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Artificial Intelligence and Academic Integrity in Virtual Higher Education: A Descriptive-Comparative Study of Student and Faculty Perceptions in Ecuador

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Abstract

The rapid adoption of generative artificial intelligence (GenAI) has created a practical problem for virtual higher education: universities must distinguish legitimate AI-supported learning from undisclosed delegation of academic work, while maintaining valid, fair, and privacy-sensitive assessment. This study compared student and faculty perceptions of AI use and academic integrity at the Technical University of Machala, Ecuador. A descriptive-comparative cross-sectional survey was administered to 1660 students and 34 faculty members during the second academic semester of 2024. The student questionnaire examined AI-use frequency, perceived academic benefit, readiness for non-assisted assessment, observation of dishonest online practices, perceived efficacy of virtual assessment, and attitudes toward proctoring. The faculty questionnaire examined suspected AI-generated submissions, responses to suspected use, perceived assessment efficacy, training, control tools, ethical judgments and proctoring. Findings indicate a transitional integrity landscape: students view AI mainly as a useful academic support, whereas faculty interpret it primarily through authorship, evidence and assessment-security concerns. Both groups report limitations in current virtual assessment, suggesting the need for AI-resilient assessment design, explicit disclosure rules, faculty development, student AI literacy, and proportional use of proctoring. The article argues against both blanket prohibition and permissive ambiguity, proposing a governance model grounded in transparent policy, authentic assessment, due process and human-centered AI literacy.

Keywords: generative artificial intelligence; academic integrity; virtual higher education; AI literacy; educational technology



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1. Introduction

The acceleration of generative artificial intelligence (GenAI) has altered the material conditions under which university students search, draft, revise, translate, summarize and submit academic work. In virtual higher education, this transformation is especially consequential because assessment already depends on mediated interaction, digital traceability and asynchronous production [1–3].

The emergence of large language models has also intensified a long-standing tension in university pedagogy: the difference between producing an acceptable academic artifact and

demonstrating durable learning. A student may now generate an essay, explanation, code fragment, or literature summary that appears fluent while only partially understanding the conceptual operations behind it; it is a curricular and assessment problem that affects the reliability of the evidence used to infer competence. The present study situates that problem within the field of virtual higher education, where the distance between process and product can become more difficult to observe [4–6].

Academic integrity is often treated administratively, as a matter of misconduct detection and sanction. However, contemporary scholarship increasingly argues that integrity must also be understood as a teaching-and-learning commitment grounded in honesty, fairness, trust, responsibility, respect and courage. In the age of GenAI, these values require reinterpretation because students may use algorithmic tools for brainstorming, language support, structuring, citation discovery or entire text generation. The ethical challenge is therefore not reducible to prohibition; it requires institutions to distinguish transparent, developmental and pedagogically justified AI use from deceptive delegation of intellectual labor [7–9].

Virtual learning environments became structurally central to higher education during and after the COVID-19 pandemic, but the rapid institutionalization of online assessment also exposed weaknesses in authenticity, security, feedback, student support and digital equity. GenAI now magnifies these vulnerabilities because it can operate outside institutional platforms while shaping work submitted inside them. For that reason, the study of AI perceptions in virtual higher education is not merely technological; it is a way to examine how students and faculty understand the legitimacy of learning evidence in digitally mediated universities. This focus aligns with research on assessment design as a socio-technical practice rather than a purely procedural activity [10–12].

The research problem becomes sharper when students and faculty interpret the same practice through different normative lenses. The core problem is not that students and faculty have different expectations of AI, but that these expectations may produce conflicting interpretations of academic evidence. For students, AI may function as an accessibility resource, an efficiency tool, a personalized tutor, or a strategy for managing academic workload. For faculty, the same use becomes problematic when it obscures authorship, weakens the traceability of student reasoning, or prevents assessment tasks from reliably demonstrating individual competence. The integrity challenge is not the existence of divergent stakeholder needs, but the absence of a shared institutional framework capable of distinguishing acceptable AI-supported learning from undisclosed substitution of intellectual work. Without such a framework, perceptions of AI can shape behavior, compliance, reporting, assessment design, and trust in the fairness of virtual higher education. Comparative analysis is essential because policy built from only one stakeholder perspective risks being either punitive and unrealistic or permissive and pedagogically weak [13–15].

Study Objective and Research Question

The objective of this study is to statistically analyze and compare the perceptions of university students and faculty regarding the use of AI tools and their perceived implications for academic integrity in virtual higher education. This objective is intentionally comparative because institutional responses to AI require evidence of both convergence and dissonance between learners and educators.

The article therefore examines patterns related to frequency of AI use, perceived improvement in academic performance, readiness for non-assisted evaluation, observations of dishonest practice, efficacy of online assessment, faculty detection of AI-generated content, training needs, and attitudes toward proctoring technologies [2,16,17].

The central research question guiding the study is:

1a. How do students and faculty in higher education perceive the relationship between AI use and academic integrity in virtual assessment contexts?

This question is accompanied by a comparative sub-question:

1b. What perceptual gaps emerge between student and faculty responses regarding online assessment efficacy, ethical AI use, and the legitimacy of proctoring as an integrity mechanism? [3,18,19].

The Latin American and virtual higher education context adds further importance to the problem because digital transformation does not occur under equal material, linguistic or institutional conditions [14,20,21]. Students may use AI to compensate for uneven prior preparation, linguistic insecurity, time constraints, work responsibilities, and limited access to academic tutoring. At the same time, faculty may lack institutional training, reliable detection methods, clear protocols or workload recognition for redesigning assessment. The integrity challenge is therefore also an equity challenge: universities must prevent deception without criminalizing students who use technology to navigate structural disadvantages [13,22,23].

Generative AI also destabilizes the evidentiary logic of traditional online assignments. When a written product can be produced, revised, and stylistically polished by a model, the final artifact alone may no longer be sufficient evidence of learning. The present study approaches student and faculty perceptions as empirical indicators of whether current virtual assessment practices are perceived as capable of performing that evidentiary function [10,24,25].

2. Theoretical Framework

2.1. Generative AI in Higher Education

Artificial intelligence in higher education should be conceptualized as a family of computational systems that support prediction, recommendation, generation, classification, tutoring, feedback, and decision-making [26–30]. Generative AI represents a particularly disruptive subset because it produces plausible linguistic, visual, and symbolic outputs in response to prompts, thereby entering domains historically associated with human authorship and disciplinary reasoning [31–35]. In higher education, the significance of GenAI is therefore not restricted to automation; it concerns the redistribution of cognitive labor between learner, teacher, institution, and machine [36–40]. This redistribution requires theoretical attention to pedagogy, ethics, assessment and governance [20,41,42].

Generative AI modifies the meaning of academic assistance. Traditional academic support includes tutoring, peer discussion, library guidance, editing, feedback and assistive technologies. GenAI can perform elements of all these activities at scale, but without the relational accountability, disciplinary judgment or institutional transparency normally associated with educational support.

The theoretical challenge is to distinguish AI as scaffold from AI as substitute: scaffolded use supports student thinking, whereas substitutive use conceals the absence of independent intellectual engagement. This distinction is central to academic integrity in virtual education [9,12,43].

2.2. Academic Integrity, Authorship and Ethical Agency

Academic integrity theory provides the normative foundation for this distinction. Bertram Gallant's teaching-and-learning approach argues that integrity is not only compliance but an educational outcome that institutions must cultivate. Bretag's work similarly frames integrity as a whole-of-institution responsibility involving policy clarity, assessment design, student education and consistent procedures. In the context of GenAI, these principles imply that universities should not merely detect misuse after submission but teach

students how authorship, citation, evidence and accountability operate when algorithmic tools are involved [7,8,32].

The literature on contract cheating is especially relevant because it analyzes what happens when students outsource assessed work to external agents. Although GenAI is not identical to contract cheating, both phenomena disrupt the relationship between submitted product and student competence. The difference is that GenAI is inexpensive, immediate, socially normalized, and often ambiguously framed as assistance rather than outsourcing. This makes the integrity boundary harder to communicate and enforce. Theoretical insights from contract cheating therefore help explain why assessment design and institutional culture are more sustainable responses than detection alone [10,32,44].

Assessment theory contributes a complementary lens. Constructive alignment holds that learning outcomes, teaching activities and assessment tasks must form a coherent system. When GenAI can complete or heavily transform an assessment product, alignment may be weakened because the task no longer elicits the intended evidence of learning. The solution is not necessarily to abandon digital or written assessment but to redesign tasks so they require situated judgment, iterative process evidence, oral explanation, local data, personal reflection and disciplinary decision-making that cannot be reduced to generic text production [4,5,10].

Authentic assessment is central to this redesign agenda because it evaluates students through tasks that resemble meaningful disciplinary, professional or civic practices. In AI-rich environments, authenticity must include not only real-world relevance but also transparency regarding tool use, justification of decisions, and demonstration of process. A student who uses AI to explore alternative arguments can still demonstrate learning if they critically evaluate, adapt, and disclose that assistance. Conversely, a polished artifact without process evidence may be less informative. Authenticity thus becomes both a pedagogical and integrity principle [11,25,45].

2.3. Proctoring, Detection, Privacy and Fairness

Online proctoring and AI-detection tools represent a security-oriented response to assessment vulnerability. Assessment security is important, especially in high-stakes contexts, but security must be balanced against validity, equity, privacy and student wellbeing. The literature warns that surveillance technologies may create an illusion of control if they are not embedded within broader assessment reform. Moreover, technical tools can shift institutional attention from learning evidence to monitoring compliance. For this reason, proctoring should be evaluated as one element of a layered integrity strategy, not as a substitute for pedagogical redesign [10,26,27].

The debate about AI-text detection illustrates the risks of technological overreliance. Empirical work has found that detection tools can be inaccurate, vulnerable to paraphrasing or obfuscation, and biased against non-native English writers. In multilingual higher education systems, this is ethically significant because false accusations may disproportionately affect students whose writing style differs from dominant linguistic norms.

Detection may support preliminary inquiry, but it should not serve as definitive proof of misconduct. Academic due process requires triangulated evidence, transparent criteria, and opportunities for students to explain their work [22,30,31]. Digital equity is another theoretical dimension. AI may reduce barriers by providing language support, immediate explanations, accessibility functions, and adaptive study assistance. Yet it may also widen inequality if students have unequal access to premium tools, devices, connectivity, prompt literacy or institutional guidance. Equity-oriented AI governance must therefore ask who benefits, who is surveilled, who is suspected and who is trained. Academic integrity policies that ignore equity risk converting technology gaps into disciplinary gaps [13,17,23].

2.4. AI Literacy, Acceptance, Self-Regulation and Governance

AI literacy extends digital literacy by requiring users to understand what AI systems can and cannot do, how outputs are generated, why hallucinations occur, how bias enters models, how prompts shape results, and how responsibility remains with the human user. In higher education, AI literacy must be disciplinary, ethical, and epistemic. Students need to learn not only how to use tools efficiently but how to evaluate evidence, disclose assistance, protect data, and preserve intellectual agency. Faculty likewise need AI literacy to redesign tasks and guide students responsibly [46–48].

The humanistic dimension of higher education must not be lost in the AI debate. Universities are not only credentialing systems; they are communities of inquiry where students learn to reason, argue, interpret, question, and take responsibility for knowledge claims. Academic integrity protects this community because it sustains trust in the relationship between evidence and authorship. If AI is integrated without ethical formation, higher education risks replacing intellectual development with output management. A human-centered AI approach therefore insists that technology should augment human agency rather than displace it [2,19,49].

AI governance in higher education requires policy coherence across curriculum, assessment, student support, faculty development, data protection, quality assurance and disciplinary procedures. International guidance emphasizes human agency, inclusion, transparency, safety, privacy, accountability and age-appropriate or context-sensitive implementation. These principles must be translated into institutional rules that specify permissible uses, disclosure requirements, prohibited practices, assessment adaptations and procedures for suspected misuse. Without such translation, ethical principles remain aspirational, and faculty are left to improvise policy at course level [2,17,18].

Quality assurance frameworks must also adapt because AI affects how institutions evidence learning outcomes. Program accreditation, course evaluation and assessment moderation increasingly need to consider whether assessments remain valid under conditions of algorithmic assistance. Institutions should ask whether each program includes AI literacy, whether assessment maps include secure or process-based evidence, whether faculty receive professional development, and whether misconduct procedures protect fairness. In this sense, AI governance becomes part of educational administration and management, not only educational technology [10,23,37].

2.5. Integrated Conceptual Model

Student-faculty perception gaps can be interpreted as indicators of institutional culture. When students view AI primarily as a productivity aid and faculty view it primarily as a threat, there is a communicative failure about the purpose of assessment and the meaning of academic work.

A mature integrity culture requires dialogue that clarifies why independent thinking matters, when assistance is legitimate, and how transparency protects both students and teachers. Comparative perception studies thus help identify where institutional culture needs repair [7,12,13]. The theoretical framework therefore integrates five dimensions:

AI as educational technology; integrity as a learning culture; assessment as evidence of competence; proctoring and detection as contested governance tools; and perceptions as predictors of adoption and ethical behavior. This integrated approach avoids narrow technological determinism and recognizes that AI in virtual higher education is simultaneously pedagogical, ethical, administrative, and sociocultural. It provides the conceptual basis for interpreting the descriptive and comparative results reported in the study [3,4,20].

This article assumes that responsible AI integration must be judged by its contribution to learning, fairness, transparency and human agency. AI tools can be educationally

valuable when they support feedback, inclusion and higher-order thinking; they become problematic when they obscure authorship, intensify surveillance or allow performance to detach from competence. The empirical analysis that follows examines whether student and faculty perceptions suggest movement toward the first scenario, risk of the second or a mixed transitional condition requiring institutional intervention [2,9,19].

3. Methodology

3.1. Research Design

This study adopted a quantitative, descriptive-comparative, and cross-sectional design to examine perceptions of artificial intelligence use, academic integrity, and virtual assessment in higher education. The design was appropriate because the purpose of the study was to identify institutional perception patterns among two stakeholder groups: students and faculty members. The study was not intended to establish causal relationships, but to provide diagnostic evidence for academic policy, assessment redesign and institutional governance.

3.2. Participants and Sampling

The study included 1694 participants: 1660 students and 34 faculty members. Students represented 98.0% of the total sample, whereas faculty members represented 2.0%. The student sample was obtained through non-probabilistic convenience sampling and included students from different academic programs, levels, and schedules. The faculty sample was intentional, as faculty members were selected because of their direct experience with virtual teaching, online assessment, and the evaluation of academic work potentially involving AI assistance. Data collection was conducted during one active academic term at the institution, corresponding to a four-month academic period. Given the non-probabilistic sampling strategy and the unequal size of the two groups, the findings should be interpreted as context-specific diagnostic evidence rather than as statistically generalizable estimates (see Table 1).

Table 1. Participants and sampling characteristics.

Group	n	Percentage of Total Sample	Sampling Strategy	Profile
Students	1660	98.0%	Non-probabilistic convenience sampling	Students from different programs, levels, and schedules
Faculty members	34	2.0%	Intentional sampling	Faculty with experience in virtual teaching and online assessment
Total	1694	100%	—	Higher education stakeholders

3.3. Instruments and Constructs

Two ad hoc structured questionnaires were used. The instruments were differentiated because students and faculty occupy distinct roles in the academic integrity ecosystem. The student questionnaire contained six items addressing frequency of AI use, perceived improvement in academic performance, preparedness for traditional assessment after AI use, observation of dishonest online practices, perceived efficacy of virtual assessment, and opinion regarding proctoring tools such as Proctorizer.

The faculty questionnaire contained eight items addressing detection or suspicion of AI-generated content, measures adopted after detection, perceived effectiveness of online evaluations, attitudes toward detection and control tools, perceptions of students’ ethical AI use, training received, perceived security of virtual assessment, and valuation of proctoring as an integrity measure.

Both questionnaires used Likert-type scales and closed categorical questions. The instruments were not standardized international scales. Rather, they were designed for the institutional context of this study and subjected to external expert content validation before data collection (see Table 2).

Table 2. Instruments and main constructs.

Instrument	Number of Items	Main Constructs
Student questionnaire	6	AI-use frequency; perceived academic benefit; preparedness for non-assisted assessment; observation of dishonest online practices; virtual assessment efficacy; proctoring opinion
Faculty questionnaire	8	AI-generated content detection; response measures; online assessment efficacy; control tools; ethical perception of student AI use; training; assessment security; proctoring value

3.4. Content Validation

Content validity was addressed through expert review. Three academic peers from other Ecuadorian universities acted as external expert reviewers. They assessed the relevance, clarity, coherence, and contextual adequacy of the questionnaire items in relation to the study objectives, target population, and constructs of AI use, academic integrity, and virtual assessment.

No Intraclass Correlation Coefficient (ICC) was calculated. Therefore, the validation process should be understood as qualitative and criterion-based expert content validation, not as psychometric validation based on inter-rater reliability. Future studies should incorporate formal measures of expert agreement, such as ICC or Aiken's V, and should also test internal consistency when coherent multi-item scales are developed.

3.5. Data Collection and Ethical Considerations

Data were collected through an internal institutional questionnaire administered virtually within the university. Participation was voluntary and anonymous. Before completing the survey, participants were informed about the purpose of the study, the voluntary nature of participation, the anonymous treatment of responses, and the exclusive academic use of the data. Completion of the questionnaire was considered evidence of informed consent.

The study did not receive formal approval from an Institutional Review Board (IRB), and therefore no IRB approval number is available. No identifying information was collected. The study did not seek to investigate individual misconduct, but to analyze aggregate perceptions of AI use, academic integrity, and virtual assessment for academic and institutional diagnostic purposes.

3.6. Data Processing and Analytical Strategy

The data were prepared for descriptive and comparative analysis. The analytical plan considered frequency distributions, percentages, measures of central tendency and dispersion for the questionnaire items. Because the student and faculty instruments were differentiated, direct comparison was limited to conceptually aligned constructs, such as virtual assessment efficacy and the valuation of proctoring tools.

Although the initial analytical plan considered chi-square tests, Mann–Whitney U tests, correlation matrices, principal component analysis and cluster analysis, these procedures require item-level frequency tables or raw response matrices. Since the present report is based only on aggregate methodological information, no inferential or multivariate

statistics are reported. Consequently, the results are presented as descriptive institutional findings and interpreted with appropriate caution.

3.7. Methodological Limitations

The main methodological limitations are the non-probabilistic sampling strategy, unequal group sizes, reliance on self-reported perceptions, absence of formal psychometric validation, and lack of item-level statistical reporting. These limitations do not invalidate the study’s diagnostic value, but they restrict statistical generalization and prevent advanced inferential or multivariate interpretation. The findings should therefore be read as contextually meaningful evidence for institutional reflection, policy development and future research design.

4. Results

4.1. Sample Description

The final study sample consisted of 1694 participants, including 1660 students and 34 faculty members. Students represented the largest group in the study, accounting for 98.0% of the sample, whereas faculty members represented 2.0%. This distribution reflects the institutional focus of the study on student perceptions, while also incorporating faculty perspectives as a complementary source of evidence regarding virtual assessment, AI-generated work, and academic integrity (see Table 3).

Table 3. Sample composition.

Group	n	%
Students	1660	98.0
Faculty members	34	2.0
Total	1694	100.0

4.2. Descriptive Scope of the Student Questionnaire

The student questionnaire examined six dimensions related to AI use and academic integrity in virtual higher education. These dimensions were: frequency of AI use, perceived improvement in academic performance, preparedness for traditional assessment after AI use, observation of dishonest online practices, perceived efficacy of virtual assessment, and opinion regarding proctoring tools.

Because item-level frequencies were not available for this revised report, the results are presented at the level of measured constructs rather than through percentage distributions by response category. The available data confirm that the student instrument was designed to capture both instrumental and ethical dimensions of AI adoption. Instrumental dimensions included AI-use frequency, perceived academic benefit, and academic preparedness. Ethical and assessment-related dimensions included dishonest online practices, virtual assessment efficacy, and proctoring opinion (see Table 4).

Table 4. Student questionnaire dimensions.

Dimension	Analytical Meaning
Frequency of AI use.	Measures the extent to which students report using AI tools for academic tasks.
Perceived academic benefit.	Assesses whether students believe AI improves academic performance.
Preparedness for traditional assessment.	Examines whether AI use is perceived as compatible with independent assessment readiness.
Observation of dishonest online practices.	Captures student awareness of integrity risks in virtual environments.
Perceived efficacy of virtual assessment.	Measures confidence in online assessment practices.
Opinion on proctoring tools.	Explores student attitudes toward technological control mechanisms.

4.3. Descriptive Scope of the Faculty Questionnaire

The faculty questionnaire examined eight dimensions related to AI-generated academic work, online assessment, and institutional readiness. These dimensions were: detection or suspicion of AI-generated content; measures adopted after detection; perceived effectiveness of online evaluations; attitudes toward detection and control tools; perceptions of students’ ethical AI use; training received; perceived security of virtual assessment; and valuation of proctoring.

The faculty instrument therefore focused on the evaluative and governance dimensions of AI in virtual higher education. Faculty responses were especially relevant because instructors are responsible for assessing student work, identifying possible integrity risks, and applying institutional or course-level criteria when AI use is suspected (see Table 5).

Table 5. Faculty questionnaire dimensions.

Dimension	Analytical Meaning
Detection or suspicion of AI-generated content.	Examines whether faculty perceive AI-generated work in student submissions.
Measures adopted after detection.	Identifies faculty responses to suspected AI use.
Effectiveness of online evaluations.	Assesses faculty confidence in virtual assessment.
Attitudes toward control tools.	Explores views on detection and monitoring mechanisms.
Perception of students’ ethical AI use.	Captures faculty judgments regarding responsible or irresponsible AI use.
Training received.	Measures institutional preparation for AI-related assessment challenges.
Security of virtual assessment.	Assesses perceived reliability of online assessment environments.
Valuation of proctoring.	Explores faculty attitudes toward proctoring as an integrity mechanism.

4.4. Descriptive Interpretation of Stakeholder Perspectives

The available results indicate that the study addresses two complementary stakeholder perspectives. The student questionnaire captures how learners perceive AI as part of their academic practices, including its usefulness, possible benefits, and relationship with assessment preparedness. The faculty questionnaire captures how educators perceive AI in relation to authorship, academic evidence, assessment security, ethical use, and institutional readiness.

The central finding is therefore not a statistically tested difference between both groups, but a descriptive and conceptual contrast between their roles within the academic integrity system. Students are positioned as users of AI tools in learning and assessment contexts, whereas faculty are positioned as evaluators of academic evidence and guardians of assessment validity. This role-based distinction is important for institutional governance because AI policies must be understandable to students, workable for faculty, and aligned with quality assurance requirements.

4.5. Comparative Results Based on Available Data

Because the two questionnaires were differentiated and item-level frequencies were not available, formal chi-square tests, *p*-values, Cramér’s V, Mann–Whitney U statistics, and multivariate estimates cannot be reported. Direct statistical comparison would require equivalent items, coded response categories, and observed frequencies for each group. In the absence of those data, the comparison remains descriptive and construct-based.

The available comparative evidence shows that both instruments addressed related concerns: AI use, virtual assessment efficacy, ethical implications and proctoring. However, the emphasis differed by stakeholder group. The student questionnaire focused on AI

use, perceived benefit and preparedness, whereas the faculty questionnaire focused on detection, ethical concern, assessment security and training. This difference reflects the distinct positions of students and faculty in the virtual assessment process (see Table 6).

Table 6. Construct-based comparison between student and faculty instruments.

Analytical Construct	Student Questionnaire	Faculty Questionnaire	Type of Comparison Possible
AI use	Frequency of AI use	Detection or suspicion of AI-generated content	Conceptual comparison
Academic benefit/risk	Perceived improvement in performance	Perception of students' ethical AI use	Conceptual comparison
Assessment validity	Preparedness for traditional assessment; virtual assessment efficacy	Effectiveness and security of online evaluations	Conceptual comparison
Academic integrity	Observation of dishonest online practices	Measures adopted after suspected AI use	Conceptual comparison
Technological control	Opinion on Proctorizer	Valuation of proctoring and control tools	Conceptual comparison
Institutional readiness	Not directly measured	Training received	Faculty-only descriptive construct

Figures 1 and 2 are included to visually summarize the core descriptive information used throughout the study and to illustrate the empirical and conceptual basis of the research. Figure 1 summarizes the number of items included in each questionnaire, reflecting the differentiated structure of the student and faculty instruments. Figure 2 provides a construct map that links the main analytical dimensions addressed in both instruments, showing how student- and faculty-related variables were organized around AI use, academic integrity, and virtual assessment.

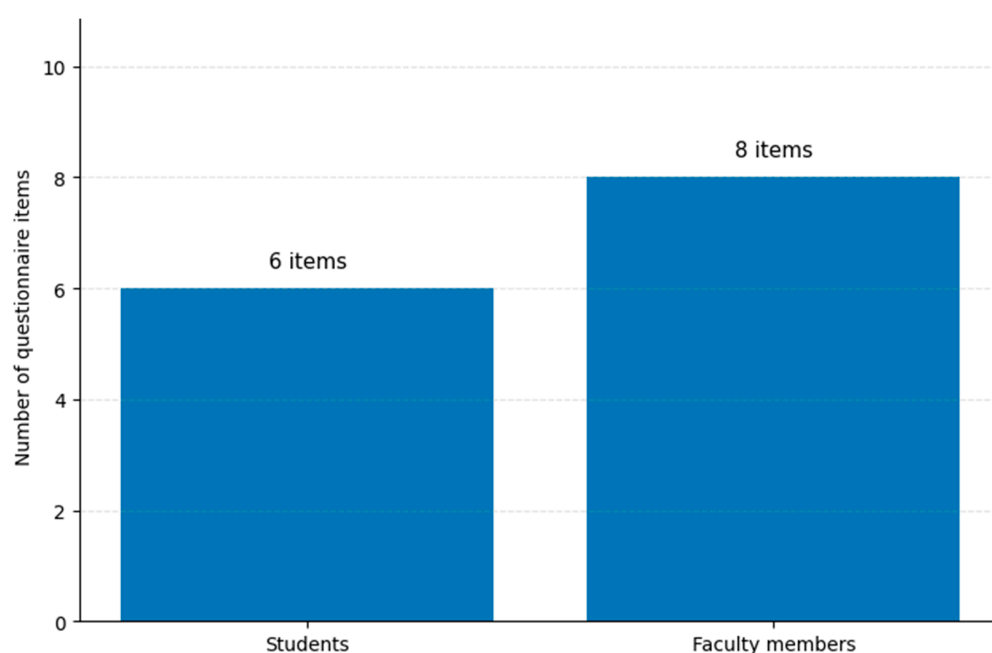


Figure 1. Number of questionnaire items by stakeholder group.

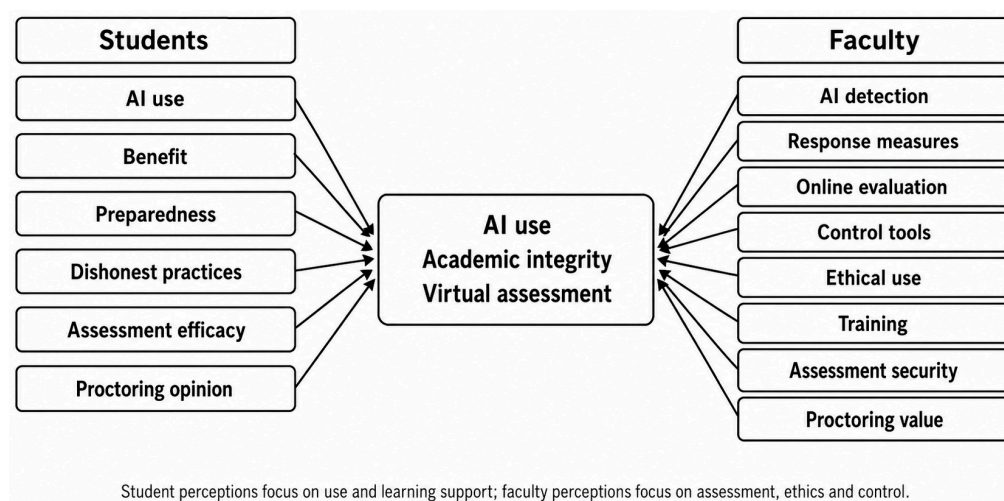


Figure 2. Construct map of AI use, academic integrity and virtual assessment.

Figure 2 summarizes the construct-level organization of the two questionnaires and illustrates how the study operationalized the relationship between AI use, academic integrity and virtual assessment. The student instrument focused on AI use, perceived academic benefit, assessment preparedness, dishonest practices, assessment efficacy, and proctoring opinion, reflecting the learner-centered dimensions of AI adoption.

In contrast, the faculty instrument emphasized AI detection, response measures, online evaluation, control tools, ethical use, training, assessment security, and proctoring value, reflecting the evaluative and institutional dimensions of AI governance. This visual organization clarifies that the study did not treat students and faculty as identical analytical groups, but as complementary stakeholders positioned differently within the academic integrity ecosystem. This figure supports the descriptive-comparative logic of the study by showing how both instruments converge around a shared analytical core while preserving role-specific constructs.

The results provide an institutional diagnostic view of AI and academic integrity in virtual higher education. The study documents the participation of a large student group and a smaller intentional faculty group during one active four-month academic term. It also establishes a differentiated measurement structure: students were surveyed about AI use and learning-related perceptions, while faculty were surveyed about assessment, detection, ethics, and institutional readiness.

Due to the absence of item-level data, the study does not report inferential or multi-variate statistics. Therefore, claims about statistical significance, association strength, factor structure, or cluster segmentation are not made. The findings should be interpreted as descriptive evidence of the institutional relevance of AI use, academic integrity and virtual assessment. Future studies should collect and report item-level response distributions to enable chi-square testing, effect-size estimation, correlation analysis, PCA, and more robust comparative modeling.

5. Discussion

The findings confirm that GenAI has become a structural issue for virtual higher education rather than a peripheral academic misconduct concern. Student use and faculty detection indicate that AI is already embedded in the everyday ecology of academic production and evaluation.

This requires universities to move beyond reactive debates about whether AI should be allowed and toward principled decisions about how AI can be integrated without

weakening learning evidence. The discussion therefore interprets the results as a call for educational governance rather than technological alarm [1,2,14].

The student perception of AI as moderately beneficial aligns with studies showing that learners value GenAI for idea generation, language assistance, explanation, and personalized support. However, the reported low readiness for traditional assessments complicates a purely positive interpretation. It suggests that AI-supported performance may not always correspond to durable competence. This finding supports the need for pedagogical designs that require students to transform AI assistance into personally understood knowledge through critique, practice, reflection, and independent demonstration [13,39,41].

The faculty perception of recurrent AI-generated content reflects a crisis of evidentiary confidence. Faculty are not simply resisting innovation; they are questioning whether submitted work remains a valid basis for academic judgment. This concern is legitimate because assessment is the mechanism by which universities certify competence. However, the response should not be limited to suspicion. Faculty need institutional support to redesign assessment, communicate expectations, and evaluate process evidence in ways that protect both academic standards and student rights [4,8,10].

5.1. Bridging Student and Faculty Perceptions

The perceptual gap between students and faculty reveals an ethical communication problem. Students may not always understand why undisclosed AI assistance threatens fairness, while faculty may underestimate the extent to which students experience AI as ordinary academic infrastructure. This gap can produce conflict, inconsistent expectations, and distrust. A constructive institutional response should create shared language around acceptable use, disclosure, prohibited delegation, and responsible experimentation. Policy should be educative before it is punitive [7,12,17].

The shared skepticism about current virtual assessment efficacy is perhaps the most productive finding because it creates a point of convergence. If both groups recognize limitations, institutions can use that recognition to initiate participatory assessment reform. Such reform should include program-level mapping of learning outcomes, identification of AI-vulnerable tasks, development of authentic assessments, and integration of oral, practical, reflective, and process-based evidence. The aim is not to make cheating impossible but to make genuine learning more visible and dishonest delegation less useful [5,11,45].

5.2. Beyond Detection: Assessment Redesign and Integrity Culture

The results challenge institutions that rely primarily on proctoring or detection tools. While these tools may have a role in specific contexts, they cannot resolve the deeper pedagogical issue: many assessments were designed for a pre-GenAI evidentiary environment.

Proctoring may secure a test session, and detection may flag a text, but neither guarantees meaningful learning. A sustainable strategy must therefore combine secure assessment moments with richer evidence of student reasoning before, during and after task completion [4,10,30].

The ambivalent perception of Proctorizer and similar tools should be interpreted through the ethics of surveillance. Remote proctoring can redistribute risk from the institution to students by requiring camera access, environmental monitoring and behavioral tracking. It may also disadvantage students with unstable internet, crowded homes, disabilities, anxiety, or limited devices.

Therefore, any use of proctoring should satisfy principles of necessity, proportionality, transparency, accessibility, and data minimization. Trust cannot be built through surveillance alone [23,26,27]. The findings also raise the issue of multilingual equity. In contexts where students write in a second or additional language, AI may function as

language support, but AI detectors may also misclassify linguistically constrained writing as machine-generated. This creates a serious fairness problem for international and multi-lingual higher education. The institution must therefore avoid treating AI-detection scores as definitive evidence and should develop investigative procedures that consider drafts, oral explanations, version histories, and student interviews [22,30,31].

5.3. Faculty Development, Student AI Literacy and Policy Clarity

Faculty training emerges as a central implication. The study's results suggest that many faculty members are asked to preserve academic integrity without adequate preparation for AI-era assessment. Professional development should not be limited to tool demonstrations; it should include AI epistemology, prompt literacy, hallucination detection, assignment redesign, rubric adaptation, ethical feedback, and due process. Faculty should also be supported through workload recognition because redesigning assessment is intellectually demanding labor [2,25,40].

Student training is equally important. Many students may use AI without fully understanding authorship, data privacy, bias, hallucination, citation fabrication, or disclosure obligations. An integrity-centered AI curriculum should teach students to document prompts, evaluate outputs, verify sources, explain transformations, and decide when AI use is inappropriate. Such training should be embedded across programs rather than delivered as a generic orientation module because acceptable AI use varies by discipline, task, and learning outcome [9,23,46].

The discussion also suggests that academic integrity should be reframed as relational trust. When institutions respond to AI mainly by policing students, they may erode the trust necessary for open conversations about learning support and ethical uncertainty. When they ignore misuse, they erode the trust of honest students and faculty. The challenge is to build a culture where expectations are explicit, support is available, assessment is meaningful, and misconduct procedures are fair. This cultural approach is more robust than either permissiveness or punitive surveillance [7,8,33].

5.4. Quality Assurance, Governance and Equity

The results connect directly with higher education quality assurance. If online assessments are perceived as weak, then program credibility and graduate competence may be questioned. Quality assurance processes should therefore include AI-resilient assessment audits: identification of tasks vulnerable to undisclosed AI delegation, mapping of secure evidence points, review of feedback quality, and documentation of student AI literacy outcomes. AI governance should become a routine component of curriculum management and accreditation preparation [3,10,37].

The findings also support a differentiated policy model. A blanket ban on AI is likely unenforceable and may suppress legitimate educational uses, whereas unrestricted use may undermine authorship and assessment validity. A more nuanced model should define categories such as prohibited use, permitted use with disclosure, encouraged formative use, and required independent performance. This model should be communicated in course syllabi, assessment instructions, rubrics, and student guidance. Clarity reduces ambiguity and supports consistent decision-making [2,17,18].

The moderate student perception of performance improvement may also reflect the commodification pressures present in contemporary higher education. When students experience assessment primarily as grade production, tools that optimize output become attractive. The integrity response must therefore address assessment meaning, workload distribution, feedback practices, and student belonging. AI misuse is more likely when

students feel disconnected from the purpose of learning or overwhelmed by demands. Humanistic pedagogy remains essential in technological environments [21,49].

The study's findings can inform assessment redesign at several levels. At the task level, instructors can require process logs, oral checks, annotated AI-use statements, and source verification [50–55]. At the course level, they can combine formative AI-supported tasks with summative independent demonstrations [55–60].

At the program level, curriculum committees can identify signature assessments that require authentic, contextual, or supervised performance [60–65]. At the institutional level, leaders can create policy, training, and quality assurance mechanisms. This multilevel approach matches the systemic nature of the problem [4,5,10].

The role of AI as a learning scaffold should not be dismissed. Used responsibly, AI can help students rehearse explanations, compare arguments, receive formative feedback, and access alternative representations of complex content. The problem arises when students mistake AI output for understanding or when assessment design rewards product fluency without evaluating reasoning. Therefore, the pedagogical challenge is to move from AI-assisted production to AI-supported learning. This distinction should guide institutional policy and classroom practice [20,39,41].

The results also suggest a need for participatory governance. Policies developed without student input may be perceived as punitive, while policies developed without faculty input may be impractical. Institutions should involve students, faculty, academic integrity officers, instructional designers, data protection experts, and quality assurance staff in developing AI guidelines. Such participation can improve legitimacy, contextual relevance, and compliance. It also reflects the democratic ethos of higher education as a community of inquiry [8,18,23].

5.5. Limitations and Future Research

This study has several limitations. The non-probabilistic sampling strategy, unequal group sizes, reliance on self-reported perceptions, and limited item-level statistical reporting restrict generalizability and statistical precision. The small faculty sample is particularly relevant because it limits stronger comparisons between stakeholder groups. Future research should use validated scales, larger and more balanced samples, longitudinal designs and mixed-method approaches. Further analyses should examine differences by discipline, academic level, modality, gender and prior AI training. Interviews or focus groups would also clarify why students and faculty interpret AI use, academic integrity and virtual assessment differently [66–70].

6. Conclusions

This study shows that GenAI is already reshaping academic integrity and virtual assessment in higher education. Students perceive AI as useful for academic support, efficiency, and feedback, whereas faculty associate it with authorship uncertainty, assessment validity, and fairness. The main challenge is not AI use itself, but the institutional misalignment between AI-assisted production and evidence of independent learning. Therefore, universities should move beyond prohibition, detection-only strategies, and excessive reliance on proctoring. Effective governance requires clear disclosure rules, AI literacy for students, faculty development, authentic and process-based assessment, due process, and privacy-sensitive technological controls.

The findings also indicate that assessment redesign should be programmatic rather than isolated, linking classroom practices with curriculum management and quality assurance [70,71]. Future research should employ validated instruments, larger faculty samples,

mixed methods and longitudinal designs. Academic integrity in AI-mediated higher education must be taught, assessed and governed as a shared institutional responsibility.

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Informed Consent Statement: Informed consent was obtained digitally from all participants before completing the questionnaire. Participants were informed that their participation was voluntary, anonymous, and intended exclusively for academic and institutional diagnostic purposes. Completion of the questionnaire was considered evidence of consent.

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