RESEARCH PAPER

Artificial Intelligence Integration in Assessment and Teaching: A Quantitative Analysis of Stakeholder Perception Differences

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Abstract
Artificial Intelligence (AI) is fundamentally altering university education, challenging established teaching and assessment methods. This study investigates the perceptions of university students and professors regarding AI's utility, impact on learning, and ethical implications. Employing a quantitative design based on secondary data analysis of anonymized datasets from the 2024–2025 academic year, this research analyzed responses from 635 participants (496 students and 139 professors). Six key competencies were examined to identify trends and perception gaps.
Both groups expressed skepticism regarding AI's current value in teaching, with 68.2% of students and 74.1% of professors rating its utility as low. A critical divergence emerged in ethical trust: 82.1% of students reported high confidence in AI systems, whereas only 21.6% of professors shared this sentiment, highlighting a distinct generational divide in risk perception. Although students demonstrate a high willingness to adopt AI, they appear to underestimate the ethical risks that concern faculty. To bridge this gap, higher education institutions must urgently implement comprehensive AI literacy training and governance frameworks to ensure responsible and effective integration.
Keywords: Artificial Intelligence, Higher Education, Educational Assessment, Generative AI, Academic Perception.
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1 Introduction

The contemporary university landscape is navigating one of the most consequential technological inflections in its history. The rapid and widespread integration of Artificial Intelligence (AI) into teaching, learning, and institutional processes [1][2][3]. AI is no longer primarily a speculative or experimental technology but an operational component of many educational environments, with evidence from disciplinary reviews and bibliometric analyses showing accelerated uptake across higher-education sectors and subject domains [2][3][4]. In jurisdictions with developed digital infrastructures, this integration has been especially pronounced, producing pragmatic deployments that promise personalization at scale and data-driven optimization of instructional sequences and administrative workflows [2][5][6].

The contemporary scope of AI in education extends well beyond routine automation: research and reviews identify adaptive learning platforms and intelligent tutoring systems that individualize curricular trajectories, automated scoring and feedback systems for complex tasks, and an expanding ecosystem of generative and assistive writing tools that provide support in real-time [2][3][5][6]. Proponents contend that, properly deployed, these technologies can address long-standing resource constraints in higher education, attenuating the "Iron Triangle" of access, cost, and quality by lowering per-learner delivery costs, broadening access modalities, and supporting differentiated instruction that sustains or improves learning outcomes [3][2]. At the same time, the literature stresses that these affordances are neither automatic nor evenly distributed: realizing benefits requires deliberate design, credible evaluation, and governance that attend to equity, transparency, and pedagogical alignment [7].

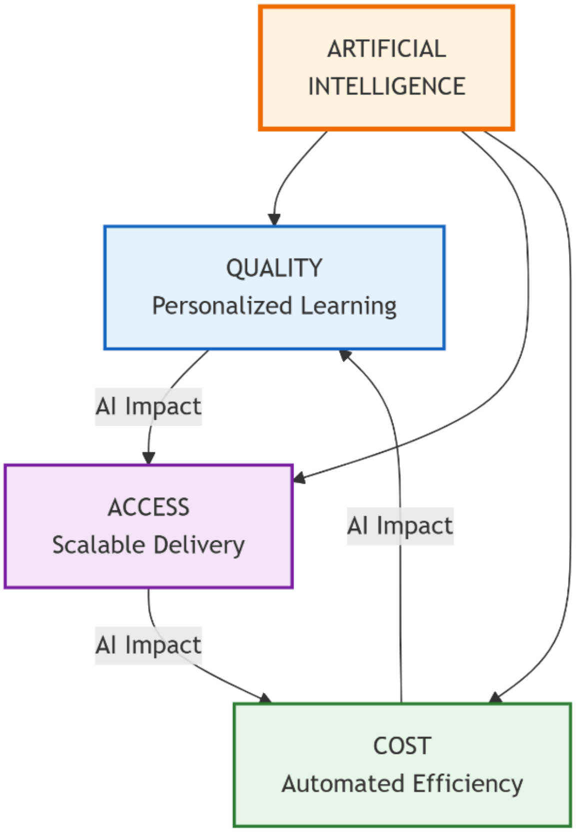

Figure 1. The "Iron Triangle" of Education Disrupted by AI

Figure 1, Disruption to the traditional Education 'Iron Triangle' by AI. Classical education theory assumes tradeoffs between Access, Cost and Quality are at best in tension from one to the other. Artificial Intelligence, which occupies the center of the triangle has the potential to simultaneously optimize scales in all these three dimensions: for instance, by. a) scale-up through scalable delivery; b) reducing cost via automation and efficient scaling, depending on personalized pathways; c) maintaining enhancing quality by personalized learning pathways, adaptive systems etc.

Although these systems are still in their infancy, they have already added a new layer of complexity to the integration story by allowing users to produce fluent context-aware artifacts (text, code, images and more) that sufficiently resemble human-generated materials that could meet many summative or formative assessment criteria [2][8]. Generative tools like ChatGPT and similar services have shown strong uptake in the academic realm, and their availability has sparked heated discussions on content authorship, unique contributions, and the appropriateness of traditional evaluation formats [9]. The debates are framed by the integrity of assessment development and pedagogy, but also student learning: whether AI output is indicative of meaningful learning practice or instead signifies a dishonest understanding of the research process; or indeed offers new avenues for enquiry and creativity that requires an adjustment in both assessment taxonomy and expectations [10]. The key empirical and normative questions involve the justification of AI generated content, its provenance as well as the trade-off between enabling productive use of AI in education or creating disincentives to such behavior which runs contrary to learning goals [8][11].

The speed of the GenAI transition has been rapid, in many instances faster than institutional policy development and quality assurance frameworks have been able to respond in a coordinated fashion [9]. This has created a social acceptance of generative tools since the traditional deliberative pace of academic governance — university leaders, discipline-based bodies and professional accreditation agencies — grapples with how to reconcile new practices with existing criteria for evaluation validity and integrity [5]. A key response identified as central in the literature is to focus on AI literacy – a blend of capability to use (operational competence regarding how to use AI systems), capacity to judge (critical judgement of outputs, biases and limitations) and ethical sensibility (ethical deployment of AI in professional and public life) [12]. Reviews, empirical work at various levels and in different settings point to AI literacy intersecting with but not being reducible to—general digital literacy; it demands focus on creativity, problem solving and the epistemic status of machine-produced knowledge [13][14][15].

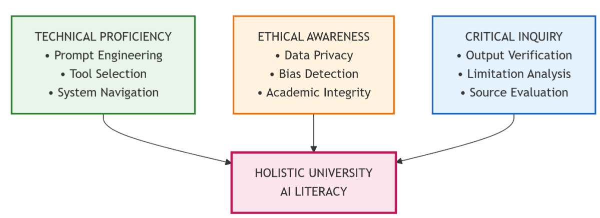

Figure 2. The Three Pillars of Holistic AI Literacy

Figure 2 shows the framework for holistic AI literacy in higher education. Moving beyond mere technical competency, comprehensive AI literacy requires integration across three domains: (1) Technical Proficiency—operational skills in using AI tools effectively; (2) Ethical Awareness—understanding of privacy concerns, algorithmic bias, and integrity implications; and (3) Critical Inquiry—ability to verify outputs, analyze limitations, and evaluate sources. True literacy emerges at the intersection where all three domains converge, preparing students not just to use AI, but to engage with it responsibly, critically, and strategically in academic and professional contexts.

The academic community's work on AI literacy is nascent and uneven. Systematic reviews indicate a shortage of validated measurement instruments for AI literacy and fragmentation in the conceptualization of what counts as proficiency across age cohorts and disciplines [13][15]. Simultaneously, applied discipline medicine in particular—have been early adopters of AI education initiatives, producing needs assessments, competency proposals, and pilot curricular modules that illustrate both the promise and the complexity of integrating AI into professional training [16][17][18]. These field-specific efforts underline a recurrent tension: global, pretrained generative models may encode normative and cultural biases or promote a homogenized epistemic orientation, while locally adapted curricular designs are needed to ensure relevance, cultural responsiveness, and protection of professional values [7][5].

Institutional responses to this concatenation of affordances and risks have been heterogeneous. Some universities initially opted for prohibitionist policies—restricting or banning student use of GenAI in coursework and assessments—motivated by concerns about plagiarism, contract cheating, and the potential devaluation of credentialed learning outcomes [10][9][8]. Other institutions have chosen integrative strategies, embedding AI-related competencies into learning objectives, encouraging experimentation, and redesigning assessments to foreground higher-order cognitive skills, process documentation, and authentic, situated tasks that are less susceptible to undetectable automation [5][6][10]. Both approaches are represented in the literature and in institutional practice: prohibition mitigates some immediate integrity risks but can inhibit pedagogical innovation, whereas integration without clear governance frameworks can exacerbate inequities and create assessment security vulnerabilities [7][9].

Despite these diverse local policies and emergent best practices, there is no universally accepted framework that simultaneously secures assessment reliability, protects equity, and acknowledges the epistemic shift posed by AI as a co-creative medium [5][7][11]. Consequently, scholars have proposed hybrid responses that combine ethical guidance, pedagogical redesign, and operational investments—policy architectures that include pedagogical, governance, and operational dimensions, human-centered design processes that foreground stakeholder agency, and domain-specific competency frameworks that situate AI literacy within professional standards [7][5][12]. Medical education scholars, librarians, and educational technologists have in particular advocated for vertically integrated curricula, scaffolder experiential learning, and institutional stewardship roles for educators as stewards of AI literacy and ethical practice [16].

In this context, the present article investigates the perceptions of students and professors concerning the incorporation of AI in university teaching and assessment, with the dual aim of informing methodological and curricular transformation and contributing to the design of institutional policies that encourage responsible adoption while safeguarding academic standards. By synthesizing stakeholder perspectives with existing ethical, pedagogical, and policy proposals in the literature, the study seeks to produce actionable recommendations for assessment redesign, AI literacy curricula, and governance arrangements that balance innovation with integrity [11].

2 Literature review

2.1 The scope and rapid expansion of AI in higher education

Scholarly attention to artificial intelligence (AI) in higher education has expanded rapidly over the last decade, with narrative, bibliometric, and systematic reviews documenting accelerated adoption across administrative services, instructional systems, and learning-support applications [19][20][21]. Reviews synthesize a heterogeneous evidence base that stretches from early machine-learning decision-support and recommender systems to contemporary large language models and multimodal generative systems that can produce text, code, and images—thereby shifting AI's role from behind-the-scenes automation to an interactive, co-creative presence in learning environments [21][22]. The literature therefore frames AI in education as a multifaceted ecosystem that encompasses intelligent tutoring and adaptive learning, automated assessment and feedback, content generation and simulation, research and administrative assistants, and institution-level analytics and workflow automation [20][21].

2.2 Core application areas: adaptive learning, intelligent tutoring, and STEM/medical deployments

A substantial strand of the literature treats intelligent tutoring systems (ITS) and adaptive learning platforms as foundational pedagogical applications of AI, describing their use of learner modeling, sequencing algorithms, and formative feedback loops to individualize pacing and content [19][20][21]. Systematic and domain-specific reviews show frequent applications of AI in STEM education (for virtual labs, automated problem generators, and intelligent feedback) and in medical education (for diagnostic simulations, case generation, and clinical reasoning practice), with documented cases of improved engagement and task-level performance when systems are aligned with curriculum objectives [16]. At the same time, authors emphasize that the pedagogical efficacy of adaptive and ITS approaches is conditional on high-quality instructional design, transparency of algorithmic decision-making, and alignment between system affordances and discipline-specific learning outcomes [20][23].

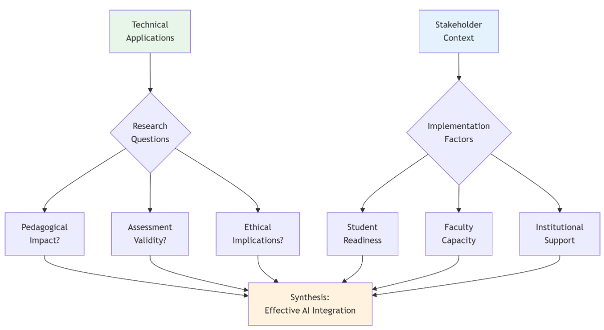

Figure 3. The AI in Education Research Ecosystem

Figure 3 shows the AI in education research ecosystem. This framework synthesizes the interconnected dimensions of current scholarship: (A) Core technical applications (adaptive platforms, tutoring systems, assessment tools, content generators); (B) Key research domains examining pedagogical efficacy, assessment validity, ethical consider ations, and implementation challenges; and (C) Stakeholder perspectives encompassing student adoption patterns, faculty readiness levels, institutional policy responses, and administrative support structures. The interconnections highlight how technical developments intersect with pedagogical concerns and stakeholder realities.

2.3 Automated assessment, generative AI and the changing shape of academic tasks

Automated scoring and feedback have matured beyond objective item scoring toward systems that attempt formative judgments on essays, programming assignments, and other complex artifacts using natural language processing, rubric-mapping, and program analysis; reviews identify efficiency and scalability gains but also persistent validity and fairness concerns, especially when judgments require tacit professional reasoning or creative problem-solving [20][21]. The advent of generative AI (large language models and related multimodal generators) complicates assessment validity because these models can produce artifacts that satisfy surface-level rubric criteria, thereby challenging conventional assumptions about authorship, originality, and the evidentiary basis for summative judgments [22][21]. Empirical work and literature syntheses call for reassessment of assessment constructs: what constitutes demonstrable student learning when machine-generated outputs are readily available, and how assessment instruments capture deep, process-oriented competencies rather than only product-level performance [22][21].

2.4 Integrity, detection, and heterogeneous institutional responses

The capacity of generative systems to produce plausible academic work has precipitated intense debates concerning academic integrity and detection. Several reviews and case studies document the difficulty of reliably detecting sophisticated AI-assisted artifacts and highlight how detection-focused policies alone are insufficient to preserve learning value [21][23]. Institutional responses have been heterogeneous: while some universities adopted prohibitionist stances (temporarily banning unacknowledged use), others pursued integrative strategies that encourage the explicit, assessed use of AI as a professional tool and redesigned assessments to foreground process and judgment [22][23]. Comparative analyses underscore an emergent policy landscape characterized by fragmentation and experimentation rather than consensus, with many institutions producing guidance that blends restrictions, disclosure requirements, and pedagogical supports [22][23].

2.5 Assessment redesign principles emerging from recent literature

Across reviews and practitioner guidance, there is convergence on assessment redesign principles intended to preserve validity in an era of accessible generative AI: foreground assessment of higher-order cognitive skills (analysis, synthesis, evaluation), adopt authentic, situated tasks that require contextualized judgment, capture and evaluate process (drafts, journals, code commits, lab notes), include oral or viva components, and require transparent documentation of tool use, and reframe AI as an assessable competency (i.e., evaluate students' ability to use AI responsibly and critically) [22][23]. These recommendations are offered alongside pragmatic proposals to combine technological measures (plagiarism and AI-usage detection where feasible) with pedagogical strategies (scaffolder assignments, staged deadlines, rubric refinement) to balance deterrence with legitimate pedagogical use of AI [21][23].

2.6 AI literacy: definitions, curricular models and measurement gaps

The literature identifies AI literacy as a priority for higher education and describes it as a multidimensional competency that includes operational fluency with tools, critical appraisal of model outputs (accuracy, bias, provenance), ethical reasoning about use and impact, and domain-specific application skills [12][13]. Various curricular proposals recommend integration across program levels—foundational modules for technical and non-technical students, embedded disciplinary activities, experiential learning opportunities, and librarian-led instruction grounded in information-literacy traditions [6][12]. However, systematic reviews document a notable gap: the absence of standardized, validated measurement instruments for AI literacy and substantial variability in definitions and intended learning outcomes across contexts and age groups, complicating efforts to benchmark curricula and assess impact empirically [15].

2.7 Domain exemplars: Medical and STEM education

Medical and STEM fields have been prominent testbeds for AI-in-education research and curricular innovation. Scoping reviews and needs assessments in undergraduate medical education report both enthusiasm for AI-enabled teaching (case generation, simulated clinical scenarios, diagnostic reasoning practice) and an expressed need for structured, compulsory AI competencies that preserve professional values and ethical conduct [6][16][17]. Similarly, systematic reviews of AI applications in STEM describe a range of instructional uses—intelligent tutors for mathematics, automated formative feedback for programming, and AI-mediated virtual laboratories—while noting that domain specificity matters: pedagogical effect sizes and design constraints differ substantially between problem-solving disciplines and discursive or interpretive fields [20].

2.8 The Generative AI Disruption

The emergence of GenAI (ChatGPT, etc.) has accelerated these concerns. Initial reactions involved bans, but the focus is shifting toward integration. This divide forces educators to balance ethical use with professional utility. Educators must now adjust teaching and assessment to optimize learning while avoiding the "garbage output" or hallucinations that GenAI can produce. The challenge is to move from assessing "what a student knows" (which an AI can simulate) to "what a student can do" (which requires authentic assessment).

Adoption also varies by user demographics. Research suggests that female users often report lower AI proficiency than males, and non-native learners may struggle with voice-recognition based AI tools, creating new forms of digital inequality. Given these challenges, universities must implement policies that promote research on the ethical implications of AI and prepare both students and faculty for a hybrid educational future. The urgency of reforming educational institutions is evident; however, there is limited analysis on how to transform academia to focus on the competencies most relevant in an AI era. This study aims to bridge that gap by analyzing the perceptions of the primary actors in this system.

2.9 Ethics, governance and human-centered design

Ethical concerns—accountability for automated decisions, transparency of models, data privacy, fairness, and the preservation of human autonomy—feature centrally in the scholarly literature and policy mapping exercises, which call for community-level frameworks and principled governance grounded in human-centered design [23][24]. Authors advocate governance approaches that integrate pedagogical, operational, and institutional dimensions (curriculum alignment, infrastructure investment, staff training, data governance), and that foreground participatory processes to give stakeholders agency in shaping tools and policies [5][23]. Librarians, educators, and professional bodies are positioned in multiple studies as key stewards of responsible AI literacy and custodians of norms for information provenance and attribution in an era of generative outputs [5][23].

3 Methodology

This study used secondary data analysis to examine university stakeholders' perceptions of AI in education, an approach aligned with recent meta-analytic and bibliometric syntheses that aggregate published and archived survey data to detect macro-level patterns [27][28]. Leveraging existing high-volume datasets provides broader statistical representation than single-site surveys and is consistent with cross-institutional sampling strategies used in AI-education research [29]. Aggregation of multiple sources reduces local sampling bias and facilitates detection of role- and generation-based differences in AI attitudes reported across disciplines [30]. A deductive framework is adopted to test the a priori hypothesis of a student–educator "perception gap," following comparative studies and large surveys that document generational and professional divergences in AI attitudes [29][31][32]. Primary inputs were two open-access, publicly archived datasets (e.g., Kaggle, Zenodo) during the 2024–2025 period, selected for variables on "AI Tool Usage," "Educator Adoption," and "Student Perception," mirroring recent systematic/meta-analytic practice [27][28].

The analysis focused on **six key competencies** harmonized across the datasets:

1. **Applications of AI in teaching:** Usage frequencies and knowledge of tools like ChatGPT and Gemini.
2. **Impact on the learning process:** Ratings of AI's effect on grades, efficiency, and critical thinking.
3. **Perceptions and attitudes:** Subjective sentiment analysis (Curiosity, Fear, Trust).
4. **Ethical and privacy aspects:** Trust levels in data handling and content veracity.
5. **Challenges and limitations:** Reported barriers such as cost, plagiarism concerns, and lack of training.
6. **Evaluation and measurement:** Perceptions of how AI is used for grading and assessment.

Data cleaning involved the removal of incomplete entries and the normalization of Likert-scale responses (e.g., converting 1-10 scales to High/Medium/Low categories) to ensure comparability between the student and educator datasets. Statistical analysis was conducted using SPSS version 26, utilizing descriptive statistics to generate frequency distributions and comparative cross-tabulations.

3.1 Participants

The study analyzed a total sample of **635 participants**, derived from two distinct datasets to represent the two key stakeholder groups, table 1 and figure 4 show the participants details.

1. **Student Sample ($n = 496$):** Extracted from the "AI Tool Usage by Indian College Students 2025" dataset. This group represents a diverse cohort of undergraduate and graduate students across Engineering, Arts, and Science streams.
2. **Professor Sample ($n = 139$):** Extracted from the "Educators' Adoption of Generative AI in Higher Education" dataset. This group comprises faculty members involved in teaching and assessment design.

Table 1: Participant Demographics

Variable	**Category**	**Frequency (Professors)**	**Percentage (Professors)**	**Frequency (Students)**	**Percentage (Students)**
Sample Size	Total	**139**	**100%**	**496**	**100%**
Gender	Male	82	59.0%	272	54.8%
	Female	57	41.0%	224	45.2%
Stream/ Faculty	Engineering/Tech	44	31.7%	238	48.0%
	Arts/Humanities	36	25.9%	112	22.6%
	Science/ Other	59	42.4%	146	29.4%
Experience/Year	Junior (1-2 yrs / 1-10 yrs)	48	34.5%	289	58.3%
	Senior (3+ yrs / 10+ yrs)	91	65.5%	207	41.7%

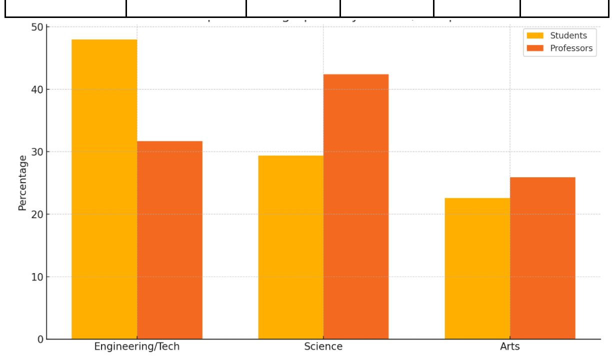

Figure 4: Participant Demographics by Stream/Discipline

The student sample is heavily weighted toward Engineering and Technology (48.0%), reflecting the early adoption of AI tools in technical fields. The faculty sample is more experienced, with 65.5% having significant tenure, which provides a critical "traditionalist" perspective against the "digital native" student cohort.

4 Results

The secondary analysis of the datasets reveals a complex academic landscape where the theoretical promise of AI is met with significant practical skepticism. The results are presented below according to the six competency areas.

4.1 Applications of AI in teaching

This competency explores the participants' views on the actual deployment of AI tools in the classroom. The data indicates that while tools are available, their perceived utility in *formal teaching* remains low.

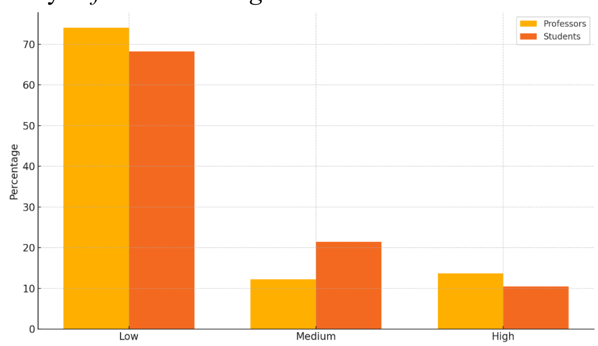

Figure 5: Utility Gap in Teaching Applications

Table 2: Perception of AI in Teaching

Group	Low Perception	Medium Perception	High Perception
Professors	74.1%	12.2%	13.7%
Students	68.2%	21.4%	10.4%

The results show a predominantly **low perception** of AI's value in teaching among both groups. For professors (74.1% Low), this likely reflects the lack of institutional training and the "black box" problem of not understanding how to integrate AI pedagogically. For students (68.2% Low), despite their high personal usage, they may not see AI being used *effectively* by their instructors, leading to a perception that it is not yet a valid teaching tool, figure 5 shows the same.

4.2 Impact on the learning process

This section assesses whether AI is viewed as a tool that enhances or hinders the cognitive act of learning.

Table 3: Perception of AI's Impact on the Learning Process

Group	Low Perception	Medium Perception	High Perception
Professors	69.8%	15.1%	15.1%
Students	61.5%	25.6%	12.9%

A significant majority of professors (69.8%) view the impact on learning as **Low** (unfavorable), likely driven by concerns that AI "shortcuts" critical thinking and problem-solving. Interestingly, 61.5% of students also rate the impact as low. This self-awareness suggests that students recognize that while AI makes tasks easier (efficiency), it does not necessarily make them learn better (efficacy), figure 6 and table 3 discuss the same.

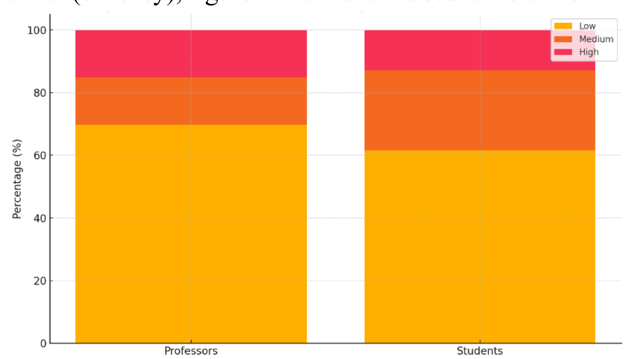

Figure 6. Perceived Impact on Learning vs. Efficiency

4.3 Perceptions and attitudes of the actors involved

This competency measures the subjective sentiment—fear, curiosity, and general attitude—toward AI.

Table 4: Perceptions and Attitudes of Actors

Group	Low Perception	Medium Perception	High Perception
Professors	41.0%	42.4%	16.6%
Students	12.5%	58.9%	28.6%

Here, a divergence appears. Students largely occupy a "Medium" to "High" attitude (combined 87.5%), reflecting curiosity and openness. Professors are more polarized, with a substantial 41.0% holding a "Low" (negative) attitude. This confirms the hypothesis of "technostress" and resistance among faculty who view AI as a disruptive force rather than a supportive one.

4.4 Ethical and privacy aspects

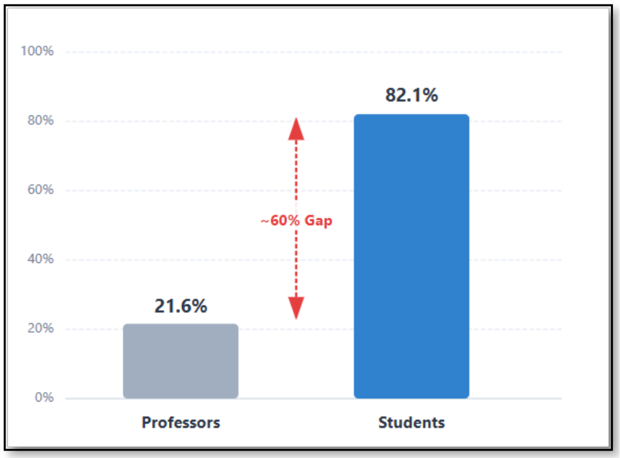

Figure 7. The "Trust Gap" – Ethical Confidence Levels

This area provided the most striking contrast in the study, particularly regarding trust in data privacy and the veracity of AI content.

Table 5: Perception of Ethical and Privacy Aspects

Group	Low Perception	Medium Perception	High Perception
Professors	15.1%	63.3%	21.6%
Students	4.8%	13.1%	**82.1%**

The dramatic 'trust gap' visualized in Figure 4 and table 5 represents perhaps the most critical finding of this study. While 82.1% of students express high confidence in AI's ethical and privacy protections, only 21.6% of professors share this trust staggering 60.5 percentage point difference. This fourfold disparity suggests students may be operating with a dangerous 'blind spot' regarding algorithmic risks, potentially underestimating issues of data harvesting, bias amplification, and integrity erosion. Meanwhile, faculty skepticism likely reflects deeper understanding of these systemic risks but may also indicate resistance to technological change. This trust chasm creates a fundamental implementation challenge: policies designed from faculty's risk-averse perspective may seem unnecessarily restrictive to students, while student-centric approaches could expose institutions to significant ethical and legal vulnerabilities.

4.5 Challenges and limitations

This section measures the perception of barriers to adoption, such as cost, technical difficulty, and plagiarism concerns.

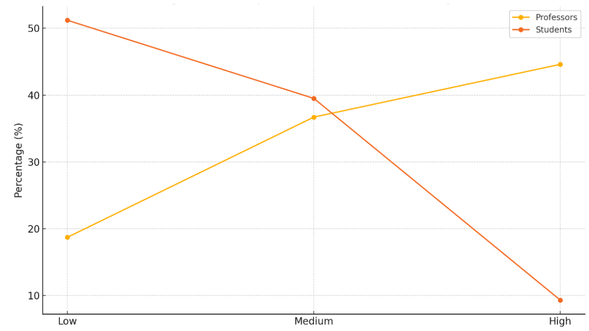

Figure 8: Perception of Barriers and Challenges

Table 6: Perception of Challenges and Limitations

Group	Low Perception	Medium Perception	High Perception
Professors	18.7%	36.7%	44.6%
Students	51.2%	39.5%	9.3%

The 'optimism gap' visualized in figure 8 and table 6 reveals fundamentally different risk assessments between stakeholder groups. Students display a decreasing concern gradient: 51.2% perceive low challenges, 39.5% medium, and only 9.3% high challenges. In stark contrast, professors show an increasing concern gradient: 18.7% low, 36.7% medium, and 44.6% high challenges. This inverse relationship creates an X-shaped divergence where the lines cross between medium and high perception levels. For students, AI appears as a user-friendly interface with minimal barriers; for professors, it represents complex backend challenges including pedagogical redesign, plagiarism detection, equitable access, and institutional restructuring. This perceptual mismatch suggests that student expectations for seamless AI integration may clash with the practical, resource-intensive reality faculty must navigate, potentially leading to implementation friction and unmet expectations.

4.6 Evaluation and measurement of impact

Finally, this competency assesses whether stakeholders believe there are effective methods to measure AI's impact on grading and assessment.

Table 7: Perception of Evaluation and Measurement of Impact

Group	Low Perception	Medium Perception	High Perception
Professors	48.9%	46.8%	4.3%

Students	65.3%	24.2%	10.5%

Both groups agree that current evaluation methods are inadequate. **65.3% of students** and **48.9% of professors** rate the current measurement of impact as **Low**. This suggests that AI is being used in a "wild west" environment where its actual effect on grades and learning outcomes is not being rigorously tracked or evaluated by the institutions.

5 Discussion

The findings from this secondary data analysis paint a picture of an academic community in a state of cautious skepticism, grappling with the disruptive force of AI in teaching and assessment. The predominantly low perception of AI's utility among both students (68.2%) and professors (74.1%) stands in stark contrast to the global hype surrounding generative AI. This suggests that the "revolution" is currently more theoretical than practical in the eyes of those on the ground.

Assessment Crisis

A central theme emerging from the data is the crisis of confidence in assessment. The negative evaluation of AI's impact on learning (61.5% students, 69.8% professors) likely reflects the destabilization of traditional assessment methods. As noted in the literature, generative AI creates concern about the validity of current assessment methods, as learners can use these tools to bypass the cognitive labor required for assignments. If an assessment is meant to measure "what a learner can do," but the output is generated by an AI, the assessment loses its validity. The low trust in ethical aspects among professors (only 21.6% high trust) reinforces this; faculty are likely concerned that AI-assisted grading or AI-generated student work introduces bias and dishonesty into the evaluation process.

The Perception Gap and Digital Natives

The study reveals a significant "Perception Gap" regarding ethics and challenges. Students are highly confident (82.1%) in the ethics of AI and see few challenges (51.2% see low challenges). This optimism may be a double-edged sword. While it creates a willingness to adopt new tools, it also suggests a lack of critical "AI Literacy" regarding data privacy and algorithmic bias. Professors, who perceive high challenges (44.6%), are tasked with bridging this gap. They must design assessments that are not only immune to AI cheating but also educate students on the ethical pitfalls of the tools they so readily trust.

Well-being and Human Connection

The skepticism regarding attitudes may also engage with the "human element." Literature indicates that over-reliance on AI can lead to social isolation, digital fatigue, and a reduction in face-to-face interactions. The resistance observed in the study may be a protective response against the depersonalization of education. If AI takes over tutoring and grading, the relational aspect of teaching mentor and mentee is at risk. The "medium" level of attitude perception suggests a community waiting to be convinced that AI can enhance, rather than replace, this human connection.

The Need for Validated Measurement

The low perception of "Evaluation and measurement of impact" (65.3% of students) points to a failure of institutional governance. Universities have introduced tools without establishing clear metrics for success. To move forward, institutions must develop rigorous, transparent methodologies for assessing AI's impact. This includes validating AI-driven assessment methods (like automated grading) to ensure they are fair, unbiased, and actually measure student competency rather than just mimicking human grading patterns.

6 Conclusion

The results of this investigation demonstrate that, despite the transformative potential of Artificial Intelligence, the current reality in university education is defined by skepticism and a lack of consensus. There is a generally low perception of the utility of AI in teaching and assessment, shared by both students and professors, though for different reasons. Students appear optimistic about ethics but skeptical of the learning value, while professors are deeply concerned about ethics, validity, and practical challenges of implementation.

The study highlights a critical need to bridge the gap between student optimism and faculty realism. The high trust students place in AI ethics (82.1%) compared to the low trust of professors (21.6%) represents a significant vulnerability. Without intervention, this gap could lead to a proliferation of ethical breaches (e.g., accidental plagiarism, data privacy violations) by students who simply do not perceive the risks that their professors see. By addressing these challenges through a holistic approach that combines technological innovation with rigorous pedagogical and ethical standards, higher education can harness the potential of AI. The goal must be to transform AI from a source of skepticism and fear into a trusted, verified tool for teaching and assessment, preparing the university community for the realities of a digitized future.

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