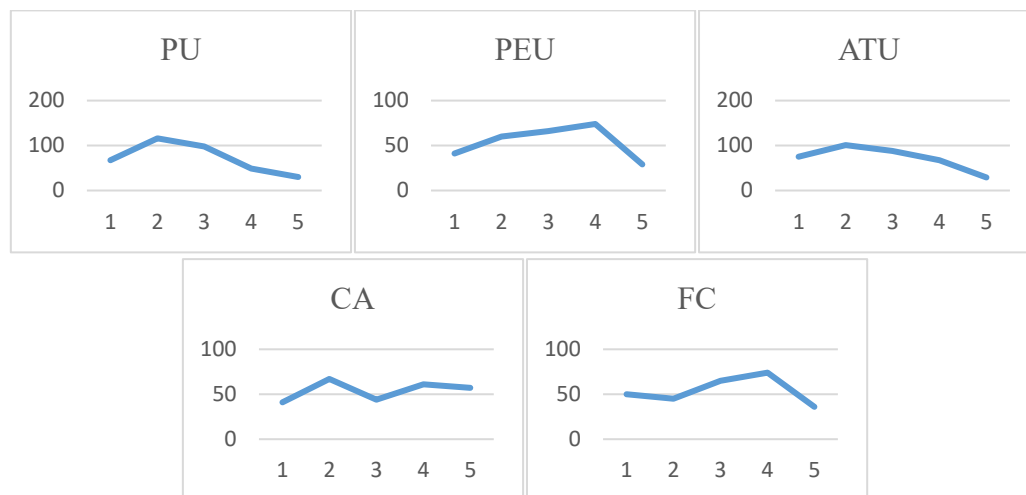
* *The level of technology acceptance was calculated by taking the average of the first three factors.*

The overall mean technology acceptance score was 2.74 (SD = 0.95) on a five-point scale, placing students' acceptance at a moderate level, slightly below the scale midpoint of 3.00. This suggests that students, on average, neither strongly endorsed nor strongly rejected the AI-powered secure online examination system. Among the three core acceptance factors, Perceived Ease of Use had the highest mean (M = 2.96, SD = 1.09), approaching the scale midpoint, indicating that students found the system relatively manageable to operate. Perceived Usefulness (M = 2.61, SD = 1.06) and Attitude Toward Use (M = 2.65, SD = 1.05) fell below the midpoint, suggesting that students were somewhat uncertain about the system's benefits and held slightly unfavorable attitudes toward its use.

Regarding the supplementary factors, Computer Anxiety yielded the highest mean across all five factors (M = 3.10, SD = 1.10). It is important to note that this factor is reverse-coded relative to the others: higher scores on CA reflect greater anxiety. A mean above the midpoint indicates that students, on average, experienced moderate to elevated anxiety when using the system. Facilitating Conditions scored at the midpoint (M = 3.00, SD = 1.10), indicating moderate perceptions of available support. The standard deviations across all factors ranged from 1.05 to 1.10, reflecting substantial individual variability in responses and suggesting that student experiences with the system were far from uniform. To contextualize these findings, a mean score of 2.74 on a five-point scale corresponds to the "disagree" to "neutral" range, indicating that the average student perception leans slightly toward uncertainty rather than clear rejection. The relatively narrow spread of mean scores across the three core factors (ranging from 2.61 to 2.96) suggests that perceptions of usefulness, ease of use, and attitude were broadly aligned rather than divergent, which strengthens the interpretive coherence of the overall acceptance score.

The full range of responses (1 to 5) was observed for every factor, further confirming the heterogeneity of student perceptions. To better understand students' acceptance of AI-powered online exams on a factor-by-factor basis, Figure 3 shows the total number of students' choices for each factor.

Figure 3. Total number of choices for 5-point Likert-type TAM scale



An examination of the response distributions presented in Figure 3 reveals distinct patterns across factors. For PEU and FC, the distributions were left-skewed (negatively skewed), indicating that a greater proportion of students selected higher agreement values. Conversely, PU and ATU exhibited right-skewed (positively skewed) distributions, with more students expressing disagreement. The CA factor displayed a bimodal pattern, with the most frequently selected options being “2” and “4,” suggesting a polarized response distribution. This bimodal pattern indicates that the sample can be roughly divided into two groups: students who reported relatively low anxiety (selecting “2”) and those who reported relatively high anxiety (selecting “4”) about taking AI-powered online exams.

Selected student statements are presented below to illustrate students’ perspectives on AI-powered online exams across the identified factors.

“The questions themselves are already complex, and on top of that, the camera system is very effective, conversations and everything are being recorded. The likelihood of students being able to cheat is one in a million.” [S3]

“It would be better if it were applied in verbal/social science courses, but it should not be used at all in quantitative courses. If they are going to implement it, they should do so in verbal courses. If it were like that [in quantitative courses], I would rather it not exist at all [laughs].” [S14]

“They would truly get what they deserve. After all, there would be no room for things like ‘I will talk to the instructor and pass’ or ‘I will cheat’ and so on — the possibility of cheating would be zero percent. Everything would be reflected on that paper. Whatever they know or do not know would all be there, with no additional advantages.” [S10]

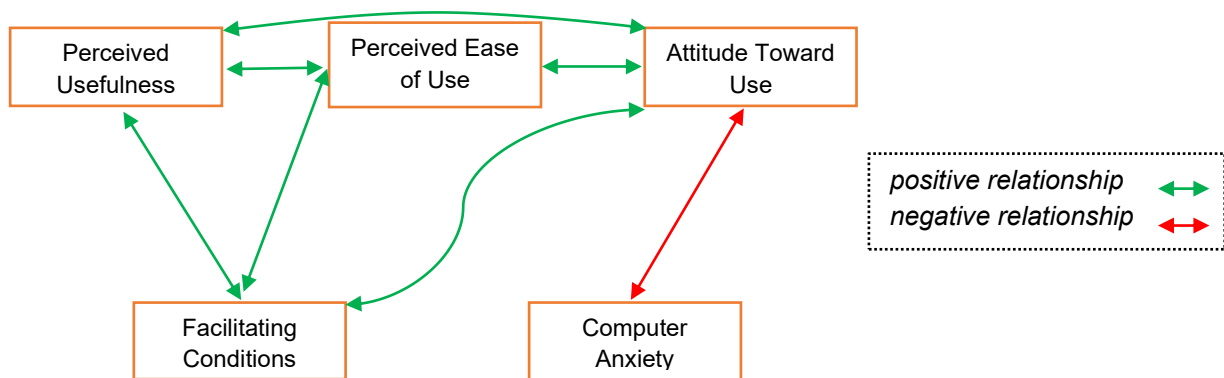
“I could not even move my eyes; I was afraid. Not because I was actually going to cheat, but I was worried that my gaze might accidentally drift, and I feared whether I would be accused of something like that. What if it were misunderstood, you know [laughs].” [S19]

“When a question is marked, a small pop-up window should appear asking ‘Are you sure about this question? Shall we move on to the next one?’, and then proceed, so that the person does not accidentally skip two questions at once.” [S9]

RQ2: Relationships Among the TAM Factors

The second research question examines the existence of a statistically significant bilateral relationship among the TAM factors. Appendix 4 shows the results obtained as a result of questioning the bilateral relationships among the five factors using the Pearson correlation coefficient method. To provide a visual summary of these relationships, Figure 4 shows these statistically significant relationships with green (positive) and red (negative) arrows.

Figure 4. Statistically significant relationships among the TAM factors



The correlation analysis revealed statistically significant positive correlations ($p < .05$) among PU, PEU, ATU, and FC. The strongest correlation was observed between PU and ATU ($r = 0.80$, $p < .001$), indicating a strong positive association between students' perceptions of usefulness and their attitudes toward using the system. PEU and FC also showed a strong positive correlation ($r = 0.70$, $p < .001$), suggesting that students who perceived greater availability of technical support also found the system easier to use. Moderate positive correlations were found between PU and PEU ($r = 0.64$, $p < .001$), PEU and ATU ($r = 0.64$, $p < .001$), PU and FC ($r = 0.55$, $p < .001$), and ATU and FC ($r = 0.56$, $p < .001$).

Regarding Computer Anxiety, only one statistically significant correlation was found: a weak negative correlation between CA and ATU ($r = -0.24$, $p = .03$). This indicates that higher levels of anxiety were associated with less favorable attitudes toward using the system, although the effect size was small. The correlations between CA and the remaining factors (PU: $r = -0.16$, $p = .13$; PEU: $r = -0.02$, $p = .82$; FC: $r = 0.18$, $p = .09$) were not statistically significant, suggesting that anxiety operated relatively independently of students' perceptions of usefulness, ease of use, and facilitating conditions.

RQ3: Factors Affecting Students' Acceptance

The third research question identifies the factors that influence students' acceptance of the AI-powered security-enhanced online examination systems in terms of the following five TAM factors: (1) Perceived Usefulness, (2) Perceived Ease of Use, (3) Attitude Toward Use, (4) Anxiety, and (5) Facilitating Conditions. The qualitative findings from the semi-structured interviews with 20 students are presented below, organized by TAM factor. For each factor, the key categories, codes, and illustrative student quotes are summarized in the accompanying tables, followed by an interpretive narrative that contextualizes the findings.

Perceived Usefulness

Students' views on the Perceived Usefulness of AI-powered secure online exams are classified under four categories in Table 2: (a) adequacy of the security measures, (b) deterrence of the security measures, (c) efficiency of students' preparation for the exam, and (d) effectiveness of AI-assisted surveillance.

Table 2. Factors affecting Perceived Usefulness of AI-powered secure online exams

Categories	Codes
<i>a) Adequacy of the security measures</i>	
Adequate in the computer lab	*Camera monitoring is enabled, *Audio recording is active, *Questions are presented in randomized order, *Opening new browser tabs is restricted *A proctor is present, *Returning to previous questions is not permitted.

Adequate at home	*Camera monitoring is enabled, *Audio recording is active, *Opening new browser tabs is restricted.
Insufficient at home	*Notes could be written on the wall behind the screen, *Students may find alternative ways to circumvent the system, *Notes could be written directly on the screen, *Assistance could be received from another person positioned behind the screen, *An additional camera should be installed in the room, *Materials could be placed behind the screen, *A second computer, tablet, or mobile device could be utilized.
<i>b) Deterrence of the security measures</i>	
I've never tried to cheat	*Camera monitoring was active, *Audio recording was in place, *I was afraid of being caught, *A proctor was present, *The allotted time was insufficient.
I tried to cheat but failed	*Questions were presented in randomized order, *Camera monitoring was active, *Audio recording was in place, *A proctor was present.
<i>c) Efficiency of students' preparation for the exam</i>	
Made me feel compelled to study for the exam	*I felt compelled to study more diligently.
Increased the amount of time I had to study for the exam	*Due to the inability to engage in cheating, *Due to the inability to return to unanswered questions, *Due to the heightened sense of anxiety associated with computer-based testing, *Due to the concern that the allotted time would be insufficient.
Increases my academic achievement	*Academic achievement increases as students are compelled to study due to the inability to cheat, *It leads to higher scores on university entrance examinations, *Education is elevated to new dimensions.
<i>d) Effectiveness of AI-assisted surveillance</i>	
AI-assisted surveillance is effective	*Camera and audio monitoring effectively prevent cheating, *A proctor may overlook instances of dishonesty, *In AI-powered online examination systems, each student is individually monitored by a virtual proctor.

The findings presented in Table 2 reveal a nuanced picture of students' perceptions of the system's usefulness. Within the category of adequacy of security measures, students' perceptions differed based on the exam setting (home vs. computer lab). Students have expressed that the technical measures in AI-powered online exams will be sufficient for the exams to be held in the computer laboratory, but those measures may not be sufficient at the home environment. For instance, students identified specific vulnerabilities in the home setting, such as the ability to place notes behind the monitor, receive assistance from another person outside the camera's view, or use a secondary device, which they felt were adequately controlled in the supervised laboratory environment. The second category of PU concerns the deterrence of security measures in the system. In this regard, most of the students have stated that they could not cheat in the exams because the technical measures in the system were deterrent enough. Notably, even students who reported attempting to cheat (e.g., by looking at a neighbor's screen) described being thwarted by features such as question randomization and camera monitoring. The third category of PU is related to the efficiency of exam preparation, and students stated that they work harder while preparing for exams and that it has a positive effect on their academic success as they take the exam more seriously. Several students provided specific examples of increasing their study time from approximately one hour to three or more hours when they knew the

exam would be administered through the secure system. The fourth category called the effectiveness of AI-assisted surveillance, has revealed that taking camera images, recording audio, and having some restrictions in the software are the factors that enable students to find this system effective. Students contrasted the system favorably with traditional human proctoring, noting that the automated system monitors each student individually and continuously, whereas a single instructor may be unable to observe an entire classroom simultaneously.

In order to illustrate students' perspectives regarding Perceived Usefulness of AI-powered secure online exams, selected student statements are presented below.

"We were afraid to even lift our heads. If there had been no camera system, cheating might have been possible; however, the camera system was in place. The camera continuously monitors the student, and there is also an audio recording system. This is typically how cheating would occur, but since both monitoring systems are present, it is effectively prevented." [S1]

"When we took the exam for the second time, we had already learned from our first experience, which led us to adjust our study approach. We felt compelled to study more out of concern that we might not pass. Although we had already prepared, we studied an additional three to five hours" [S15]

"I was not able to cheat in the laboratory exam; however, in other exams we have taken, we cheated like everyone else. The system is effective in preventing cheating, because video and audio recordings are in place, cheating is not easy. If someone attempts to cheat, the exam is cancelled." [S20]

Perceived Ease of Use

Students' views on the Perceived Ease of Use of AI-powered secure online exams are classified under three categories in Table 3: (a) level of education, (b) structure of courses, and (c) question answering method.

Table 3. Factors affecting Perceived Ease of Use of AI-powered secure online exams

Categories	Codes
<i>a) Level of education (students can find it easy to use)</i>	
Middle school, high school and university	*Younger students may lack sufficient computer proficiency, *Implementation should commence at the middle school level to allow students to become accustomed to the system, *The system should be utilized at the high school level to enhance success in university entrance examinations, *Cheating behavior typically begins at the high school level, *Implementation should commence at the high school level to allow students to become familiarized with the system, *Younger students may experience elevated levels of stress, *Computer laboratories may not be available in all educational settings.
Not at primary school	*Children may not yet have the necessary awareness or understanding.
<i>b) Structure of courses (Suitable for AI-Powered Online Exams)</i>	
Only verbal courses	*Only the exams of verbal courses, since students cannot do numerical operations without pen and paper
All courses	*If there is a calculator on the screen, in the exams of all courses
<i>c) Question answering method</i>	
Multiple choice method as it is advantageous in terms of answering speed	*Multiple-choice examinations are advantageous in terms of response speed, *Expressing oneself within a limited timeframe is challenging in conventional written examinations, *Writing errors may occur in conventional written examinations,

	Immediate disclosure of results in multiple-choice examinations is beneficial, *Conventional written examinations require more extensive preparation, *Multiple-choice questions serve as effective recall prompts, *Scoring in conventional written examinations is subjective, whereas it is objective and definitive in multiple-choice examinations.
Open-ended method as distractors can mislead	*Distractors in multiple-choice options may be misleading, *My typing speed is fast.

As shown in Table 3, participants indicated that a minimum education level of high school or university would be necessary for users to find the system easy to use. Students raised concerns about younger learners' computer proficiency and suggested that implementation should be gradual, beginning at the middle school level to allow familiarization before high-stakes use at higher education levels. Students have also stated that AI-powered online exams can provide ease of use for only exams of verbal courses since numerical operations could not be done without a pen and paper. However, some students noted that if an on-screen calculator were provided, the system could be extended to quantitative courses, though this might create disparities based on students' familiarity with digital calculation tools. Lastly, they emphasized that the multiple-choice method would provide ease of use instead of open-ended questions due to the effect of writing speed and difficulty in expressing answers in a limited time.

In order to illustrate students' perspectives regarding Perceived Ease of Use of AI-powered secure online exams, selected student statements are presented below.

"I believe these exams would be more suitable for verbal subjects, and I do not think they would be appropriate for mathematics exams. In this respect, the system could be beneficial. It appears to be well-suited for multiple-choice assessments in verbal courses." [S8]

"In quantitative exams, the system could be used if a calculator were provided on the screen. However, this would still introduce certain differences among students. Those with prior experience using such tools might have an advantage, while others could become anxious and struggle, particularly since they would need to enter their responses within the system. Some students genuinely do not know how to use a calculator effectively; there are even those who cannot calculate square roots. In a stressful exam setting, they may not know what to compute or may become overwhelmed and fail to complete the task. Nevertheless, the system could still be advantageous. Students who understand the underlying logic of the problems and are familiar with using the calculator could perform well. Those who have practiced and are accustomed to the tool would benefit, whereas others might not..." [S11]

"I believe this system would be particularly beneficial at both the high school and university levels. Cheating is more common in high school; I know this from personal experience. In my opinion, high school teachers often do not place sufficient emphasis on preventing it. Therefore, if such a system were implemented in high schools, students would advance based on their actual performance and merit. It would certainly contribute positively to the university admission process." [S13]

Attitude Toward Use

Students' views on the Attitude Toward Use of AI-powered secure online exams are classified under two categories in Table 4: (a) desire for justice and (b) preference for the exam environment.

Table 4. Factors affecting Attitude Toward Use of AI-powered secure online exams

Categories	Codes
<i>a) Desire for justice (academic honesty)</i>	
I would like to use in all exams to ensure justice	*I desire the prevention of cheating to ensure fairness, *I expect every student to receive the grade they deserve, *I do not want instructors to provide assistance to students during examinations.
I do not want to use because I cannot cheat	*Increased security measures induce stress, *We are unable to cheat.

<i>b) Preference for the exam environment</i>	
I prefer to use in a computer laboratory	*Someone can cheat at home, *Computer lab helps me get in the mood for exams.
I prefer to use at home	*Home is more comfortable, *I could engage in cheating at home.

Table 4 reveals that the desire for academic justice was the primary driver of positive attitudes. The majority of the students have emphasized the sense of justice and stated that they wanted this system to be used in all exams so that everyone could get the grade they deserve. It is particularly noteworthy that some students expressed frustration not only with peer cheating but also with perceived instructor favoritism, suggesting that the system's automated and objective grading was seen as a safeguard against multiple forms of unfairness. A minority of students expressed negative attitudes, explicitly acknowledging that their opposition stemmed from the inability to cheat, a finding that underscores the honest self-reporting facilitated by the interview format. The second category obtained from the statements of the students about the ATU is related to the environment preferences. The majority of the students have stated that they wanted everyone to attend the online exams in a computer laboratory instead of at home since it would be safer.

In order to illustrate students' perspectives regarding Attitude Toward Use of AI-powered secure online exams, selected student statements are presented below.

"I would like everyone to take the exam under equal conditions, using an enhanced and secure camera monitoring system. To be candid, it is frustrating when someone who has not studied achieves a higher grade than I do." [S2]

"I prefer the exam to be conducted in a laboratory setting. It should not be held at home. In the laboratory, there is a sense of seriousness and awareness that one is part of a formal examination process. At home, there is inevitably a degree of comfort and informality; however, in the laboratory environment, I feel more secure. There is a greater sense of discipline and seriousness, which makes it more suitable for me." [S12]

Anxiety

Students' views on the Anxiety of AI-powered secure online exams are classified under three categories in Table 5: (a) anxiety for misdetection, (b) anxiety for camera surveillance, and (c) anxiety about not being able to return to marked questions.

Table 5. Factors affecting Anxiety of AI-powered secure online exams

Categories	Codes
<i>a) Anxiety for misdetection</i>	
Worry about misunderstanding	*Eyes may inadvertently wander at times, *We occasionally glance at the instructors.
<i>b) Anxiety for camera surveillance</i>	
Being watched by camera disturbed	*Due to concerns regarding the identity of the individual monitoring through the camera, *Due to the effort to remain within the camera's field of view, *Due to encountering such a system for the first time, *Due to the camera causing difficulties in maintaining concentration.
Being watched by camera not disturbed	*As I believe the camera does not exert a negative influence, whereas an instructor potentially could, *As I consider it necessary for the purpose of examination security, *As no human observer is monitoring through the camera.
<i>c) Anxiety about not being able to return to the marked questions</i>	
It should be possible to return to the marked question	*The inability to return to previous questions induces stress,

	*We may recall the answer at a later point during the examination.
It should not be allowed turn as it may enable cheating	*To prevent cheating by looking at the work of adjacent examinees.

The anxiety findings presented in Table 5 are particularly important given that Computer Anxiety was the highest-scoring factor in the quantitative analysis ($M = 3.10$). The misdetection category revealed that students expressed concern regarding the possibility of being falsely flagged for academic dishonesty during examinations as a consequence of system misidentification. Students described specific situations, such as involuntarily glancing sideways while reading or looking up at the instructor, that they feared would be misinterpreted as cheating behavior by the AI system. This finding highlights a tension between the security objectives of the system and the natural physical behaviors of exam-takers. Another anxiety is about camera surveillance and the students highlighted that the anxiety caused by the camera surveillance stemmed from not knowing who was watching from the camera and making an effort to stay in the camera's view. Interestingly, several students who reported that camera monitoring did not disturb them attributed this to the knowledge that the monitoring was automated (i.e., performed by AI) rather than by a human observer, suggesting that the agent of surveillance (human vs. machine) influences anxiety levels. The third dimension of anxiety is related to the inability to return to marked or skipped questions. Although this prevention is suggested by the literature (Cluskey Jr. et al., 2011; Giruzzi et al., 2022; Moten et al., 2013), the majority of the students stated that it causes anxiety. Some students noted that this restriction, while stressful, also motivated them to prepare more thoroughly for the exams.

In order to illustrate students' perspectives regarding Anxiety of AI-powered secure online exams, selected student statements are presented below.

"The absence of a back button was very problematic. Because at that moment you might not remember [the answer], you move on to the next question, and then you remember it — that was a bit frustrating. Other than that, it was good in terms of monitoring; no one was looking around, everyone was just focused on their own exam." [S7]

"It was uncomfortable because I could not fully relax. I was worried that my eyes might unintentionally wander. In a traditional exam, I can simply lower my head and focus on my paper as I wish. In this format, I kept wondering whether I should look at the camera or at the questions, trying to ensure that my gaze did not shift elsewhere, and the time passed quickly. I felt uneasy because I thought the computer might assume I was attempting to cheat. Apart from that, it was fine." [S14]

Facilitating Conditions

Students' views on the Facilitating Conditions of AI-powered secure online exams are classified under two categories in Table 6: (a) presence of a proctor in the exam environment and (b) availability of support tools in the system.

Table 6. Factors affecting Facilitating Conditions of AI-powered secure online exams

Categories	Codes
<i>a) Presence of a proctor in the exam environment</i>	
There should be a supervisor to provide support	*To be able to receive technical assistance, *To be able to ask questions regarding the examination, *As a means of circumventing the system may potentially be found, *To ensure the solemnity of the examination environment, *To prevent any individual from distracting others during the examination.
No need for supervisors as cheating cannot be done	*The software alone is already sufficient to prevent cheating.
<i>b) Availability of support tools in the system</i>	

There should be a calculator	*To be able to solve questions involving numerical computations.
There should be a warning system	*A warning message could be displayed if the camera fails to detect the examinee's face, *A warning message could be issued to individuals attempting to cheat, *A confirmation prompt could be incorporated when proceeding to the next question.

The findings in Table 6 indicate that students' perceptions of facilitating conditions centered on two main areas. The reasons why students want to have a proctor in the laboratory during the exams were to get technical support by asking questions and to get help with the exam. An important observation from the implementation process was that technical support needs diminished considerably between the first and second exam administration, suggesting that familiarity with the system reduces the need for human assistance. Regarding the availability of support tools in the system, the students have stated that the use could be facilitated by the presence of a calculator plug-in on the screen and by increasing the information messages with the warning system. Students specifically suggested that the system should provide real-time visual feedback, such as a warning message when the camera cannot detect the student's face or when potentially suspicious behavior is identified, rather than recording infractions silently for later review. This preference for transparency in AI-mediated monitoring is a notable finding with implications for system design.

In order to illustrate students' perspectives regarding Facilitating Conditions of AI-powered secure online exams, selected student statements are presented below.

"There should be a proctor, but specifically for technical support purposes. If students encounter an issue and raise a question, there is nothing they can do in the absence of an instructor." [S2]

"In quantitative exams, it would be useful to have a calculator available in the corner [of the screen]. But again, it would create differences. Those who have experience with it would have an advantage, while others might get nervous since they would have to work on the system, they could also lose points because of that." [S11]

Discussions

This section interprets and contextualizes the findings in relation to the existing literature and the theoretical framework of the TAM.

Students' Moderate Acceptance and Its Implications (RQ1)

The moderate overall acceptance level ($M = 2.74$) observed in this study is consistent with the broader literature on students' mixed reactions to proctoring technologies. The existing literature on students' acceptance of online exams has shown that some of the students find online exams comfortable, fast, efficient, and flexible in the measurement and evaluation process (Saban et al., 2010). However, the literature also expresses that students' opinions may differ depending on the situation of increasing security in online exams. For instance, some of the students may be more limited in accepting the examination system due to the prevention of cheating in the exam (Sirakaya et al., 2015). Therefore, when the findings of this research are evaluated within this framework, the moderate acceptance of the system can be explained, on the one hand, by the flexibility and other contributions of the online exams, and on the other hand, by the discomfort caused by the increased security against cheating.

Relationships Among TAM Factors (RQ2)

The strong positive correlations observed among PU, PEU, ATU, and FC are consistent with the theoretical predictions of the TAM framework (Davis, 1989) and align with prior empirical findings. Although there are many studies in the literature examining the technology acceptance of students for e-learning systems, studies examining technologies for secure online examination systems are very

limited. Nevertheless, statistically significant bilateral relationships detected in those limited number of studies overlap with this research. For instance, Dizon (2016) has examined students' perceptions of internet-based tests with the TAM and has expressed that there is a positive relationship between PU and PEU factors. In addition, Jiang et al. (2023) found the same relationships when they examined student acceptance of online proctoring using an extended technology acceptance model. Moreover, that research also found a positive relationship between PU and online proctoring acceptance. The relationship between FC and PEU was supported in a study on the acceptance and use of computer-based assessment conducted by Terzis and Economides (2011). Finally, Imtiaz and Maarop (2014) reviewed technology acceptance studies in education and found the following important causal relationships for e-assessments, including but not limited to: PEU to PU and FC to PEU. Therefore, the existing literature supports the findings of this research on statistically significant relationships.

The negative correlation between Computer Anxiety and Attitude Toward Use ($r = -0.24$, $p = .03$), while statistically significant, was relatively weak. This finding is noteworthy because it suggests that anxiety, although present, does not overwhelmingly determine students' attitudes toward the system. The qualitative data provide a possible explanation: some students reported that their anxiety diminished between the first and second exam, suggesting that familiarity and experience may attenuate the negative influence of anxiety on attitudes over time. From a theoretical perspective, the pattern of correlations observed in this study provides empirical support for the applicability of the TAM framework to the specific domain of AI-powered secure online examinations. The strong correlation between PU and ATU ($r = 0.80$) and between PEU and FC ($r = 0.70$) suggests that the core mechanisms of technology acceptance theorized by Davis (1989) and extended by Venkatesh et al. (2003) operate as predicted even in high-stakes, surveillance-intensive assessment contexts. The relatively independent behavior of CA from the other factors (with only one significant, weak correlation) suggests that affective responses to AI-powered surveillance may constitute a distinct dimension of acceptance that warrants dedicated attention in future TAM extensions for AI-mediated educational technologies. The polarization in anxiety responses observed in the descriptive findings (with the sample dividing into relatively low- and high-anxiety groups) warrants further investigation, as it may reflect different levels of prior experience with online examinations or varying attitudes toward surveillance technologies.

Qualitative Insights and Practical Implications (RQ3)

The fourteen factors identified through the qualitative analysis extend the quantitative findings by revealing the specific mechanisms through which students form their acceptance judgments. Several findings deserve particular emphasis.

Some studies in the literature (Brouwer et al., 2017; Gudiño Paredes et al., 2021) have shown that secure online systems have positive reflections on the learning process. As opposed to this, there are also studies expressing that increasing security negatively affects the exam score (Fask et al., 2014) or that there is no difference (Hylton et al., 2016). At this point, the difference in the effect of security-enhanced examination systems on students may be due to the cultural differences of the students. As a matter of fact, it is known that in some cultures, students behave as if there is supervision in the unsupervised exam in the classroom, and there is no difference between taking the exam with or without supervision (Rios & Liu, 2017).

The finding that students' desire for academic justice was the primary driver of positive attitudes has important implications for how institutions communicate about AI-powered exam security. Framing these systems as tools for ensuring fairness and protecting honest students, rather than as surveillance mechanisms for catching cheaters, may enhance acceptance. In the existing literature, Gretes and Green (2000) have stated that online exams may have different effects on the exams of different courses. In addition, Johnson (2006) has stated that student success may differ according to the question format.

The distinction students drew between human and AI monitoring is also noteworthy. Students who reported that camera surveillance did not disturb them frequently attributed this to the knowledge that

monitoring was performed by an AI system rather than a human observer. This finding suggests that the perceived agency of the proctor influences anxiety levels and has implications for how institutions describe the monitoring process to students.

According to Blau and Eshet-Alkalai (2017), students find cheating in exams unethical. The present findings extend this observation by showing that students are not only opposed to cheating on ethical grounds but also may be receptive to technological enforcement of integrity standards, particularly when they perceive that the absence of enforcement creates unfair advantages for dishonest peers. This interpretation should be treated with caution, however: as the responses summarised in Table 2 suggest, the observed behaviour may partly reflect the constraints imposed by the system rather than students' attitudes alone, and further research is needed to disentangle these explanations. While taking into account the opinion of the students who stated that the measures in this system can be overcome if they attend the exam at home, the following situations can also be evaluated: (i) the students used the system only in the computer laboratory, (ii) the opinions about the home environment were based on interpretation, and (iii) all the students stated that the system prevented cheating in the laboratory environment.

The relationship between facilitating conditions and the diminishing need for technical support across exam administrations aligns with the suggestion by Coşkun and Mardikyan (2016) that practice exams can increase comfort with online exam systems. Sánchez et al. (2013) have expressed that technical support should be provided well in order to use the e-learning platform effectively. Based on the present findings, institutions implementing AI-powered exam systems should consider providing pre-exam tutorials or practice sessions to reduce initial anxiety and technical support needs, which may in turn positively affect students' acceptance of the system. It is important to acknowledge that the findings of this study should be interpreted within the cultural context in which the research was conducted. As Rios and Liu (2017) have noted, students' attitudes toward proctoring and academic integrity can vary across cultural settings. The strong emphasis on fairness and justice observed among participants in this study may reflect cultural values that prioritize collective equity in educational contexts. Future cross-cultural research would help determine the extent to which these findings generalize to other educational and cultural settings.

Conclusion and Suggestions

This research has examined higher education students' technology acceptance of AI-powered secure online exams based on quantitative and qualitative data within the framework of five TAM factors. The results have shown that students' acceptance level was moderate. At this point, qualitative data have revealed that students who want to cheat in online exams have a low level of technology acceptance, while those who want everyone to get the grade that they deserve are high. Thus, it has been concluded that students' acceptance of AI-powered secure online exams differs according to the students' perspectives on academic integrity in online exams.

The research has also determined fourteen factors affecting students' acceptance of AI-powered online exams and the factors that are related to each other. These factors and relations help us understanding the impact of AI-based security features on students' technology acceptance. Taking these factors into account, the acceptance level of students can be increased and thus the transition to AI-powered secure online exams can be facilitated. For instance, depending on the revealed findings of this research, in order to positively affect students' perceptions about the usefulness of an online examination system, the AI-powered security measures of the system should be sufficient, deterrent, and effective. In addition, preventing cheating in the exams arouses the feeling of studying more time for the exam and positively affects the Perceived Usefulness in this aspect. To enable students to Perceive Ease of Use, these kinds of systems can be used at the high schools and universities, in the exams of oral courses, and with multiple-choice answering methods. It is interpreted that participation in the online exam from the computer laboratory of the institution (instead of at home) and the presence of a supervisor for technical support in the exam environment will facilitate the use of the system. In order to reduce the

anxiety of being watched by the camera, it can be said to the students that the proctor is AI, not human. In order to reduce the concerns of misdetection, information can be given that there is a right to appeal if the determination is incorrect.

Suggestions for Future Studies

The system used in this study prevented students from advancing to the previous question, which is recommended in the literature as a safety measure (Cluskey Jr. et al., 2011; Giruzzi et al., 2022; Moten et al., 2013). However, this blocking was highly criticized by the students. Therefore, future studies may focus on developing solutions that address students' concerns while maintaining the integrity of security features. Additionally, future research should (a) replicate this study with larger and more diverse samples across multiple institutions and cultural contexts to enhance external validity, (b) employ longitudinal designs to examine how students' acceptance evolves over repeated exposure to AI-powered examination systems, (c) investigate the system's effectiveness in home-based settings to complement the laboratory-based findings of this study, and (d) explore the integration of real-time feedback mechanisms (such as the warning system suggested by participants) and their impact on both anxiety reduction and acceptance. Furthermore, comparative studies examining student acceptance of different AI-powered proctoring systems with varying levels of security features would contribute to a more nuanced understanding of which specific design characteristics most strongly influence technology acceptance.

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Appendices

Appendix 1. Security features to prevent cheating

Image and voice restriction	Full-screen restriction
✓ Preventing exam participation without allowing webcam and microphone access	✓ Running the web browser in full-screen mode
✓ Displaying a warning message on the screen if no face is detected from the camera for 15 seconds	✓ If exiting the full screen is detected, hide the questions until they switch back to the full-screen
✓ Blocking the sound output of the device	Restrictions on questions
Virtual machine and second screen restriction	✓ Displaying the questions one by one on the screen
✓ Preventing virtual machine and/or second screen users from seeing questions	✓ Displaying the questions in random order
Mouse and keyboard restriction	✓ Displaying the options in random order
✓ Preventing the use of a shortcut and function keys from the keyboard	✓ Inability to return to previous/answered questions
✓ Displaying a warning message to the user in case of pressing any key on the keyboard	✓ Showing only questions that have not been answered before to those who are allowed to take the exam a second time
✓ Disabling right click function of the mouse	Time-related measures
Login restriction	✓ Ability to start each exam only within the allowed time frame
✓ If one has participated in the exam once, it is prevented from retaking without the approval of the instructor	✓ Receiving the remaining exam time info from the server
✓ Inability to enter the exam except for predefined IP addresses	✓ Exiting the exam automatically when the exam period ends
	✓ Subtracting the time spent by those who are allowed to take the exam for the second time, from the total time in calculating the remaining exam time

Appendix 2. AI-powered security features to detect cheating

Image processing	Analysis of logs regarding time and usage information
✓ Detection of multiple people (faces) looking at the screen	✓ Detection of those who leave the full screen, use a second monitor/virtual machine, and run a different program in the exam (with the time spent outside the exam screen)
✓ Detection of no face in the image (not looking off the screen or no one in front of the screen)	✓ Identifying those who answer difficult questions in a short time
✓ Forbidden object detection (phone, book, etc.)	✓ Detection of those waiting for a long time without answering
Voice analysis	✓ Detection of those who started the exam outside the allowed time range
✓ Detection of moments when silence is broken in the exam	✓ Identification of those who completed the exam in a longer time than the given time
Analysis of IP address logs	Analysis of logs for option ticking
✓ Detection of taking the exam from outside the allowed IP	✓ Detection of those who marked the correct option after marking the wrong option
✓ Detection of a person taking an exam from more than one IP	✓ Detection of those who marked the same wrong option

✓ Detection of a person taking more than one exam from one IP	✓ Detection of the difference between the first and second answers of those who took the exam for the second time with the approval of the administrator
✓ Detection of more than one person taking one exam from one IP	Analysis of logs regarding keyboard usage
	✓ Detection of the difference in the speed of using the keyboard
	✓ Detection of using prohibited keys from the keyboard

Appendix 3. Cronbach's alpha values for each TAM factor

Factors	Number of items	Cronbach's alpha
PU	4	0.920
PEU	3	0.848
ATU	4	0.879
CA	3	0.700
FC	3	0.790
<i>Total</i>	<i>17</i>	<i>0.893</i>

Appendix 4. Bilateral relationships among the TAM factors

Factors	PU		PEU		ATU		CA		FC	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
1) PU	.	.								
2) PEU	0.64	0.00	.	.						
3) ATU	0.80	0.00	0.64	0.00	.	.				
4) CA	-0.16	0.13	-0.02	0.82	-0.24	0.03	.	.		
5) FC	0.55	0.00	0.70	0.00	0.56	0.00	0.18	0.09	.	.

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Author's Contributions (CRediT)

Arif Cem Topuz: Data collection, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft. Selçuk Karaman: Conceptualization, Data curation, Methodology, Project administration, Supervision, Validation, Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

Sustainable Development Goals (SDGs)

This study is linked to the following SDGs: Quality education (SDG 4), Industry, innovation and infrastructure (SDG 9), and Peace, justice, and strong institutions (SDG 16).

Authors' Disclosures

For the translation and localization of content, ChatGPT (free version) was employed. Human translators subsequently reviewed and adjusted the translations to ensure accuracy, cultural appropriateness, and contextual relevance. The final text was thoroughly reviewed and approved by the authors to ensure it accurately reflects the intended research outcomes and ethical standards. The authors also assessed and addressed potential biases inherent in the AI-generated content. The final version of the paper is the sole responsibility of the human authors

Data Accessibility Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics and Consent

The required informed consent was obtained from participants and ethics approval was obtained from the Ethics Committee of Ardahan University in Türkiye (decision no. 46639018/29 and dated 04 May 2015).

Funding Information

Not applicable.

Acknowledgements

This research was produced from the doctoral thesis titled "Development of a security-enhanced online examination system and examining the technology acceptance level" conducted by the first author under the supervision of the second author at Ataturk University, Institute of Education Sciences in Türkiye.

Competing Interests

The authors have no competing interests to declare.

Article History

Received: April 26, 2026 – Accepted: June 7, 2026.

Suggested citation:

Topuz, A. C., & Karaman, S. (2026). Do Students Embrace AI-Powered Academic Integrity? Examining Students' Technology Acceptance of Security-Enhanced Online Exams. *Asian Journal of Distance Education*, 21(2), 1-27. <https://doi.org/10.5281/zenodo.21440730>



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