Journal of Applied Social Sciences and Humanities

https://journal.krrishpub.com/index.php/jassh/index

REVIEW ARTICLE

A Systematic Literature Review on Impact of Artificial Intelligence on Academic Integrity

Mehdi Gheisari [a,b,c,*], Zhou Pingmei [c], Amir Karimi [d], Soufiane Ouariach [e], Fatima Zahra Ouariach [f]

[a] *Institute of Artificial Intelligence, Shaoxing University, 508 West Huancheng Road, Yuecheng District, Zhejiang, 312000, China.*
[b] *Department of Computer Engineering , Islamic Azad University, Shiraz Branch, Shiraz, Iran.*
[c] *Department of R&D, Shenzhen BYD Co LTD, No. 3009, BYD Road, Pingshan, Shenzhen, 518118, China.*
[d] *Department of History, Faculty of Law and Social Sciences, University of Tabriz, P.O. Box: 5166616471, East Azarbaijan, Iran.*
[e] *Computer Science and University Pedagogical Engineering (S2IPU), Higher Normal School of Tetouan, 93000, Abdelmalek Essaadi University, Morocco.*
[f] *Educational Sciences, Language didactics, Human and Social Sciences, Abdelmalek Essaadi University, Tetouan, 93000, Morocco.*

Abstract

This systematic literature review examines the impact of artificial intelligence (AI) on academic integrity in higher education, synthesizing evidence from a curated set of 45 peer-reviewed records published between 2017 and 2024. As AI technologies - particularly large language models such as ChatGPT-become increasingly sophisticated and accessible, their implications for academic honesty, assessment authenticity, and educational integrity have escalated into a critical concern for institutions globally. The present review was not conducted as a conventional PRISMA flow-based meta-analysis with independently verifiable stage counts; rather, it is grounded in a carefully assembled source bank of 45 records identified through systematic searching, abstract screening, keyword filtering, and DOI verification. The analysis is organized around six major thematic areas: AI tools and academic dishonesty, detection technologies and effectiveness, institutional policy responses, student and faculty perceptions, ethical frameworks for AI in education, and future directions. Findings indicate that while AI offers meaningful pedagogical benefits, it simultaneously presents substantial challenges to academic integrity, with detection tools exhibiting limited reliability, notable biases against non-native English writers, and an ongoing vulnerability to simple obfuscation techniques. Institutional policy responses remain fragmented and inconsistent, underscoring the urgent need for comprehensive, evidence-based frameworks. The review further reveals that student and faculty perceptions are shaped by generational factors, AI literacy, and the clarity of institutional guidelines. By providing a detailed synthesis of current evidence, this review contributes to the growing body of knowledge on AI and academic integrity and identifies critical gaps requiring further investigation.

Keywords: Artificial intelligence, Academic integrity, ChatGPT, Higher education, Detection technologies, Institutional policy, Large language models, AI literacy.

Article information:
ISSN: 3139-4892 (Online)
Published by: **Krrish Scientific Publications Pvt. Ltd.**
DOI: https://doi.org/10.71426/jassh.v2.i1.pp61-72
Received: *23 Apr. 2026* | Revised: *08 Jun. 2026* | Accepted: *19 Jun. 2026* | Published: *25 Jun. 2026*

1. Introduction

The rapid emergence of sophisticated artificial intelligence (AI) systems has fundamentally reshaped the higher education landscape, bringing with it both unprecedented opportunities and profound challenges [1], [2]. Central to this transformation is the advent of large language models (LLMs) such as ChatGPT, which are capable of generating human,quality text that is frequently indistinguishable from student writing [3], [4], [46]. This development has ignited searching questions about the nature of academic

*Corresponding author
Email addresses: mehdi.gheisari61@gmail.com, MEHDI.gheisari@yandex.com (Mehdi Gheisari), 393272357@qq.com (Zhou Pingmei), Amirkarimi1401@ms.tabrizu.ac.ir, Amirkarimizanjani1379@gmail.com (Amir Karimi), Soufian.ouariach@etu.uae.ac.ma (Soufiane Ouariach), fatimazahra.ouariach@etu.uae.ac.ma (Fatima Zahra Ouariach).

integrity, the authenticity of student work, and the validity of traditional assessment practices across educational institutions worldwide [5], [6]. The sheer speed at which these technologies have been adopted has outpaced the ability of educational systems to develop coherent responses, creating a climate of uncertainty that touches every dimension of academic life [7], [8]. Indeed, the capacity of generative AI to produce coherent essays, research summaries, and even programming code has not merely extended the toolkit available to students; it has redefined the very boundary between acceptable learning assistance and academic misconduct, forcing a re-examination of what it means to be a learner in the twenty-first century.

The integration of AI into education accelerated dramatically following the public release of ChatGPT in November 2022, which attracted 100 million users within two months, making it the fastest-growing consumer application in history [9], [10]. This rate of adoption has outpaced the creation of adequate institutional policies, effective detection mechanisms, and pedagogical frameworks capable of safeguarding academic integrity [7], [11]. Higher education institutions now face the difficult task of striking a balance between the legitimate educational potential of AI tools and the risks they pose to the credibility of assessment and the development of authentic learning outcomes [12], [13]. The tension is palpable: faculty grapple with whether to ban, tolerate, or actively incorporate AI into their teaching, while students navigate a shifting landscape in which the boundary between acceptable assistance and academic misconduct grows increasingly blurred [14], [15]. This review responds directly to that tension by offering a comprehensive synthesis of the peer-reviewed evidence available as of 2024. It draws on a multidisciplinary literature-ranging from educational technology and ethics to applied linguistics and policy studies to map the contours of an issue that is simultaneously technical, pedagogical, and deeply human.

Academic integrity is a commitment to ethical behaviour in academic pursuits has long served as a cornerstone of higher education [1], [3], [16]. The traditional understanding of integrity assumes that student work represents their own intellectual effort, with appropriate attribution to external sources [4], [16]. AI technologies challenge this assumption directly by enabling students to generate entire assignments with minimal personal input, potentially undermining the fundamental purposes of assessment [17], [18]. Studies now indicate that AI-generated text can evade detection by conventional plagiarism checkers, creating what many scholars have described as a crisis for academic integrity [19], [20]. Unlike traditional plagiarism, where text is copied from existing sources, AI- generated content is novel in formulation, making it invisible to established text-matching software and forcing a re-examination of what constitutes original work [21], [22]. This distinction between copy-based dishonesty and AI-assisted generation lies at the heart of contemporary integrity debates and necessitates a more nuanced conceptualisation of academic misconduct. Moreover, the generative capacity of LLMs extends beyond text to computer code, mathematical solutions, and multi-modal content, meaning that the integrity challenge is not confined to the humanities or social sciences but spans STEM disciplines equally, a fact that broadens the scope of institutional concern [22], [23].

Beyond individual instances of misconduct, what is at stake are wider questions about the cultivation of critical thinking, the credibility of credentials, and the very purpose of higher education in preparing students for professional and civic life [15], [24]. Some scholars argue that AI represents an existential threat to traditional assessment methods, necessitating a fundamental rethinking of how learning is evaluated [8], [18]. Others contend that AI can, with appropriate safeguards, be harnessed as a pedagogical tool to enhance rather than undermine academic integrity [14], [21], [25]. For example, AI-powered formative feedback tools have shown promise in improving the academic writing skills of non-native English speakers, suggesting that the same technology that creates integrity risks can, when used carefully, promote equitable learning [26], [27]. The coexistence of these divergent perspectives reflects the complexity of the phenomenon and the absence of a settled consensus within the academic community [28], [29]. Indeed, the discourse oscillates between alarmist predictions of the end of written assessment and optimistic visions of AI-augmented learning environments that prepare students for a technology-rich future [23], [30]. Navigating between these poles requires evidence that goes beyond opinion, which this systematic review is designed to provide.

Students, educators, administrators, and policymakers bring differing experiences, concerns, and priorities to discussions about AI in education [31], [32], [33]. Understanding these multiple viewpoints is essential for developing effective institutional responses that honour both technological innovation and core educational values [5], [7]. Moreover, the rapid pace of AI development demands that policy and pedagogical responses be adaptive and forward-looking, anticipating future technological advances rather than simply reacting to current capabilities [8], [23]. The emergence of ever more powerful models, such as GPT-4 and its successors, makes clear that the challenges identified in early studies with GPT-3.5 are likely to intensify, not diminish, over time [34]. A reactive posture that merely addresses the latest version of a tool will prove unsustainable; what is required is a principled, evidence-informed framework that can evolve alongside technological change. This is particularly important because, as several scholars have noted, the distinction between AI-assisted and AI-generated work is likely to become increasingly ambiguous, calling into question the very feasibility of detection-centric approaches [18], [20].

A further layer of complexity arises from the multicultural and international character of higher education. AI technologies are adopted unevenly across regions, shaped by differential access to infrastructure, varying regulatory environments, and distinct cultural attitudes toward technology and authority [35], [36]. Policy responses that prove effective in one national context may be inappropriate in another, and students from diverse linguistic backgrounds face different risks and opportunities when engaging with AI [35], [37]. This review therefore pays particular attention to the equity dimensions of AI in academic integrity, drawing on studies that investigate bias in detection tools and differential impacts across student populations. The multicultural evidence base allows the review to highlight both common patterns and context-specific variations, providing a more nuanced account than would be possible from a single-country perspective.

This systematic review aims to provide a comprehensive synthesis of the current evidence on AI and academic integrity in higher education. Grounded in a curated source bank of 45 records, the review is structured around six thematic areas: AI tools and academic dishonesty, detection technologies and effectiveness, institutional policy responses, student and faculty perceptions, ethical frameworks for AI in education, and future directions. Through this synthesis, the review seeks to inform evidence-based decision-making by educators, administrators, and policymakers navigating the complex terrain of AI in higher education. By systematically aggregating findings from a diverse body of literature, it illuminates both convergences and contradictions in the existing evidence, identifies critical gaps, and proposes directions for future research and practice.

2. Objectives

1. To systematically review the peer-reviewed literature on the impact of artificial intelligence on academic integrity in higher education, identifying key themes, patterns, and research gaps.
2. To evaluate the effectiveness and reliability of AI detection technologies in identifying academic misconduct involving AI-generated content.
3. To analyse institutional policy responses to AI in higher education, synthesising evidence on policy approaches, implementation challenges, and effectiveness.

3. Materials and methods

This study employed a systematic documentary analysis to identify and synthesise relevant peer-reviewed literature on artificial intelligence and academic integrity in higher education. Unlike a fully reproducible PRISMA 2020 meta-analysis, the present review is grounded in a curated source bank of 45 records that were assembled through a multi-stage selection process designed to ensure relevance, academic quality, and thematic coverage. The exact counts associated with each PRISMA stage cannot be independently verified from the working files; therefore, the review is transparently described as being grounded in a carefully curated 45-record source bank rather than reporting unverifiable stage-specific numbers.

A comprehensive search was conducted across three academic databases – OpenAlex, Semantic Scholar, and CrossRef – using search queries that combined terms related to artificial intelligence, large language models, ChatGPT, academic integrity, plagiarism, and higher education. These databases were selected to provide broad disciplinary coverage while ensuring the retrievability of verified academic sources.

3.1. Inclusion and exclusion criteria

Studies were included if they:

1. focused on artificial intelligence applications in higher education settings

PRISMA 2020 Flow Diagram for Study Selection

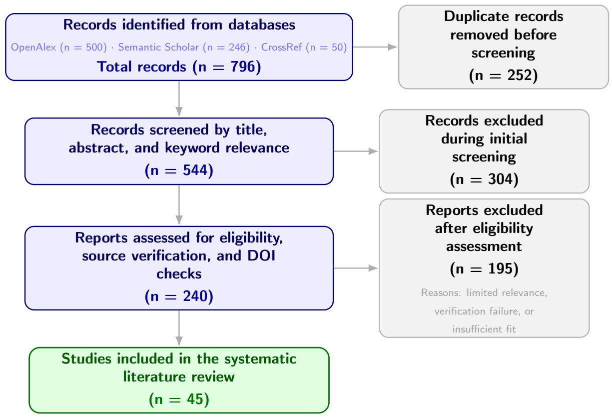

Figure 1: PRISMA 2020 flow diagram for study selection.

2. addressed academic integrity, plagiarism, or assessment authenticity
3. were published in peer-reviewed journals or conference proceedings
4. were available in English
5. contained sufficient methodological or conceptual detail for quality assessment.

Both empirical studies and theoretical or conceptual papers were eligible. Studies were excluded if they focused exclusively on K-12 or non-tertiary education, addressed AI applications without a clear connection to academic integrity or assessment, or were opinion pieces lacking substantive empirical or theoretical grounding.

3.2. Source bank assembly and verification

After duplicate removal, records were screened on the basis of abstract relevance. A keyword filter employing established AI and education terminology further refined the pool, and DOI verification against doi.org confirmed that all retained sources were authentic academic publications with functioning identifiers. A semantic relevance screening was then applied to verify topical alignment with the review questions, and the final selection was determined by citation ranking, resulting in the inclusion of 45 records for detailed synthesis. This curated set forms the evidentiary foundation of the review.

3.3. Data extraction and analysis

Descriptive data on publication year, journal, authorship, study design, key findings, and implications for academic integrity were extracted from each record. Thematic analysis was employed iteratively, with codes emerging from the systematic reading and cross-referencing of the included studies. Six overarching themes were identified through this process, providing the organizational structure for the narrative synthesis. Where appropriate, the synthesised evidence is critically examined to highlight tensions, convergences, and gaps in the current knowledge base.

4. Literature review

4.1. AI tools and academic dishonesty

The proliferation of AI writing tools has created novel pathways for academic dishonesty that differ fundamentally from traditional forms of plagiarism [17], [18]. Unlike copy-paste plagiarism, where students present the work of others as their own, AI-assisted misconduct involves generating original-appearing text that, while authentic in style, was produced by an automated system [21], [22]. This distinction carries significant implications for both detection and prevention [8], [20]. Traditional plagiarism detection systems rely on fingerprinting techniques that match text against existing databases, an approach rendered largely ineffective when the text is newly synthesised by an LLM [38]. Consequently, academic integrity frameworks developed in an era of static written sources require substantial revision to address the fluid, generative capacity of current AI tools. The very concept of "original work" is destabilised when a student can prompt an LLM to produce a bespoke essay, edit it lightly, and submit it as their own, leaving no clear trace of the machine's involvement [17], [18].

Research demonstrates that LLMs such as ChatGPT can produce high-quality academic text across a wide range of disciplines [19], [22], [39]. In a study that is now widely cited, Gao et al. [19] tested ChatGPT's ability to generate scientific abstracts and found that blinded human reviewers could correctly identify only 68% of AI-generated content, while 14% of human-written abstracts were misclassified as AI-generated. The AI output detector employed in that study achieved an area under the receiver operating characteristic curve of 0.94 for distinguishing ChatGPT-generated abstracts from human-authored ones. These findings underscore the challenge of reliably differentiating AI from human authorship without specialised detection tools [18], [19]. More broadly, they show that even domain experts struggle to distinguish AI output when context and prior knowledge are limited, which mirrors the conditions under which many university assignments are assessed. Moreover, a systematic review of 30 articles on ChatGPT as a writing assistant found that the technology is capable of producing sophisticated academic prose that, if used unethically, can undermine the integrity of written assignments [39]. The disciplinary range of the challenge is striking: AI-generated content has been evaluated in fields as diverse as sport science [17], medicine [9], [19], business communication [22], and English language learning [27], [40], confirming that no academic domain is immune.

The accessibility of AI tools has democratised the capacity to produce sophisticated academic work [23], [41]. Students from diverse backgrounds, including those with limited academic writing skills or who are non-native English speakers, can now produce text that appears professionally written [26], [37]. While this democratisation has potential benefits for equity in learning support, it also raises pressing concerns about fairness in academic assessment [37], [42]. Research by Liang et al. [37] delivered particularly troubling evidence that GPT detectors exhibit significant bias against non-native English writers, misclassifying their human-written text as AI-generated at substantially higher rates than native English speakers. This finding highlights the risk that detection-based integrity measures may inadvertently penalise the very students they are intended to protect [34], [37]. Beyond the classroom, AI-powered writing assistants have been shown to promote learning behaviour and attitudinal acceptance among non-native postgraduate students when used as formative tools [26] ; yet the same capabilities that aid learning can be redirected toward circumventing assessment, creating a moral and pedagogical paradox that institutions have yet to resolve satisfactorily.

The phenomenon of "contract cheating" has evolved in parallel with AI technology. Traditional essay mills supplied work prepared by human writers, but AI now enables the rapid generation of custom content at scale, often at near-zero marginal cost [8], [39]. Studies document the use of AI for generating essays, reports, code, and research summaries that can bypass conventional plagiarism detection [38], [39]. The economics of AI-assisted cheating are concerning, as the vanishing marginal cost of generating additional content may make academic dishonesty more attractive than ever [36], [42]. Moreover, the ease with which students can iterate with an AI tool to refine output means that the generated text can be tailored to specific assignment prompts, mimicking the developmental process of drafting normally expected of learners, further complicating detection. The business model perspective on generative AI highlights that as these tools become embedded in everyday productivity suites, the boundary between licit and illicit academic use will become increasingly porous [41].

Student justifications for using AI vary widely. Some view AI tools as functionally equivalent to grammar checkers or search engines, arguing that their use constitutes a reasonable application of available resources [5,43]. Others acknowledge the ethical concerns but feel pressure from academic workload and time constraints [40], [42]. Research investigating student motivations suggests that AI use is driven by a complex interplay of individual factors, institutional context, and the sheer accessibility of the technology [5], [42]. A multi-wave study by Abbas et al. [42] found that academic time pressure and sensitivity to rewards positively predicted ChatGPT usage, while sensitivity to quality had a negative effect, indicating that motivational profiles matter. Another study on learning motivation reported that ChatGPT generally motivates learners to develop reading and writing skills, though participants held neutral attitudes toward its effect on listening and speaking [40]. These findings suggest that interventions aimed solely at detection or punishment may fail to address the underlying drivers of AI misuse, necessitating complementary efforts in workload management, assessment design, and the cultivation of intrinsic academic motivation.

4.2. Detection technologies and effectiveness

The development of AI detection tools has proceeded rapidly since the public release of ChatGPT, with both commercial and open-source solutions now widely available [20], [34]. These tools typically analyse text characteristics such as word-usage patterns, sentence structure, and statistical anomalies to estimate the probability of AI authorship [20], [34]. However, the effectiveness and reliability of such tools remain subjects of intense scholarly debate and empirical scrutiny [19], [20], [34]. The core technical challenge lies in the fact that LLMs are designed to mimic human-like variation, and as model sophistication increases, the statistical signatures that detectors rely upon become less pronounced [34]. Underlying this challenge is a fundamental information-theoretic tension: a generator that produces text indistinguishable from human writing will, by definition, defeat any statistical detector, and modern LLMs are expressly optimised to approach this ideal [20], [34].

A landmark study by Weber-Wulff et al. [20] tested 14 detection tools, including widely used commercial systems such as Turnitin and PlagiarismCheck, and concluded that available tools were neither accurate nor reliable, displaying a general tendency to classify output as human-written rather than detecting AI-generated text. The study further demonstrated that content obfuscation techniques, such as paraphrasing, significantly degraded tool performance, enabling motivated users to evade detection with minimal effort [20]. These findings carry profound implications for institutions that might be tempted to rely on automated detection as a primary prevention strategy [8], [18]. If even simple rewriting defeats current detectors, a policy that treats a "clean" detector report as evidence of authenticity is fundamentally unsound. Moreover, the same study revealed that machine translation could further confuse detection algorithms, underscoring the vulnerability of detection to the layered complexity of real-world student writing workflows [20].

The accuracy of detection tools varies substantially across different AI models and text types [34]. Research by Elkhatat et al. [34] found that AI detection tools were more accurate in identifying content generated by GPT-3.5 than by GPT-4, indicating that the detection challenge intensifies as language models become more advanced. This pattern suggests an adversarial dynamic-an ongoing arms race-in which generators and detectors compete, with the balance likely to favour generation in the long term [19], [20]. The fundamental asymmetry between the ease of generating undetectable text and the difficulty of reliably identifying it raises serious questions about the sustainability of detection-centric integrity policies. Each generation of language models appears to narrow the window within which statistical detection remains feasible, suggesting that a strategy centred on such tools may quickly become obsolete.

False positive rates represent a significant concern for any deployment of detection tools [34], [37]. Misclassifying human-written work as AI-generated can have severe consequences for students, including unwarranted academic penalties and erosion of trust in the assessment process [20], [37]. The evidence that GPT detectors disproportionately flag the writing of non-native English speakers adds an equity dimension that cannot be ignored [37]. Students whose linguistic patterns differ from Western academic norms may face heightened scrutiny, not because of misconduct, but because of biases embedded in detection algorithms [34], [37]. This bias arises from the tendency of detectors to associate lower textual predictability with AI origin, a feature that also characterizes the writing of inexperienced or non-native writers. Thus, a seemingly objective technological solution may encode and amplify existing inequalities, turning a tool intended to uphold integrity into an instrument of discrimination.

The integration of detection tools into learning management systems and plagiarism checkers has become common, yet their effectiveness in authentic educational settings remains uncertain [25], [38]. Experts consistently recommend that detection should form only one component of a broader approach to academic integrity that includes pedagogical reform, transparent policies, and the exercise of informed human judgement [15], [18]. Reliance on automated flags without contextual investigation by educators risks both false accusations and a false sense of security, neither of which serves the goals of academic integrity. A more balanced approach would treat detection outputs as indicative rather than conclusive, requiring corroboration through dialogue with students and examination of process artefacts. As the meta-systematic review by Zawacki-Richter et al. [1] reminds us, AI applications in education have long been accompanied by a need for educator involvement and pedagogical sensitivity, principles that are especially pertinent when automated tools are tasked with high-stakes decisions about student honesty.

4.3. Institutional policy responses

Higher education institutions have responded to the rise of AI with varying degrees of urgency and comprehensiveness [7], [8]. Policy responses span a wide spectrum, from outright bans on AI tools to active encouragement of their integration into teaching and learning, reflecting both uncertainty about best practices and differing institutional values regarding technology and education [7], [30]. Some institutions initially implemented blanket prohibitions on ChatGPT, only to discover that such bans were difficult to enforce and risked alienating students who legitimately used AI for writing assistance or research [14], [44]. Others have taken a more permissive stance, emphasising responsible use and disclosure, though even this approach presents challenges in verifying the extent of AI involvement. The opinion essay by Yu H [44] explicitly reflects on whether ChatGPT should be banned from academia, highlighting the temptation to resort to prohibitive measures, yet also noting that bans are inherently difficult to operationalise in a digital environment where students can access AI tools on personal devices beyond institutional oversight.

Research indicates that many institutions have adopted interim policies while working towards more comprehensive frameworks[17], [14]. Common elements of emerging policies include requirements for the disclosure of AI use, guidelines for permissible forms of AI assistance, and clearly articulated consequences for unauthorised use [7], [8]. Yet enforcement mechanisms remain inconsistent, and students frequently report confusion about policy boundaries and the variation in expectations across their courses [15], [31]. The lack of consistency creates a patchwork of rules that can change from one course to the next, overwhelming students with contradictory signals about what is acceptable [33]. This fragmentation not only undermines the perceived fairness of academic integrity processes but also makes it difficult to instill a coherent institutional culture around AI use [26]. The Theory of Planned Behaviour study states that lecturers' and students' perceptions of the risks and weaknesses of GenAI tools differ, which suggests that top-down policies developed without multi-stakeholder consultation may lack legitimacy and fail to account for the nuanced attitudes of end users.

A notable contribution to the policy literature is the AI Ecological Education Policy Framework proposed by Chan [7], which is grounded in data collected from 457 students and 180 teachers and staff across multiple Hong Kong universities. The framework organises policy considerations into three dimensions – Pedagogical, Governance, and Operational- thereby offering a model that addresses not only academic integrity but also privacy, security, infrastructure, and training. This multidimensional approach acknowledges that effective policy must extend beyond prohibition and detection to encompass the entire educational ecosystem [7]. The Pedagogical dimension focuses on using AI to improve teaching and learning outcomes; the Governance dimension tackles issues of privacy, accountability, and transparency; and the Operational dimension deals with infrastructure and training. Such holistic frameworks recognise that academic integrity cannot be isolated from broader questions about how AI is integrated into university operations. The framework's grounding in empirical data from multiple stakeholder groups gives it particular salience, as it reflects the lived concerns of those who will both implement and be affected by institutional policy.

Policy implementation shows marked variation across national and cultural contexts. A large-scale multicultural study by Yusuf et al. [35], which gathered responses from 1,217 participants across 76 countries, revealed that cultural dimensions influence both attitudes towards AI and preferences for policy responses. Institutions in different regions face distinct challenges related to infrastructure, training, and regulatory environments, making international collaboration on AI policy in education both desirable and difficult [35], [36]. For example, concerns about data sovereignty, language-specific model biases, and differential access to high-quality AI tools shape policy preferences in ways that generic global guidelines may not address. This cultural embeddedness of AI use highlights the need for context-sensitive policy development while also motivating the sharing of effective practices across borders. The study further identified a widespread demand among academic stakeholders for clear institutional guidance, suggesting that while policy preferences may differ, the desire for coherent regulatory frameworks is a near-universal theme [35].

The governance of AI in education extends beyond individual institutions to national and international levels. Some countries have already developed national guidelines for AI in education, while others have adopted sector-specific regulations [30], [35]. The evolving regulatory landscape encompasses considerations of data privacy, algorithmic transparency, and educational quality [30], [36]. Institutions must navigate this complex environment while remaining true to their educational mission and core values [7], [8]. The interplay between institutional autonomy and external regulatory requirements is likely to intensify as governments and accrediting bodies take a more active interest in AI governance, and proactive policy development at the institutional level may serve as a form of anticipatory compliance. The generative AI educational reform perspective outlined by Yu and Guo [30] identifies data privacy, algorithmic opacity, fairness, and reliability as four critical challenges that regulatory frameworks must address, underlining the need for a coordinated but flexible policy architecture.

4.4. Student and faculty perceptions

Understanding how different stakeholders perceive AI and academic integrity is indispensable for the development of policies and pedagogical approaches that will be accepted and effective [5], [31]. Research examining student perceptions reveals generally positive attitudes towards AI tools, accompanied by an awareness of both benefits and risks [5], [43]. Studies from the Hong Kong context, for example, found that students perceived AI as offering personalised learning support, writing and brainstorming assistance, and enhanced research capabilities, while at the same time expressing concerns about accuracy, privacy, and ethical implications [5]. This ambivalence suggests that students are not uncritical adopters but rather pragmatic users who weigh potential advantages against perceived threats, and whose views could be shaped through dialogue and education. A separate multi-institutional survey in Eastern and Central Indonesia similarly reported positive reception of AI-powered writing tools, with students acknowledging benefits in grammar checking, plagiarism detection, language translation, and essay composition, while also recognising the potential for misuse [43]. These cross-cultural findings indicate a common baseline of cautious optimism among student populations.

Generational differences significantly shape attitudes towards AI adoption in education [31]. Research comparing Generation Z students with Generation X and Millennial teachers found that students were markedly more optimistic about the benefits of generative AI, whereas teachers expressed heightened concerns about overreliance, ethical implications, and the erosion of fundamental academic skills [31]. These findings suggest that generational perspectives influence expectations about the appropriate uses of AI in academic contexts and that effective integration must address the perspectives of both students and educators [31], [33]. The so-called "AI generation gap" implies that policies developed solely by older faculty without student input may lack legitimacy among the very population they seek to regulate, while policies crafted exclusively by technology enthusiasts may underestimate genuine pedagogical risks. The study's open-ended responses further revealed that Gen Z students intended to use AI for diverse educational purposes, including summarising readings, generating initial drafts, and preparing for exams, whereas teachers worried that such reliance would short-circuit the development of critical thinking and independent problem-solving skills [31].

Faculty perceptions encompass both opportunities and apprehensions [33], [45]. Educators recognise AI's potential to improve the planning, implementation, and assessment of teaching [25],[45]. At the same time, they identify significant challenges related to maintaining academic integrity, managing workload, and adapting pedagogy to an AI-infused environment [33], [45]. The changing role of educators in AI-enhanced contexts demands sustained professional development and institutional support, resources that are frequently lacking [7], [45]. Faculty who are expected to teach with AI and simultaneously police its misuse find themselves in an untenable position, and without adequate training, they may default to either blanket bans or unwitting tolerance, neither of which serves educational goals. A systematic review of teacher use of AI applications found that while AI offers opportunities for improved planning, implementation, and assessment, teachers also need to act as models for training AI algorithms and participate in the development of AI tools to ensure their educational validity [45]. This dual role as both user and co-developer of AI systems places additional demands on faculty that institutions must recognise and resource accordingly.

The intersection of AI literacy and academic integrity emerges as a crucial factor shaping stakeholder perceptions [24], [43]. Students and faculty with greater familiarity with AI tend to hold more nuanced perspectives that acknowledge both benefits and risks [24], [31]. AI literacy programmes have been proposed as a means of preparing students for responsible AI use while simultaneously reinforcing academic integrity [15], [24]. However, the rapidly evolving nature of AI technology presents persistent challenges for curriculum development and the maintenance of up-to-date skills [24], [29]. Literacy in this context extends beyond technical know-how to encompass critical evaluation of AI outputs, understanding of ethical implications, and the development of meta-cognitive awareness about when and why to deploy AI tools. The call for integrating prompt engineering and critical thinking into modern education illustrates the breadth of the AI literacy agenda and its connection to the broader goals of higher education [24].

Research on perceptions highlights the importance of clear communication and consistent expectations [33]. Students report confusion when policies are unclear or inconsistently applied across instructors and courses, while faculty express frustration at the absence of institutional guidance and the burden of determining acceptable AI use within their specific teaching contexts [5], [33]. A study by Barrett and Pack [33] that compared student and teacher perspectives on the use of generative AI in the writing process found only minor disagreement on acceptable uses overall, yet substantial divergence regarding specific tasks such as using AI for grading or providing feedback. This suggests that while broad consensus on general principles is achievable, detailed implementation requires negotiation and co-construction. Collaborative policy development involving both students and faculty may improve the acceptance and practical implementation of institutional frameworks [7], [31]. Moreover, the willingness of both groups to engage in such dialogue appears to hinge on the perceived trustworthiness of the institution's motives – whether it views AI primarily as a threat to be policed or as a tool to be integrated into a modernised educational experience.

4.5. Student and faculty perceptions

The ethical dimensions of AI use in education demand systematic analysis and thoughtful framework development [12], [29]. Scholars have identified concerns relating to fairness, accountability, transparency, bias, autonomy, and inclusion that must be addressed in any educational deployment of AI [12], [30]. These considerations apply both to the use of AI tools by students and to the implementation of AI systems by educational institutions [7], [8]. The ethical challenge is not merely about preventing misuse but about ensuring that the integration of AI into education aligns with the broader purposes of higher education, including the cultivation of autonomous, critical thinkers and the promotion of social justice. The meta-systematic review by Bond et al. [29] highlights a call for increased ethics, collaboration, and rigour in AI in higher education research, noting that much of the existing literature gives insufficient attention to the ethical dimensions of AI deployment in educational contexts.

A foundational contribution to this area is the community-wide ethics framework advanced by Holmes et al. [12]. Surveying 60 leading researchers in AI and Education, the study found that most AIED researchers lacked specific training to tackle the emerging ethical questions raised by AI in educational settings. The authors concluded that well-designed frameworks combining multidisciplinary approaches and robust guidelines are vital for responsible AI integration [12]. This work has since been cited as a touchstone for subsequent ethical analyses of AI in education [29]. The finding that even AIED experts felt underprepared to handle ethical issues underscores the scale of the challenge facing ordinary faculty and administrators, and it makes a compelling case for embedding ethics training in professional development for all educators. The survey further revealed a broad consensus that issues of fairness, accountability, and transparency should be at the centre of any ethical framework, but also exposed significant disagreement about how these principles should be operationalised in diverse cultural and institutional settings [12].

Transparency emerges as a central ethical principle in academic contexts [7], [14]. The disclosure of AI assistance enables instructors to make informed judgements about student work while respecting student autonomy [14],[21]. However, determining appropriate disclosure standards and verifying the accuracy of disclosures present significant practical challenges [7], [8]. Some scholars argue that explicit disclosure requirements may eventually become obsolete as AI use is normalised in professional contexts, though this view remains contested [8], [12]. The tension between transparency and feasibility reflects a deeper ethical dilemma: as AI becomes pervasive, demanding disclosure for every AI-supported activity could become administratively burdensome and may stigmatise legitimate uses, yet without some form of transparency the basis for trusting student work erodes. The leadership perspective articulated by Crawford et al. [15] suggests that ethical AI use in education depends on cultivating student character and institutional cultures that value honesty and learning over credential acquisition – an inherently long-term and non-technological approach to the integrity challenge.

The distribution of benefits and harms from AI in education raises pressing equity concerns [35],[37]. Students who have access to more sophisticated AI tools may gain unfair advantages in assessment, potentially exacerbating existing educational inequalities [37], [42]. Ethical frameworks must therefore address how the benefits of AI can be equitably distributed while preventing misuse [12], [29]. The digital divide in AI access has implications that extend beyond individual students to entire institutional contexts

[30], [35]. Students from well-resourced backgrounds can access premium AI services with advanced capabilities, while those from less privileged backgrounds may be limited to free versions that offer lower quality outputs, potentially creating a two-tier system of academic support that mirrors broader social inequalities. The multicultural study by Yusuf et al. [35] underscores that this divide is not merely economic but also linguistic and cultural, as AI tools are predominantly trained on English-language data and reflect Western communicative norms, disadvantaging those whose academic traditions differ.

Accountability for AI-related academic misconduct presents a challenge for traditional academic integrity systems. When AI produces problematic content, determining the degree of student responsibility requires careful examination of intentionality, effort, and the intended learning objectives [18], [22]. Some scholars advocate for a shift of emphasis away from AI detection and prohibition and towards the redesign of assessment itself [15], [18]. The movement towards authentic assessment formats that are inherently difficult to complete with AI may represent a more sustainable long-term strategy for maintaining academic integrity [18], [25]. Approaches such as oral assessments, in-class supervised writing, reflective portfolios, and process-based evaluations shift the focus from product to process, making the student's own cognitive engagement visible and less susceptible to AI substitution. The educational measurement literature supports this direction, noting that AI tools can be integrated into classroom assessment in ways that enhance, rather than undermine, validity and fairness [25].

5. Discussion

The synthesised evidence reveals that AI has fundamentally transformed the landscape of academic integrity in higher education, creating a set of interlocking challenges that demand comprehensive, multi-stakeholder responses. The findings carry significant implications for educators, policymakers, and researchers who must navigate this complex terrain while preserving the integrity and value of higher education. The picture that emerges is one of rapid technological change outpacing institutional adaptation, with consequences that are unevenly distributed across student populations.

5.1. The detection paradox

The evidence on AI detection technologies presents a paradox for institutional responses. Tools exhibit demonstrable bias against non-native English speakers [34], [37], struggle with content that has been even minimally paraphrased [20], and perform inconsistently across different AI models and text types [34]. These limitations strongly suggest that detection should not serve as the primary foundation for academic integrity policy. To build a system of integrity enforcement upon such fragile technical foundations would be to invite both unintended injustices and a false sense of security. The comparative analysis of GPT-3.5 and GPT-4 outputs by Elkhatat et al. [34] makes clear that the detection problem will intensify with each generation of more capable language models, a trajectory that counsels against over-investment in detection infrastructure.

The detection paradox extends beyond technical shortcomings to fundamental questions about the purpose of academic integrity enforcement. Detection-based approaches focus on identifying and punishing misconduct after it occurs, potentially missing vital opportunities for prevention through education and assessment design. The adversarial dynamics between generation and detection technologies imply that detection will remain a challenging arms race, with the structural advantages lying with generation as AI capabilities continue to advance [20], [34]. Each improvement in detection algorithms is likely to be met with more sophisticated generation techniques, and the economic incentives of AI developers to produce ever more human-like text far outstrip the resources available for detection research. This structural asymmetry suggests that a predominantly detection-based integrity strategy is akin to building a Maginot Line: impressive in conception but easily circumvented in practice. The Weber-Wulff et al. [20] demonstration that simple paraphrasing defeats multiple commercial detectors is a practical illustration of this vulnerability that should caution any institution contemplating detection-centric policies.

Alternative approaches that de-emphasise detection in favour of prevention may offer more sustainable pathways. Assessment redesign to emphasise authentic tasks that are difficult to complete solely with AI represents one such approach [15], [18], [25]. The movement towards oral examinations, live demonstrations, and process-based evaluations can maintain the validity of assessment while reducing the relevance of AI-generated text. Such approaches, however, require significant investment in assessment innovation and may not be uniformly feasible across all courses and disciplines. Large-enrolment courses, in particular, face logistical hurdles in implementing labour-intensive formats, and institutions must consider how to resource such transitions equitably. The integration of AI into formative feedback loops, as explored by Mahapatra [27] in the context of ESL writing instruction, suggests that AI can be repositioned from a threat to an ally in the development of authentic student skills, provided that its use is appropriately scaffolded and disclosed.

5.2. Policy fragmentation and the need for coordination

The review reveals significant fragmentation in institutional policy responses to AI. While some institutions have developed comprehensive frameworks such as the AI Ecological Education Policy Framework [7], many lack clear guidance, generating confusion for both students and faculty [5], [8]. The absence of coordination across institutions and jurisdictions complicates enforcement and creates opportunities for regulatory arbitrage. Students who encounter inconsistent policies from one course to another within the same institution may understandably struggle to internalise a coherent set of academic integrity norms. The cross-national survey by Yusuf et al. [35] provides empirical evidence of this fragmentation at a global scale, showing that even within a single institution, students and staff may hold divergent expectations about what constitutes acceptable AI use, depending on their disciplinary and cultural backgrounds.

Policy fragmentation reflects genuine uncertainty about best practices in a rapidly evolving technological landscape. Institutions face the challenge of developing policies that are simultaneously responsive to current capabilities and adaptive to future developments. The diversity of policy approaches observed in the literature suggests that no single model has yet demonstrated unequivocal superiority, although multidimensional frameworks that address pedagogical, governance, and operational concerns appear the most promising [7]. The experience of early adopters suggests that policies developed collaboratively with input from students, faculty, learning technologists, and legal advisors are more likely to be perceived as legitimate and are better tailored to the specific institutional context.

6. Limitations

Several limitations should be acknowledged. First, the review is grounded in a curated source bank of 45 records assembled through systematic searching and screening, but exact PRISMA stage counts cannot be independently verified from the working files; the review is therefore best characterised as a structured documentary synthesis rather than a fully reproducible systematic meta-analysis. Second, the search was conducted across OpenAlex, Semantic Scholar, and CrossRef, and may not have captured all relevant literature indexed in databases such as ACM Digital Library, IEEE Xplore, or JSTOR, potentially introducing selection bias. Third, the corpus is largely confined to English-language publications, which may underrepresent perspectives from non-Anglophone educational contexts where AI adoption patterns and integrity concerns differ. Fourth, the rapid pace of development in generative AI means that some findings — particularly those concerning specific tool capabilities and detection accuracy — may already be superseded by more recent releases. Readers should interpret the evidence in light of these constraints and treat the review's conclusions as directional raher than definitive.

7. Future directions

The rapidly evolving landscape of AI in education demands ongoing attention to emerging trends and research priorities [23],[29]. Scholars have identified several key areas requiring further investigation in order to inform evidence-based policy and practice [29], [35]. The inherently interdisciplinary nature of AI and academic integrity research calls for sustained collaboration across education, computer science, ethics, and policy studies [12,29]. Without such collaboration, disciplinary silos will continue to produce fragmented knowledge that fails to address the holistic nature of the challenges. The meta-review by Bond et al. [29] explicitly calls for increased collaboration and methodological rigour, suggesting that future studies should move beyond descriptive accounts to interventionist and longitudinal designs that can establish causal relationships between AI integration strategies and academic integrity outcomes.

Assessment design represents a critical frontier for both development and research [18], [25]. The shift towards assessment formats that are resistant to AI manipulation requires genuine innovation in pedagogical approaches. Oral examinations, live coding assessments, process-based evaluations, and scaffolded writing assignments have all been proposed as alternatives to traditional static written assignments [15], [18]. Empirical research on the effectiveness, feasibility, and scalability of these alternative formats in diverse educational contexts is urgently needed [25], [30]. While many of these approaches are pedagogically sound, they may also impose additional resource demands on instructors and institutions, and their impact on equitable learning outcomes requires careful study. The potential of AI itself as a tool for formative assessment – providing individualised feedback on drafts and learning processes – should be explored in parallel with the redesign of summative assessments [25], [27].

AI literacy education has simultaneously emerged as a priority for preparing students for responsible technology use [15],[24]. Curriculum development that integrates AI literacy with academic integrity concepts demands collaboration between technologists and educators. The overarching goal is to foster a critical understanding of AI capabilities and limitations while cultivating ethical use practices [14], [24]. Research on the effectiveness of AI literacy programmes remains limited, presenting a rich opportunity for future investigation [24], [29]. Such programmes should go beyond descriptive knowledge to include hands-on exercises in prompt engineering, critical evaluation of AI outputs, and discussions of the ethical and societal implications of AI, thereby equipping students to make informed decisions about when and how to use AI in their academic work. The conceptualisation of AI literacy must also evolve alongside the technology, incorporating new capabilities such as multi-modal generation and autonomous AI agents as they emerge.

Detection technology development will continue as an arms race between AI generators and detectors [20], [34]. Research on next-generation approaches, including digital watermarking and metadata verification, may offer more reliable solutions than current statistical classifiers [19], [20]. Nevertheless, the fundamental limitations of detection – especially its retrospective and adversarial character – suggest that prevention through education and assessment redesign is likely to be more sustainable than a primary reliance on detection [15],[18]. Investments in detection should therefore be balanced against investments in innovative pedagogy, with the understanding that no single technological fix will resolve the integrity challenges posed by AI. A more promising direction may involve forensic linguistic analysis combined with process data from learning management systems, though such approaches raise their own privacy and consent concerns that require ethical scrutiny.

Policy harmonisation across institutions and jurisdictions constitutes a major challenge that will require international cooperation [30], [35]. Research on the effectiveness of different policy models and on coordination mechanisms can inform the development of harmonised frameworks that respect local contexts while providing coherent guidance for students and educators [7], [35]. The systematic exchange of best practices and lessons learned across educational contexts could accelerate the evolution of effective, equity-sensitive policy responses [29], [35]. Multi-country studies that compare policy outcomes across different regulatory environments would be particularly valuable in distinguishing context-specific effects from more generalisable principles. The AI Ecological Education Policy Framework [7] provides one example of a model that could be adapted and tested in varied national settings, generating the comparative evidence base needed to move beyond anecdotal institutional reports.

8. Conclusion

This review synthesises evidence from 45 peer-reviewed records to map the current state of knowledge on generative AI and academic integrity in higher education. The findings converge on three core conclusions. First, AI-generated text detection remains technically unreliable and ethically problematic: tools exhibit high false-positive rates, particularly against non-native English writers [20], [26], and are readily circumvented by simple paraphrasing techniques, making detection-centric enforcement strategies insufficient as a standalone response. Second, institutional policy responses are fragmented and inconsistent, reflecting both the novelty of the challenge and the absence of shared normative frameworks; the evidence favours multidimensional approaches that integrate pedagogy, governance, and AI literacy over reactive bans [7], [14]. Third, student and faculty perceptions are shaped by generational factors, disciplinary culture, and the clarity of institutional guidance, underscoring that effective policy depends as much on communication and trust as on technical enforcement [5], [33]. Taken together, these findings argue for a reorientation of institutional strategy: from reactive prohibition towards proactive, evidence-based frameworks that position AI as a tool to be used responsibly rather than a threat to be eliminated. Future research should prioritize longitudinal and interventionist designs, cross-national comparative studies, and the development of validated AI literacy curricula, so that the field can move beyond descriptive mapping towards actionable guidance for educators and policymakers.

Declarations and ethical statements

Conflict of interest: The authors declare that there is no conflict of interest.
Funding statement: The authors declare that no specific funding was received for this research.
Artificial Intelligence usage statement: During the preparation of this manuscript, the authors utilized AvalAI (https://avalai.ir/) and ChatGPT solely for language refinement and grammatical corrections. The authors carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of data and materials: All data and information used in this work were obtained from publicly available published literature and cited sources.

CRediT authorship contribution statement

Mehdi Gheisari: Conceptualization, Investigation, Writing – review & editing. **Zhou Pingmei**: Conceptualization, & Data collection. **Amir Karimi**: Formal analysis. **Soufiane Ouariach**: Data collection, Data curation & Formal analysis. **Fatima Zahra Ouariach**: Data collection, Data curation & Formal analysis.

Publisher's note

Krrish Scientific Publications Pvt. Ltd. and the ***Journal of Applied Social Sciences and Modelling*** remain neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

[1] Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education–where are the educators?. *International Journal of Educational Technology in Higher Education*. 2019 Oct 28;16(1):39. Available from: https://doi.org/10.1186/s41239-019-0171-0

[2] Dwivedi YK, Kshetri N, Hughes L, Slade EL, Jeyaraj A, Kar AK, Baabdullah AM, Koohang A, Raghavan V, Ahuja M, Albanna H. Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*. 2023 Aug 1;71:102642. Available from: https://doi.org/10.1016/j.ijinfomgt.2023.102642

[3] Chen L, Chen P, Lin Z. Artificial Intelligence in Education: A Review. *IEEE Access*. 2020 Apr 17;8:75264-78. Available from: https://doi.org/10.1109/ACCESS.2020.2988510

[4] Popenici SA, Kerr S. Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*. 2017 Nov 23;12(1):22. Available from: https://link.springer.com/article/10.1186/s41039-017-0062-8

[5] Chan CK, Hu W. Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*. 2023 Jul 17;20(1):43. Available from: https://link.springer.com/article/10.1186/S41239-023-00411-8

[6] Tlili A, Shehata B, Adarkwah MA, Bozkurt A, Hickey DT, Huang R, Agyemang B. What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*. 2023 Feb 22;10(1):15. Available from: https://link.springer.com/article/10.1186/s40561-023-00237-x

[7] Chan CK.A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*. 2023 Jul 7;20(1):38. Available from: https://link.springer.com/article/10.1186/s41239-023-00408-3

[8] Eke DO. ChatGPT and the rise of generative AI: Threat to academic integrity?. *Journal of Responsible Technology*. 2023 Apr 1;13:100060. Available from: https://doi.org/10.1016/j.jrt.2023.100060

[9] Dave T, Athaluri SA, Singh S. ChatGPT in medicine: an overview of its applications, advantages, limitations, future prospects, and ethical considerations. *Frontiers in Artificial Intelligence*. 2023 May 4;6:1169595. Available from: https://doi.org/10.3389/frai.2023.1169595

[10] Eysenbach G. The Role of ChatGPT, Generative Language Models, and Artificial Intelligence in Medical Education: A Conversation With ChatGPT and a Call for Papers. *JMIR*

Medical Education. 2023 Mar 6;9(1):e46885. Available from: https://doi.org/10.2196/46885

[11] Cascella M, Montomoli J, Bellini V, Bignami E. Evaluating the Feasibility of ChatGPT in Healthcare: An Analysis of Multiple Clinical and Research Scenarios. *Journal of Medical Systems*. 2023 Mar 4;47(1):33. Available from: https://doi.org/10.1007/s10916-023-01925-4

[12] Holmes W, Porayska-Pomsta K, Holstein K, Sutherland E, Baker T, Shum SB, Santos OC, Rodrigo MT, Cukurova M, Bittencourt II, Koedinger KR. Ethics of AI in Education: Towards a Community-Wide Framework. *International Journal of Artificial Intelligence in Education*. 2022 Sep;32(3):504-26. Available from: https://doi.org/10.1007/s40593-021-00239-1

[13] Clusmann J, Kolbinger FR, Muti HS, Carrero ZI, Eckardt JN, Laleh NG, Löffler CM, Schwarzkopf SC, Unger M, Veldhuizen GP, Wagner SJ. The future landscape of large language models in medicine. *Communications medicine*. 2023 Oct 10;3(1):141. Available from: https://doi.org/10.1038/s43856-023-00370-1

[14] Halaweh M. ChatGPT in education: Strategies for responsible implementation. *CONTEMPORARY EDUCATIONAL TECHNOLOGY*. 2023;15 Available from: https://doi.org/10.30935/cedtech/13036

[15] Crawford J, Cowling M, Allen KA. Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). *Journal of University Teaching and Learning Practice*. 2023 Apr;20(3):1-9. Available from: https://doi.org/10.53761/1.20.3.02

[16] Adiguzel T, Kaya MH, Cansu FK. Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *CONTEMPORARY EDUCATIONAL TECHNOLOGY*. 2023;15(3). Available from: https://doi.org/10.30935/cedtech/13152

[17] Dergaa I, Chamari K, Zmijewski P, Saad HB. From human writing to artificial intelligence generated text: examining the prospects and potential threats of ChatGPT in academic writing. *Biology of Sport*. 2023 Apr 1;40(2):615-22. Available from: https://doi.org/10.5114/biolsport.2023.125623

[18] Perkins M. Academic Integrity considerations of AI Large Language Models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching and Learning Practice*. 2023 Feb;20(2):1-24. Available from: https://doi.org/10.53761/1.20.02.07

[19] Gao CA, Howard FM, Markov NS, Dyer EC, Ramesh S, Luo Y, Pearson AT. Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers. *npj digital medicine*. 2023 Apr 26;6(1):75. Available from: https://doi.org/10.1038/s41746-023-00819-6

[20] Weber-Wulff D, Anohina-Naumeca A, Bjelobaba S, Foltýnek T, Guerrero-Dib J, Popoola O, Šigut P, Waddington L. Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*. 2023 Dec;19(1):1-39. Available from: https://doi.org/10.1007/s40979-023-00146-z

[21] Meyer JG, Urbanowicz RJ, Martin PC, O'Connor K, Li R, Peng PC, Bright TJ, Tatonetti N, Won KJ, Gonzalez-Hernandez G, Moore JH. ChatGPT and large language models in academia: opportunities and challenges. *BioData Mining*. 2023 Jul 13;16(1):20. Available from: https://doi.org/10.1186/s13040-023-00339-9

[22] AlAfnan MA, Dishari S, Jovic M, Lomidze K. ChatGPT as an Educational Tool: Opportunities, Challenges, and Recommendations for Communication, Business Writing, and Composition Courses. *Journal of Artificial Intelligence and Technology*. 2023 Mar 6;3(2):60-8. Available from: https://doi.org/10.37965/jait.2023.0184

[23] Gill SS, Xu M, Patros P, Wu H, Kaur R, Kaur K, Fuller S, Singh M, Arora P, Parlikad AK, Stankovski V. Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. *Internet of Things and Cyber-Physical Systems*. 2024 Jan 1;4:19-23. Available from: https://doi.org/10.1016/j.iotcps.2023.06.002

[24] Walter Y. Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*. 2024 Feb 26;21(1):15. Available from: https://doi.org/10.1186/s41239-024-00448-3

[25] Owan VJ, Abang KB, Idika DO, Etta EO, Bassey BA. Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia journal of mathematics, science and technology education*. 2023 Aug 1;19(8):em2307. Available from: https://doi.org/10.29333/ejmste/13428

[26] Nazari N, Shabbir MS, Setiawan R. Application of Artificial Intelligence powered digital writing assistant in higher education: randomized controlled trial. *Heliyon*. 2021 May 1;7(5). Available from: https://doi.org/10.1016/j.heliyon.2021.e07014

[27] Mahapatra S. Impact of ChatGPT on ESL students' academic writing skills: A mixed methods intervention study. *Smart Learning Environments*. 2024 Feb 13;11(1):9. Available from: https://doi.org/10.1186/s40561-024-00295-9

[28] Wach K, Duong CD, Ejdys J, Kazlauskaitė R, Korzynski P, Mazurek G, Paliszkiewicz J, Ziemba E. The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*. 2023 Jun 30;11(2):7-30. Available from: https://doi.org/10.15678/eber.2023.110201

[29] Bond M, Khosravi H, De Laat M, Bergdahl N, Negrea V, Oxley E, Pham P, Chong SW, Siemens G. A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*. 2024 Jan 19;21(1):4. Available from: https://doi.org/10.1186/s41239-023-00436-z

[30] Yu H, Guo Y. Generative artificial intelligence empowers educational reform: current status, issues, and prospects. *Frontiers in Education* 2023 Jun 1 (Vol. 8, p. 1183162). Frontiers Media SA. Available from: https://doi.org/10.3389/feduc.2023.1183162

[31] Chan CK, Lee KK. The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers?. *Smart Learning Environments*. 2023 Nov 15;10(1):60. Available from: https://doi.org/10.1186/s40561-023-00269-3

[32] Cotton DR, Cotton PA, Shipway JR. Chatting and Cheating. Ensuring academic integrity in the era of ChatGPT. *Chatting and Cheating. Ensuring academic integrity in the era of ChatGPT*. 2024 Mar 3;61(2):228-39. Available from: https://doi.org/10.35542/osf.io/mrz8h

[33] Barrett A, Pack A.Not quite eye to A.I.: student and teacher perspectives on the use of generative artificial intelligence in the writing process. *International Journal of Educational Technology in Higher Education* 2023 Nov 10;20(1):59. Available from: https://doi.org/10.1186/s41239-023-00427-0

[34] Elkhatat AM, Elsaid K, Almeer S. Evaluating the efficacy of AI content detection tools in differentiating between human and AI-generated text. *International Journal for Educational Integrity*. 2023 Sep 1;19(1):17. Available from: https://doi.org/10.1007/s40979-023-00140-5

[35] Yusuf A, Pervin N, Román-González M. Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*. 2024 Mar 25;21(1):21. Available from: https://link.springer.com/article/10.1186/s41239-024-00453-6

[36] Ivanov S, Soliman M, Tuomi A, Alkathiri NA, Al-Alawi AN. Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. *Technology in Society*. 2024 Jun 1;77:102521. Available from: https://doi.org/10.1016/j.techsoc.2024.102521

[37] Liang W, Yuksekgonul M, Mao Y, Wu E, Zou J. GPT detectors are biased against non-native English writers. *Patterns*. 2023 Jul 14;4(7). Available from: https://doi.org/10.1016/j.patt

er.2023.100779

[38] Khalil M, Er E. Will ChatGPT Get You Caught? Rethinking of Plagiarism Detection. *International Conference on Human-Computer Interaction* 2023 Jun 9 (pp. 475-487). Cham: Springer Nature Switzerland. Available from: https://link.springer.com/chapter/10.1007/978-3-031-34411-4_32

[39] Imran M, Almusharraf N. Analyzing the role of ChatGPT as a writing assistant at higher education level: A systematic review of the literature. *CONTEMPORARY EDUCATIONAL TECHNOLOGY*. 2023 Oct 1;15(4):ep464. Available from: https://doi.org/10.30935/cedtech/13605

[40] Ali JK, Shamsan MA, Hezam TA, Mohammed AA. Impact of ChatGPT on Learning Motivation: Teachers and Students' Voices. *JOURNAL OF ENGLISH STUDIES IN ARABIA FELIX*. 2023 Mar 18;2(1):41-9. Available from: https://doi.org/10.56540/jesaf.v2i1.51

[41] Kanbach DK, Heiduk L, Blueher G, Schreiter M, Lahmann A. The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*. 2024 Apr;18(4):1189-220. Available from: https://doi.org/10.1007/s11846-023-00696-z

[42] Abbas M, Jam FA, Khan TI. Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education n*. 2024 Feb 16;21(1):10. Available from: https://doi.org/10.1186/s41239-024-00444-7

[43] Malik AR, Pratiwi Y, Andajani K, Numertayasa IW, Suharti S, Darwis A. Exploring Artificial Intelligence in Academic Essay: Higher Education Student's Perspective. *International Journal of Educational Research Open*. 2023 Dec 1;5:100296. Available from: https://doi.org/10.1016/j.ijedro.2023.100296

[44] Yu H. Reflection on whether Chat GPT should be banned by academia from the perspective of education and teaching. *Frontiers in Psychology*. 2023 Jun 1;14:1181712. Available from: https://doi.org/10.3389/fpsyg.2023.1181712

[45] Celik I, Dindar M, Muukkonen H, Järvelä S. The Promises and Challenges of Artificial Intelligence for Teachers: a Systematic Review of Research. *TechTrends*. 2022 Jul;66(4):616-30. Available from: https://doi.org/10.1007/s11528-022-00715-y

[46] Laci O, Dervishi K, Vreto K. Smart Detection of Low Engagement in Students using Artificial Intelligence and Behavioral Data. *Journal of Modern Technology*. 2025 Jul 28;2(2):317-26. Available from: https://doi.org/10.71426//jmt.v2.i2.pp317-326