



## ACADEMIC INTEGRITY AND STUDENTS' ETHICAL USE OF CHATGPT IN HIGHER EDUCATION

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### ABSTRACT

Aim/Purpose	To examine how ethical awareness, cognitive appraisal (trust and perceived usefulness), digital competence, academic performance, and gender influence university students' ethical use of ChatGPT and academic integrity.
Background	This study explores how university students' use of ChatGPT influences academic integrity in higher education. It responds to emerging integrity challenges posed by generative AI by empirically testing a model that links transparency, plagiarism avoidance, bias awareness, and responsible use to academic integrity outcomes across universities in the Gulf region.
Methodology	PLS-SEM analysis of survey data from 318 students across five Gulf-region universities; tests direct effects of four ethical variables, mediation by trust in AI and perceived usefulness, and moderation by digital literacy and CGPA.
Contribution	This study provides empirical evidence that core ethical-use dimensions significantly enhance academic integrity; clarifies the mediating roles of trust/usefulness and the moderating roles of digital literacy/CGPA; and documents gender and discipline differences in usage.
Findings	All four ethical variables positively and significantly predict academic integrity: Trust in AI and perceived usefulness act as partial mediators. Digital literacy and CGPA significantly moderate several relationships. High-performing and senior students report more frequent and effective use of ChatGPT; gender and discipline differences are evident.

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Recommendations for Practitioners	Embed digital literacy and ethical-AI training (transparency, anti-plagiarism, bias awareness, responsible use) into curricula; implement inclusive AI policies; and guide trust calibration and verification workflows to support responsible use.
Recommendations for Researchers	Extend the model across countries and disciplines; examine longitudinal effects; test additional mediators (e.g., AI anxiety, institutional policy clarity) and moderators (e.g., year of study, assessment type); compare alternative SEM and causal designs.
Impact on Society	Promotes responsible AI adoption that safeguards academic ethics, supports equitable student outcomes, and informs policy for trustworthy AI use in higher education ecosystems.
Future Research	Conduct multi-institutional replications, experimental interventions on ethics/digital literacy training, and studies of assessment design that balance AI use with integrity (e.g., oral/ authentic assessments).
Keywords	artificial intelligence, academic integrity, ChatGPT, Gulf universities, PLS-SEM, student ethical responsibility, transparency, plagiarism avoidance, bias awareness, AI trust, digital literacy, AI usefulness, responsible use

## INTRODUCTION

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### *BACKGROUND*

The rapid integration of artificial intelligence tools such as ChatGPT in the education sector has attracted significant scholarly attention (Al-Jahwari & Yousif, 2025; X. Chen et al., 2020; Rejeb et al., 2024; Shishakly, 2025; Vieriu & Petrea, 2025; Zawacki-Richter et al., 2019). From the student perspective, prior research highlights the benefits of ChatGPT for writing, language learning, research, and administrative tasks (Dwivedi et al., 2023; Fitria, 2023; Lund & Wang, 2023; Shishakly et al., 2025). These systems provide real-time feedback on grammar, programming, and problem-solving by leveraging deep learning techniques to generate contextually relevant responses (Atlas, 2023; Baidoo-Anu & Owusu Ansah, 2023; Else, 2023; Herft, 2023; Kasneci et al., 2023; Qadir, 2022; Sallam, 2023; Sok & Heng, 2023; Susnjak, 2022; Vieriu & Petrea, 2025). Despite these advantages, scholars have raised substantial ethical concerns, including academic dishonesty, over reliance on AI, misinformation, and unfair assessment practices (Rudolph et al., 2023; Sok & Heng, 2023). Although ChatGPT can reduce instructional workload and foster pedagogical innovation (Cox, 2021), it also poses risks to academic integrity, responsible use, and algorithmic fairness (Farhi et al., 2023; Qadir, 2022; Welding, 2023). Ethical AI use is therefore expected to uphold fairness, transparency, privacy, and non-discrimination (Mhlanga, 2023). Plagiarism and contract cheating remain among the most pressing concerns (Cotton et al., 2024; Roe & Perkins, 2022), while transparency in disclosing AI assistance is increasingly emphasized as a foundation of academic credibility (Lamb, 2023; C. Lee & Cha, 2025; Tlili et al., 2023).

### *RESEARCH GAP*

Although existing studies examine AI adoption and traditional academic misconduct, they offer limited empirical insight into how students conceptualize ethical responsibility when using generative AI tools. Most research focuses narrowly on plagiarism or cheating, with minimal attention to broader ethical dimensions such as transparency, responsible use, and algorithmic bias. Consequently, current academic integrity frameworks do not sufficiently account for AI-specific risks or student-level ethical decision-making. Furthermore, theoretical discussions often lack practical, evidence-based strategies to guide the ethical use of AI in educational contexts (Guerrero-Dib et al., 2020; Ramdani, 2018; Zawacki-Richter et al., 2019). Kumar et al. (2024) note that although AI technologies are reshaping

academic integrity discourse, formal guidance for responsible student usage remains scarce. Rodrigues et al. (2024) further highlight the limited empirical literature addressing AI and academic integrity. Importantly, few studies have examined how individual academic performance and demographic factors shape ethical engagement with AI tools. Prior research in educational technology suggests that academic achievement and gender are associated with differences in technology adoption, self-regulation, and ethical decision-making. (Hanham et al., 2021; Nair et al., 2025; Zhuo et al., 2023). However, the moderating roles of CGPA and gender in the use of ethical AI remain underexplored, despite their recognized importance for learning behavior, cognitive engagement, and technology-related risk-taking. Prior research generally suggests that the adoption of AI technologies is associated with improved academic performance (Chiu, 2024). Furthermore, AI has been shown to enhance student achievement, engagement, and academic performance and to support personalized learning and improved educational performance (Ma'amor et al., 2024; Mihaella & Petrea, 2025). However, research also indicates that excessive reliance on AI may reduce critical thinking and human interaction and increase the risk of academic fraud, highlighting the need for validation mechanisms and ethical regulation (Ju, 2023; Łodzickowski et al., 2024; Săseanu et al., 2024; Vieriu & Petrea, 2025).

### ***RESEARCH MODEL OVERVIEW***

To address these gaps, this study proposes an integrative framework linking AI-specific ethical practices to academic integrity. Ethical engagement with ChatGPT is conceptualized through four interrelated dimensions: transparency in disclosing AI assistance (Lamb, 2023), responsible use as a complement to critical thinking rather than a substitute (Essel et al., 2024; Iqbal & Iqbal, 2024; Parsakia, 2023), plagiarism avoidance to preserve originality (Kotsis, 2024), and awareness of algorithmic bias to support fairness and credibility in academic work (Baker & Hawn, 2022). The framework extends conventional academic integrity models by incorporating trust in AI and perceived usefulness as mediating variables that explain how ethical practices translate into integrity-related outcomes. Digital literacy and CGPA are included as moderating variables to reflect differences in technological competence and academic performance that may shape responsible AI engagement. Gender is also considered a demographic moderator, capturing variation in ethical reasoning and technology-use patterns documented in prior educational research. In this study, academic integrity is defined not only as the avoidance of cheating but also as a broader commitment to honesty, fairness, accountability, and transparent knowledge production in AI-supported learning environments.

### ***PROBLEM STATEMENT AND STUDY AIM***

The rapid diffusion of ChatGPT in higher education has outpaced the development of empirically grounded ethical frameworks to guide student behaviour. Universities currently lack robust evidence on how students ethically engage with generative AI tools and how this engagement is influenced by trust, perceived usefulness, digital competence, academic performance, and gender differences. Without such understanding, institutional policies, assessment practices, and academic integrity regulations risk being incomplete or ineffective in addressing AI-related misconduct and ethical ambiguity. Accordingly, this study aims to examine the factors influencing university students' ethical and responsible use of ChatGPT and their implications for academic integrity. Specifically, it investigates how transparency, plagiarism avoidance, bias awareness, and responsible use shape integrity outcomes, while considering the mediating roles of trust in AI and perceived usefulness, and the moderating effects of CGPA and gender as indicators of academic performance and demographic variation in technology-related ethical behaviour.

### ***RESEARCH QUESTIONS***

The following research questions were identified:

**RQ1:** How does transparency about using ChatGPT influence students' academic integrity?

- RQ2:** How does avoiding plagiarism when using ChatGPT influence students’ academic integrity?
- RQ3:** How does awareness of bias in ChatGPT influence students’ academic integrity?
- RQ4:** How does the responsible use of ChatGPT as a learning tool influence students’ academic integrity?
- RQ5:** Does trust in AI mediate the relationships between ethical usage dimensions and academic integrity?
- RQ6:** Does perceived usefulness of ChatGPT mediate the relationships between ethical usage dimensions and academic integrity?
- RQ7:** Does digital literacy moderate the relationships between ethical use dimensions and academic integrity?
- RQ8:** Do CGPA and gender moderate the relationships between ethical usage dimensions and academic integrity?

## RESEARCH MODEL

To address the research gap, the study proposed a research model that aims to empirically investigate how the ethical and responsible use of ChatGPT in academia can be enhanced through transparency, critical awareness, and digital competence, thereby promoting academic integrity and mitigating risks such as plagiarism and algorithmic bias. Figure 1 presents the conceptual framework, which identifies the key variables influencing the ethical use of AI tools in academic contexts. Existing academic integrity frameworks (e.g., Borenstein & Howard, 2021; Eaton, 2022; Macfarlane et al., 2014) primarily address traditional forms of misconduct, such as plagiarism and cheating, focusing on moral reasoning and institutional codes rather than technology-mediated ethics. However, the rise of generative AI introduces new ethical challenges that these models do not capture. To bridge this gap, the proposed framework integrates four additional variables, such as trust in AI, plagiarism and bias issues, perceived usefulness, digital literacy, and CGPA, to extend conventional integrity theories (Table 1). *Trust in AI* and *perceived usefulness* serve as mediating variables, explaining how ethical dimensions (transparency, bias awareness, plagiarism avoidance, and responsible use) influence academic integrity. Meanwhile, digital literacy and CGPA serve as moderating variables, representing how students’ technical competence and academic performance shape their responsible AI engagement.

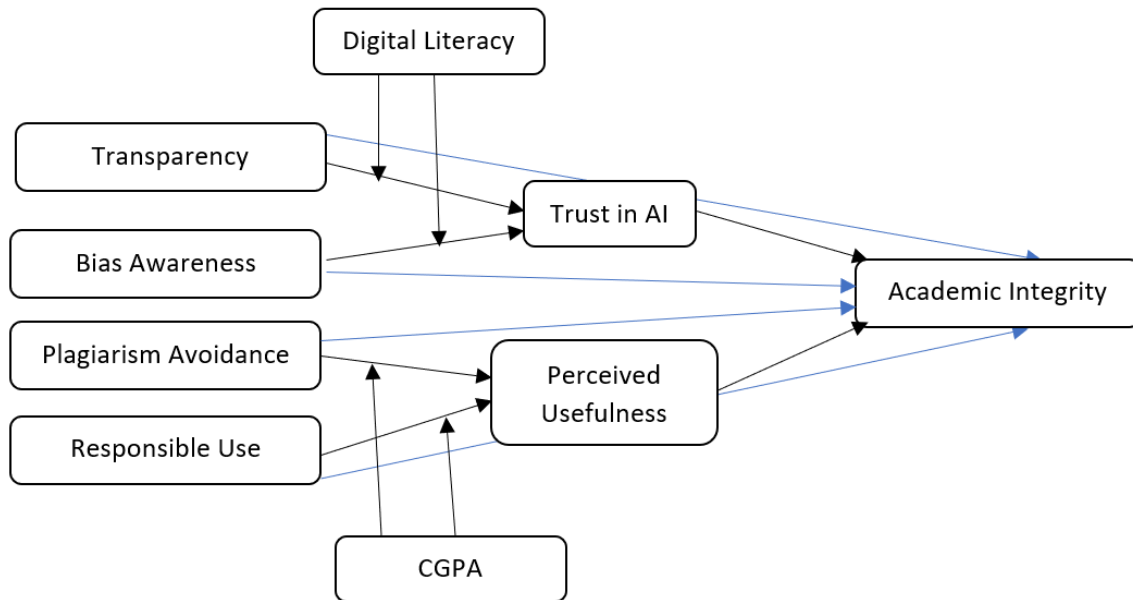


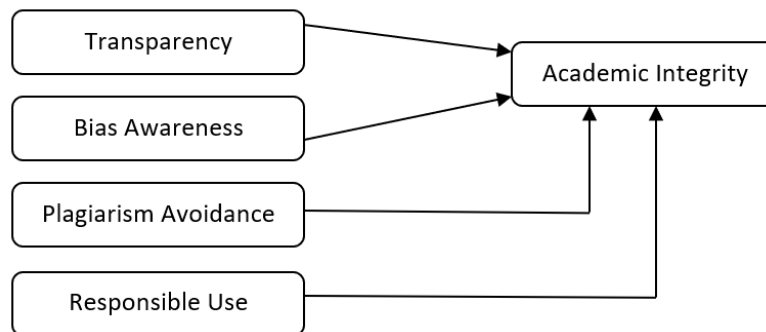
Figure 1. Ethical and responsible use of ChatGPT in academia

**Table 1. Summary of the research model variables**

Role	Variables
Direct	Transparency, bias awareness, plagiarism avoidance, responsible use
Mediating	Trust in AI, perceived usefulness
Moderating	Digital literacy, CGPA
Outcome	Academic integrity

### ***DIRECT IMPACT VARIABLES***

These independent variables are proposed to influence the ethical and responsible use of ChatGPT directly, thereby affecting academic integrity. Transparency reflects students' willingness to disclose their use of ChatGPT, fostering openness and trust, which are essential for ethical practice. Bias awareness raises students' understanding of potential AI biases, promoting the critical and ethical use of AI-generated content. Plagiarism avoidance emphasizes originality and proper citation, reinforcing ethical standards and academic honesty. Responsible use represents the constructive application of ChatGPT to support learning and creativity rather than to replace cognitive effort. The inclusion of digital literacy and CGPA as moderating variables is grounded in the Technology Acceptance Theory (TAM) and Self-Regulated Learning Theory. Digital literacy influences how effectively students apply ethical principles, with higher competence enhancing the positive impact of AI on creativity and ethical engagement (Agaoglu et al., 2025). CGPA reflects academic performance and self-regulation, as high-performing students tend to engage with AI more responsibly and uphold integrity (Qadir, 2022; Vieriu & Petrea, 2025). Together, these factors strengthen the relationship between ethical awareness and academic integrity by promoting informed and responsible use of AI. Figure 2 summarizes the direct impact of variables on academic integrity.

**Figure 2. Direct impact of variables on academic integrity**

The following hypotheses have been formulated regarding the direct impact variables:

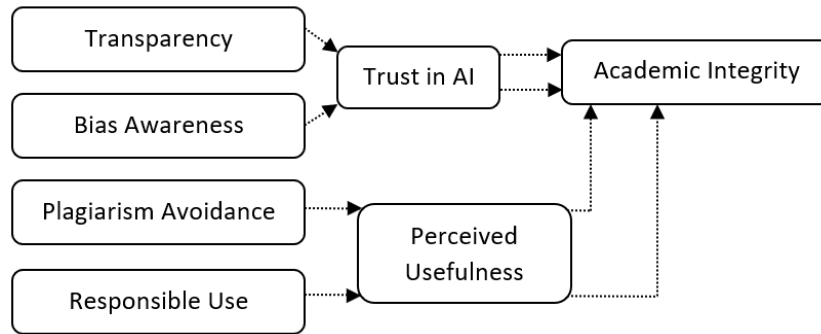
- H1:** Transparency in using ChatGPT is positively associated with students' academic integrity.
- H2:** Plagiarism avoidance in using ChatGPT is positively associated with students' academic integrity.
- H3:** Awareness of biases in ChatGPT is positively associated with students' academic integrity.
- H4:** Responsible use of ChatGPT as a learning aid is positively associated with students' academic integrity.

### ***MEDIATING VARIABLES***

The mediating variables are proposed to explain how and why the independent variables influence academic integrity. The variable 'trust in AI' refers to a student's confidence in ChatGPT's reliability,

fairness, and helpfulness. It mediates relationships among variables such as transparency, bias awareness, and academic integrity. High trust may reinforce ethical behavior or, if misplaced, undermine it, depending on the context. The perceived usefulness variable refers to the extent to which students believe ChatGPT enhances their academic performance. It acts as a bridge between responsible use and ethical decision-making, potentially leading to more frequent and varied use, thereby increasing the need for ethical guidance.

Furthermore, the mediating variables' effects of trust in AI and perceived usefulness align with the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT), clarifying how ethical perceptions shape academic integrity. Trust in AI mediates the effects of transparency and bias awareness: students who perceive ChatGPT as reliable and fair are more likely to engage ethically. In contrast, low trust reduces this effect (Al-kfairy et al., 2025). Perceived usefulness links responsible use and plagiarism avoidance to integrity, as students who find AI beneficial tend to use it appropriately. Similarly, Tao et al. (2019) emphasize that social trust and positive perceptions of usefulness strengthen adoption intentions, supporting integrity-oriented engagement with AI tools. Figure 3 summarizes the direct impact of variables on academic integrity.



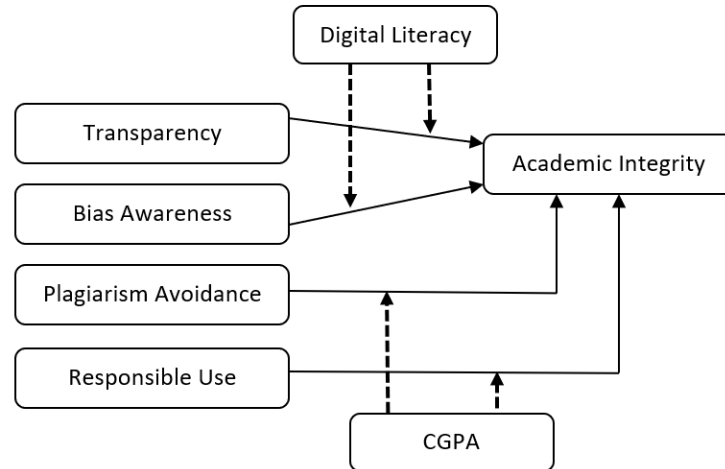
**Figure 3. Mediating variables on academic integrity**

The following hypotheses have been formulated regarding the mediating variables:

- H5a:** Trust in AI mediates the relationship between transparency and academic integrity.
- H5b:** Trust in AI mediates the relationship between bias awareness and academic integrity.
- H6a:** Perceived usefulness of ChatGPT mediates the relationship between responsible use and academic integrity.
- H6b:** Perceived usefulness of ChatGPT mediates the relationship between plagiarism avoidance and academic integrity.

### ***MODERATING VARIABLES***

The moderating variables influence the strength or direction of relationships between other variables and academic integrity. The digital literacy variable refers to students' technical and critical skills in using digital tools, including AI. It moderates the impact of transparency, bias awareness, and responsible use on academic integrity. Students with high digital literacy are more likely to use ChatGPT ethically because they understand its capabilities and limitations. The CGPA variable is included to account for academic performance level, which may correlate with or influence the ethical use of AI. It can help isolate whether the effects of the other variables hold regardless of students' academic standing. The relationships among the mediating and direct impact variables are summarized in Figure 4.



**Figure 4. Moderating variables on academic integrity**

The following hypotheses have been formulated regarding the moderating variables:

- H7a:** Digital literacy moderates the relationship between transparency and academic integrity such that the relationship is stronger at higher levels of digital literacy.
- H7b:** Digital literacy moderates the relationship between bias awareness and academic integrity such that the relationship is stronger at higher levels of digital literacy.
- H8a:** CGPA moderates the relationship between plagiarism avoidance and academic integrity such that the relationship is stronger for students with higher CGPA.
- H8b:** CGPA moderates the relationship between responsible use and academic integrity such that the relationship is stronger for students with higher CGPA.

### ***THE OUTCOME VARIABLE***

Academic integrity, the primary dependent variable in this study, reflects adherence to ethical principles such as honesty, fairness, responsibility, and transparency in academic work. In the context of AI, integrity extends beyond avoiding plagiarism or misconduct; it also involves using tools like ChatGPT responsibly, with critical awareness and disclosure of AI assistance. As Balalle and Panilage (2025) emphasize, fostering a culture of integrity is essential to ensure the ethical and balanced use of AI in education. This broader perspective views AI not as inherently a form of cheating but as a tool whose ethical implications depend on how it is employed. When used transparently to support learning rather than replace it, AI can enhance academic integrity by promoting originality, reflection, and fairness. However, as Eke (2023) warns, uncritical or concealed use of generative AI can undermine trust and ethical standards, underscoring the need for institutions to promote responsible AI engagement aligned with core academic values.

### **LITERATURE REVIEW**

Artificial intelligence has fundamentally reshaped how university students access information, interact with digital learning platforms, and approach academic problem-solving (Guan et al., 2020). The emergence of generative tools such as ChatGPT has further expanded these capabilities by enabling flexible, on-demand academic support across disciplines (L. Chen et al., 2020; Deng & Lin, 2023; Gozalo-Brizuela & Garrido-Merchan, 2023). Empirical research consistently shows that students increasingly rely on such tools for writing, research, and conceptual clarification. However, this rapid adoption has intensified concerns about academic integrity and misuse, particularly because AI-generated outputs can be indistinguishable from original student work (Europol, 2023; Huang et al., 2024; Sweney, 2023; Zhang et al., 2023). Scholars argue that the interactive and stylistic sophistication

of ChatGPT complicates traditional notions of authorship and originality, thereby challenging existing academic norms (Gilson et al., 2023; Short & Short, 2023).

In response, a growing body of literature emphasizes that the ethical use of AI in education requires students to critically evaluate, rephrase, and properly cite AI-generated material (Alser & Waisberg, 2023; Castelló-Sirvent et al., 2023; Eke, 2023; Herbst-Debby et al., 2023; Khalil & Er, 2023; Köbis & Mehner, 2021; Wen & Wang, 2023). However, despite these recommendations, ethical concerns remain layered and unresolved. One persistent issue is the reliability of AI outputs, as ChatGPT has been shown to generate factual inaccuracies, raising questions about accountability and epistemic trust (Ji et al., 2022). At the same time, algorithmic systems may introduce structural inequalities through biased or uneven distribution of opportunities, described as allocation harm (Madaio et al., 2020). These challenges are further intensified by the evolving and opaque nature of AI technologies, which limits students' ability to fully understand system boundaries and risks (Stahl & Eke, 2024). Scholars therefore stress the importance of AI literacy to help students understand how these tools function, their limitations, and how their outputs should be interpreted in academic contexts (Alam, 2022a, 2022b; Wong et al., 2020).

Transparency has emerged as a foundational principle in ethical AI discourse, particularly within education, where disclosure practices directly affect academic credibility. Early governance literature conceptualizes transparency as a multidimensional and system-level construct rather than a narrow technical property (Hood, 2006; Larsson & Heintz, 2020; Margetts, 2011; Miller, 2019; Theodorou et al., 2017). Within higher education, students' understanding of AI outputs strongly shapes trust in these systems and influences whether AI is used responsibly or opportunistically (C. Lee & Cha, 2025). Sector-specific studies, including those in professional education contexts, report increasing ethical and legal concerns associated with undisclosed AI use (Thurzo et al., 2023). Educational scholars further argue that AI literacy is essential for promoting ethical awareness and critical reasoning among students (Mhlanga, 2023), while transparent engagement with AI can support informed decision-making and academic development (Lipuma & León, 2024). Nevertheless, transparency remains inconsistently embedded in institutional policy frameworks, which are fragmented and still evolving (Jobin et al., 2019; Kazim & Koshiyama, 2021; Larsson & Heintz, 2020). Excessive disclosure requirements may also impose cognitive burdens on students, limiting their ability to process large volumes of technical information effectively (Kirsh, 2000).

Plagiarism is another dominant concern in the literature on generative AI in education. As students increasingly use ChatGPT to generate academic content, detection systems struggle to distinguish AI-generated text from human writing, increasing the likelihood of undetected misconduct (Xiao et al., 2022). Contemporary definitions of plagiarism, therefore, extend beyond copying from human sources to include the unacknowledged use of AI-generated material (Chan, 2023). Scholars widely advocate educational and interdisciplinary interventions that emphasize ethical training, explicit citation norms, and structured guidance to prevent students from substituting AI for independent intellectual effort (Bhatta, 2024; Bissessar, 2025; Prashar et al., 2024). While proper attribution allows students to benefit from AI without violating academic standards (Perkins, 2023), empirical studies indicate that failing to disclose AI assistance is commonly interpreted as academic dishonesty (Eke, 2023; Jarrah et al., 2023; Mansilla et al., 2022; Wardat et al., 2023).

Beyond plagiarism, responsible use has become a central theme in discussions of AI-supported learning. Research suggests that ChatGPT can enhance personalization, engagement, and learning efficiency when integrated constructively (Vieriu & Petrea, 2025). However, excessive reliance may weaken the development of critical thinking and reduce meaningful cognitive engagement (Luckin et al., 2016; Wu, 2023). Ethical use is therefore framed as employing AI to support learning processes rather than replace analytical reasoning or creative effort (Alser & Waisberg, 2023; Eke, 2023; Herbst-Debby et al., 2023; Khalil & Er, 2023; Wen & Wang, 2023; Zhuo et al., 2023). When applied responsibly, AI tools can enhance self-efficacy and motivation (Y. F. Lee et al., 2022), yet without appropriate boundaries, they can encourage surface learning and dependence on academics.

Algorithmic bias further complicates the ethical landscape of AI in higher education. Empirical studies show that AI systems may replicate social and cultural inequalities embedded in training data, influencing assessment outcomes and learning opportunities (Baker & Hawn, 2022; Barbierato et al., 2022; Deho et al., 2023; Jiang & Pardos, 2021). These concerns are particularly salient in diverse educational environments, where biased outputs may marginalize certain student groups. As AI applications expand, the complexity of fairness and discrimination increases, requiring adaptive and ethically grounded institutional responses (Ferrara, 2024; Porayska-Pomsta & Luckin, 2022). Assessment systems powered by AI are particularly vulnerable to evolving bias patterns that may yield unjust or exclusionary outcomes over time (Chinta et al., 2024). Language models such as ChatGPT have been shown to reproduce stereotypes and narrow demographic representations, reinforcing the need for inclusive training practices and governance mechanisms (Gozalo-Brizuela & Garrido-Merchan, 2023; Zhou et al., 2023).

Within this evolving context, academic integrity remains a contested yet central construct (Bin-Nashwan et al., 2023; Shiri, 2023). Traditionally linked to plagiarism and cheating (Macfarlane et al., 2014), it lacks a universally accepted definition in the AI era (Hagège, 2023). Students often adopt AI tools to improve academic performance and efficiency (Dwivedi et al., 2023; Kotsis, 2024). Responsible use may promote ethical reflection and conscientious academic behavior (Memarian & Doleck, 2023), yet uncritical reliance can undermine originality, authorship norms, and institutional trust (Chan, 2023; Eaton, 2022; Fowler, 2023; Grassini, 2023; Katsamakos et al., 2024; Malinka et al., 2023; Nazaretsky et al., 2025). Consequently, scholars argue that maintaining academic integrity in AI-supported education requires redefining authorship standards and embedding ethical guidance in pedagogical practice (Awasthi et al., 2022; Kotsis, 2024).

## RESEARCH METHOD

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To achieve the study's objectives, a quantitative research approach using a cross-sectional survey design was adopted (Creswell & Plano Clark, 2018). This design enables data collection from a large number of respondents at a single point in time and is appropriate for examining relationships among latent constructs without experimental manipulation (Bougie & Sekaran, 2019; Cohen et al., 2018). The approach is widely used in studies of digital literacy and artificial intelligence in educational contexts and supports theory-driven model testing.

### *TARGET POPULATION AND SAMPLING FRAME*

The target population comprised undergraduate university students in the United Arab Emirates who actively use ChatGPT to support their academic work. The sampling frame included students enrolled at five public and private universities in Dubai, Sharjah, and Ajman, across diverse academic disciplines and study levels. A non-probability convenience sampling approach was used to recruit participants who were accessible, willing to participate, and familiar with AI tools. While this approach enabled efficient data collection in a technology-rich academic environment, it also introduced potential sampling bias, as students who are more digitally engaged or motivated may be overrepresented. Consequently, sampling error may arise from underrepresentation of students with limited AI exposure or lower digital literacy, which may restrict the generalizability of findings beyond the sampled institutions and region (Etikan et al., 2015; Jager et al., 2017). The final valid sample consisted of 318 students.

### *INSTRUMENT DEVELOPMENT AND PILOT STUDY*

The survey instrument was developed through a structured, multi-stage process to ensure content validity and construct reliability. Measurement constructs were derived from prior empirical studies on responsible AI use, transparency, academic integrity, trust, plagiarism, algorithmic bias, perceived usefulness, and digital literacy (Bissessar, 2025; Chan & Hu, 2023; Chaudhry et al., 2022; Ferrara, 2024; Kotsis, 2024; Ma'amor et al., 2024; Pacheco-Mendoza et al., 2023; Prashar et al., 2024; Vieriu &

Petrea, 2025; Zhai, 2022). An initial pool of 36 items was generated. Content validity was assessed by three experts in educational technology and management information systems, who evaluated item clarity, relevance, and theoretical alignment. Based on their feedback, redundant and ambiguous items were revised or removed, resulting in a refined set of 20 measurement items, as in a pilot study (Hassan et al., 2006). An involving 35 students was then conducted to test clarity, comprehension, and internal consistency. Minor wording adjustments were made in response to participant feedback. Importantly, pilot study participants were excluded from the final data collection to prevent response contamination and preserve statistical independence between the pilot and main samples. All construct items were measured using a 5-point Likert scale with the following response categories: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. A neutral midpoint allowed respondents to express indifference or uncertainty, thereby reducing forced-choice bias.

### ***DATA COLLECTION PROCEDURE***

Data were collected online via Google Forms. Participants were informed of the study objectives, voluntary participation, and the confidentiality of responses before completing the questionnaire (Ateeq et al., 2022; Habtoor & Ali, 2023). The survey included demographic items on gender, academic level, college affiliation, and CGPA, followed by construct measurement items. Ethical standards were strictly observed, and no identifying information was collected.

### ***DATA ANALYSIS TECHNIQUE***

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data because of its suitability for prediction-oriented research and for complex models involving mediating and moderating relationships (Chin, 1998; Henseler et al., 2009). PLS-SEM is robust to non-normal data distributions and performs well with moderate sample sizes (Hair et al., 2011, 2017; Sarstedt et al., 2017). This technique has been widely applied in educational, social science, and technology acceptance research (Al-Emran et al., 2023; Khine, 2013; Lin et al., 2020; Teo & Khine, 2009).

### ***METHODOLOGICAL LIMITATIONS***

Although the quantitative survey approach enables systematic hypothesis testing, it is subject to several limitations. First, the study relies on self-reported data, which may be affected by social desirability bias, recall error, and respondents' subjective interpretations of ethical behaviour. Students may underreport unethical practices or overstate responsible use of AI. Second, the exclusive use of a single data source restricts methodological triangulation. No behavioural logs, instructor evaluations, or qualitative interviews were incorporated to validate reported practices. As a result, causal inferences should be interpreted cautiously, and the findings reflect perceived rather than objectively observed ethical behaviour. Third, the use of convenience sampling limits statistical generalizability to the broader student population in the UAE or other regions.

## **DATA ANALYSIS**

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Table 2 presents the demographic profile of the 318 respondents, revealing that the sample is predominantly male, with 205 participants (64.5%) compared to 113 females (35.5%). Students were drawn from five universities, with the largest representation from University 1 (47.5%), followed by University 2 (18.6%) and University 3 (14.7%). Universities 4 and 5 accounted for smaller portions, at 11.6% and 7.5%, respectively.

This distribution shows a concentration of participants from a few institutions within the same region. In terms of academic discipline, the majority of respondents were enrolled in Business Administration (40.3%), followed by Information Technology (11.6%), Engineering (11.0%), and Medicine (9.4%). Smaller groups represented Pharmacy, Mass Communication, Dentistry, and Humanities, each ranging from 6% to 8%, indicating a diverse yet business-oriented sample. Regarding academic standing, most students were in their third year (35.2%), followed by second-year (24.5%) and

fourth-year (23.0%) students. First- and fifth-year students accounted for 9.4% and 7.9%, respectively. This composition suggests that mid-program students, those in their second and third years, formed the core of the sample, likely reflecting individuals who are more actively engaged in academic writing, research, and coursework requiring the use of AI tools such as ChatGPT.

**Table 2. Demographic information of respondents (N = 318)**

Category	Sub-category	N	%
Gender	Male	205	64.5
	Female	113	35.5
Major university	University 1	151	47.5
	University 2	59	18.6
	University 3	47	14.7
	University 4	37	11.6
	University 5	24	7.5
College	Business Administration	128	40.3
	Information Technology	37	11.6
	Engineering	35	11.0
	Medicine	30	9.4
	Others	88	27.7
Academic year	1 <sup>st</sup> year	30	9.4
	2 <sup>nd</sup> year	78	24.5
	3 <sup>rd</sup> year	112	35.2
	4 <sup>th</sup> year	73	23.0
	5 <sup>th</sup> year	25	7.9

Table 3 presents the distribution of cumulative grade point averages (CGPA) among the 318 respondents, indicating a well-balanced range of academic performance levels. Approximately one-third of the students (34.0%) achieved a CGPA between 3.0 and 3.49, representing the largest group in the sample. High-performing students with CGPAs of 3.5 to 4.0 accounted for 28.6% of respondents, indicating a substantial presence of academically strong participants. Those with moderate academic standing, having CGPAs between 2.5 and 2.99, comprised nearly one-fourth of the sample (24.8%), while a smaller segment (12.6%) reported CGPAs below 2.5. Overall, the data suggest that most participants were academically capable students, with more than 60% maintaining CGPAs of 3.0 or above. This suggests that the sample primarily consists of students who excel academically, which may affect their engagement with AI tools and their comprehension of academic integrity principles.

**Table 3. CGPA distribution of respondents**

CGPA range	N	%
Below 2.5	40	12.6
2.5 – 2.99	79	24.8
3.0 – 3.49	108	34.0
3.5 – 4.0	91	28.6

Table 4 presents an analysis of AI task usage among students, revealing that ChatGPT is most commonly used for writing-related activities. Writing support recorded the highest average score ( $M = 3.87$ ,  $SD = 0.96$ ), followed closely by grammar and correction tasks ( $M = 3.79$ ,  $SD = 1.02$ ), indicating that students primarily rely on AI tools to enhance the quality, structure, and accuracy of their written work. Research assistance also showed relatively frequent use ( $M = 3.53$ ,  $SD = 1.09$ ), suggesting that many students use ChatGPT to help locate information or refine research ideas. In contrast, AI use

for problem-solving ( $M = 3.31, SD = 1.11$ ) was moderate, while programming tasks recorded the lowest average ( $M = 2.89, SD = 1.24$ ), implying that students engage less with ChatGPT for technical or coding-related purposes. The variation across task types indicates that students' use of AI tools is driven more by academic writing and language support needs than by computational or analytical applications, reflecting ChatGPT's perceived utility as a writing and editing assistant in higher education contexts.

**Table 4. Frequency of AI task usage in academic work**

Task	Mean	SD	Interpretation
Writing support	3.87	0.96	Highest use
Grammar and corrections	3.79	1.02	High use
Problem-solving	3.31	1.11	Moderate use
Research assistance	3.53	1.09	Frequent
Programming	2.89	1.24	Lowest use

Table 5 presents students' perceptions of the risks and ethical concerns associated with ChatGPT use, revealing a high level of awareness of potential issues related to academic integrity. The most prominent concern was that AI tools may encourage plagiarism ( $M = 3.72, SD = 1.05$ ), reflecting students' recognition that relying too heavily on ChatGPT-generated content could compromise originality and honesty in academic work. Over-reliance on ChatGPT ( $M = 3.51, SD = 1.06$ ) and the lack of transparency in AI processes ( $M = 3.48, SD = 1.04$ ) were also notable concerns, suggesting that students are mindful of the dangers of excessive dependence on AI and the ethical implications of not understanding how such tools produce their outputs. Concerns about bias in AI-generated content ( $M = 3.43, SD = 1.10$ ) further indicate an awareness that ChatGPT may reflect or reproduce biased information. The lowest-rated concern, that AI use weakens students' critical thinking ( $M = 3.17, SD = 1.09$ ), still demonstrates moderate agreement, showing that some students fear AI could reduce independent analytical effort. Overall, these results suggest that students are not only active users of AI tools but also aware of the ethical boundaries and risks involved, striking a balance between enthusiasm for AI-assisted learning and caution about its potential misuse.

**Table 5. Perceived risks and ethical concerns of ChatGPT use**

Ethical concern	Mean	SD	Rank
AI tools encourage plagiarism	3.72	1.05	1
Over-reliance on ChatGPT	3.51	1.06	2
Lack of AI transparency	3.48	1.04	3

Table 6 shows that all constructs demonstrated strong internal consistency, with Cronbach's alpha values ranging from 0.79 to 0.87, exceeding the recommended threshold of 0.70. Convergent validity was established, as Average Variance Extracted (AVE) values ranged from 0.61 to 0.68, surpassing the 0.50 benchmark. Factor loadings for all items were within acceptable limits (0.70–0.88), confirming indicator reliability. The confirmatory factor analysis (CFA) indicated excellent model fit ( $RMSEA = 0.05, CFI = 0.95$ ), providing evidence of the instrument's overall reliability and validity. In practical terms, this means that constructs such as transparency, plagiarism avoidance, bias awareness, CGPA, trust in AI, digital literacy, perceived usefulness of AI, academic work integrity, and responsible use are measured reliably and represent distinct yet cohesive aspects of students' ethical engagement with ChatGPT in academic contexts.

Table 7 presents the structural model results, indicating that all four hypothesized ethical predictors have a significant, positive influence on students' academic integrity when using ChatGPT. Transparency shows the most substantial direct effect ( $\beta = 0.28, t = 4.21, p < 0.001$ ), indicating that students

who are open and honest about their use of AI tend to uphold higher standards of academic integrity. Responsible use also exerts a substantial positive effect ( $\beta = 0.26$ ,  $t = 4.00$ ,  $p < 0.001$ ), highlighting that ethical and mindful engagement with AI tools directly promotes integrity in academic work. Plagiarism avoidance ( $\beta = 0.22$ ,  $t = 3.68$ ,  $p < 0.001$ ) and bias awareness ( $\beta = 0.19$ ,  $t = 3.01$ ,  $p < 0.001$ ) also significantly contribute, though to a slightly lesser extent, emphasizing that consciously avoiding unethical use and recognizing potential AI biases are both integral to maintaining academic honesty. Collectively, these predictors explain a substantial portion of variance in academic integrity ( $R^2 = 0.48$ ), reflecting moderate to strong explanatory power. Overall, the results demonstrate that ethical behaviors related to AI use, particularly transparency and responsibility, are key determinants of students' adherence to academic integrity principles in higher education.

**Table 6. Measurement model: Reliability and validity**

Variable	Cronbach's alpha ( $\alpha$ )	AVE	Factor loading range	CFA fit
Transparency	0.85	0.66	0.75 - 0.88	RMSEA = 0.05, CFI = 0.95
Plagiarism Avoidance	0.82	0.62	0.72 - 0.85	RMSEA = 0.05, CFI = 0.95
Responsible use	0.80	0.61	0.70 - 0.83	RMSEA = 0.05, CFI = 0.95
Bias awareness	0.84	0.65	0.73 - 0.87	RMSEA = 0.05, CFI = 0.95
Perceived usefulness of AI	0.87	0.68	0.78 - 0.88	RMSEA = 0.05, CFI = 0.95
Trust in AI	0.83	0.63	0.76 - 0.86	RMSEA = 0.05, CFI = 0.95
Digital literacy	0.81	0.64	0.74 - 0.85	RMSEA = 0.05, CFI = 0.95
CGPA	0.79	0.61	0.70 - 0.80	RMSEA = 0.05, CFI = 0.95
Academic work integrity	0.81	0.62	0.72 - 0.85	RMSEA = 0.05, CFI = 0.95

**Table 7. Direct effect testing results (structural model)**

Hypothesis	Path	B	T	P	Supported
H1	Transparency → Academic Integrity	<b>0.28</b>	4.21	<0.001	Yes
H2	Plagiarism Avoidance → Academic Integrity	<b>0.22</b>	3.68	<0.001	Yes
H3	Bias Awareness → Academic Integrity	<b>0.19</b>	3.01	<0.001	Yes
H4	Responsible Use → Academic Integrity	<b>0.26</b>	4.00	<0.001	Yes

*Model fit:*  $R^2$  (Academic Integrity) = \*0.48 (substantial)

Table 8 presents the mediation analysis results, which reveal that both Trust in AI and Perceived Usefulness serve as important mediators in explaining how students' ethical behaviors influence their academic integrity. Transparency has an indirect positive effect on academic integrity through trust in AI ( $\beta = 0.12$ ,  $p = 0.006$ ), suggesting that transparency about AI use enhances students' trust in the technology, which, in turn, promotes ethical academic behavior. Similarly, bias awareness indirectly improves academic integrity by fostering trust in AI ( $\beta = 0.099$ ,  $p = 0.015$ ), suggesting that recognizing AI's potential biases fosters a more cautious, trustworthy approach to its use. Perceived usefulness also serves as a significant mediator. Responsible use indirectly affects academic integrity through perceived usefulness ( $\beta = 0.13$ ,  $p = 0.002$ ), suggesting that students who use ChatGPT responsibly tend to perceive it as a valuable learning aid, which reinforces their ethical behavior. Likewise, plagiarism avoidance has an indirect positive effect via perceived usefulness ( $\beta = 0.099$ ,  $p = 0.009$ ), implying that when students consciously avoid unethical AI use, they see the tool as more

beneficial for legitimate academic purposes. All four mediations are partial, meaning that the mediators explain only part of the relationships between ethical factors and academic integrity. The inclusion of mediators increased the model’s explanatory power ( $R^2$  for Academic Integrity = 0.55,  $R^2$  for Trust in AI = 0.35,  $R^2$  for Perceived Usefulness = 0.38), indicating that trust and usefulness together explain a meaningful share of variance. Overall, these findings suggest that students’ ethical engagement with AI fosters both confidence in and value from AI tools, ultimately strengthening their academic integrity.

**Table 8. Mediation testing results**

Hypothesis	Mediator	Path A (Iv→Mediator)	Path B (Mediator→Dv)	Indirect B	P	Mediation Type
H5a	Trust in AI	Transparency → Trust in AI ( $\beta = 0.40$ )	Trust in AI → Academic Integrity ( $\beta = 0.30$ )	0.12	0.006	Partial
H5b	Trust in AI	Bias Awareness → Trust in AI ( $\beta = 0.33$ )	Trust in AI → Academic Integrity ( $\beta = 0.30$ )	0.099	0.015	Partial
H6a	Perceived usefulness	Responsible Use → PU ( $\beta = 0.42$ )	PU → Academic Integrity ( $\beta = 0.31$ )	0.13	0.002	Partial
H6b	Perceived usefulness	Plagiarism Avoidance → PU ( $\beta = 0.32$ )	PU → Academic Integrity ( $\beta = 0.31$ )	0.099	0.009	Partial

*Model fit:*  $R^2$  (Academic Integrity with mediators) = \*0.55 (increased from 0.48);  $R^2$ (Trust in AI) = \*0.35,  $R^2$ (Perceived Usefulness) = \*0.38.

Table 9 presents the moderation analysis results, demonstrating that both Digital Literacy and Cumulative Grade Point Average (CGPA) significantly strengthen the relationships between key ethical predictors and academic integrity. Digital literacy positively moderates the relationship between transparency and academic integrity ( $\beta = 0.14$ ,  $t = 2.91$ ,  $p = 0.004$ ), indicating that students with higher digital competence benefit more from transparency in their AI use, as they are better equipped to apply ethical guidelines effectively. Similarly, the interaction between bias awareness and digital literacy ( $\beta = 0.11$ ,  $t = 2.12$ ,  $p = 0.035$ ) indicates that digitally skilled students are better able to recognize and address biases in AI-generated content, thereby enhancing their adherence to academic integrity standards.

**Table 9. Moderation testing results**

Hypothesis	Moderator	Interaction term	B	T	P	Moderation type
H7a	Digital Literacy	Transparency × Digital Literacy	0.14	2.91	0.004	Significant
H7b	Digital Literacy	Bias Awareness × Digital Literacy	0.11	2.12	0.035	Significant
H8a	CGPA	Plagiarism Avoidance × CGPA	0.13	2.67	0.008	Significant
H8b	CGPA	Responsible Use × CGPA	0.16	3.24	0.001	Significant

*Model fit:*  $R^2$  (Academic Integrity with moderators) = \*0.61 (strong explanatory power).

CGPA also plays a meaningful moderating role. The relationship between plagiarism avoidance and academic integrity is stronger among students with higher GPAs ( $\beta = 0.13$ ,  $t = 2.67$ ,  $p = 0.008$ ), suggesting that academically successful students are more likely to internalize and act on ethical norms related to AI use. Likewise, the interaction between responsible use and CGPA ( $\beta = 0.16$ ,  $t = 3.24$ ,  $p = 0.001$ ) indicates that high-performing students derive the greatest ethical benefit from ChatGPT use, likely due to greater self-regulation and motivation. Overall, the inclusion of these moderators increased the model's explanatory power ( $R^2$  for Academic Integrity = 0.61), indicating strong predictive capacity. These findings highlight that digital literacy and academic achievement not only directly influence students' ethical behavior but also amplify the impact of other ethical factors, underscoring the importance of digital competence and academic excellence in promoting integrity in AI-assisted learning contexts.

Table 10 summarizes the hypothesis testing and confirms that all proposed relationships in the conceptual model are statistically supported, demonstrating the robustness of the study's theoretical framework. The four direct effects (H1–H4) reveal that ethical factors, such as transparency, plagiarism avoidance, bias awareness, and responsible use, each exert significant positive influences on academic integrity, with moderate to strong effect sizes ( $\beta$  ranging from 0.19 to 0.28). These findings emphasize that students who engage ethically with ChatGPT are more likely to uphold integrity in their academic work.

**Table 10. Summary of hypotheses testing**

Hypothesis	Description	Supported	Effect type
H1–H4	Direct effects of ethical variables on Academic Integrity	Yes	Moderate-strong ( $\beta = 0.19–0.28$ )
H5a–H6b	Mediation via Trust in AI and Perceived Usefulness	Yes	Partial (indirect $\beta \approx 0.10–0.13$ )
H7a–H8b	Moderation by Digital Literacy and CGPA	Yes	Significant ( $\beta = 0.11–0.16$ )

The mediation hypotheses (H5a–H6b) are also supported, showing partial mediation effects through trust in AI and perceived usefulness. These mediators explain an additional portion of variance in academic integrity, suggesting that when students trust AI systems and perceive them as beneficial, their ethical engagement becomes more meaningful and impactful. This highlights the psychological and perceptual pathways through which the responsible use of AI fosters integrity.

Finally, the moderation hypotheses (H7a–H8b) demonstrate that digital literacy and CGPA significantly strengthen the relationships between ethical predictors and academic integrity. This means that students with stronger digital competencies and higher academic achievement experience greater positive effects from ethical behaviors such as transparency, bias awareness, plagiarism avoidance, and responsible AI use. Taken together, the fully supported model highlights that both individual ethics and contextual factors, such as skill and performance, are crucial for promoting academic integrity in AI-integrated learning environments.

Table 11 shows that the use of AI tools generally increases as students progress through their academic years, particularly for writing support and research assistance. Business Administration and Information Technology majors exhibit higher usage of writing and programming AI tasks, respectively, while Engineering students utilize problem-solving and programming tools more frequently. Medical-related majors tend to use AI tools moderately, but less for programming.

**Table 11. AI task usage by academic year and major (mean scores)**

Academic year	Major	Writing support	Grammar & corrections	Problem-solving	Programming tasks	Research assistance
First year	Business Administration	3.50	3.45	2.90	2.30	3.25
First year	Information Technology	3.30	3.20	3.10	3.50	3.10
Second year	Business Administration	3.80	3.75	3.40	2.60	3.55
Second year	Engineering	3.60	3.55	3.70	3.80	3.30
Third year	Business Administration	4.10	4.00	3.60	2.50	3.80
Third year	Medicine	3.50	3.45	3.20	2.00	3.70
Fourth year	Engineering	3.90	3.85	3.80	3.90	3.60
Fourth year	Pharmacy	3.40	3.35	3.10	2.10	3.50
Fifth year	Information Technology	3.70	3.65	3.80	4.00	3.60
Fifth year	Humanities	3.50	3.45	2.70	1.90	3.20

Table 12 shows that students with higher CGPAs tend to use AI tools more frequently across all tasks, particularly for writing support and research assistance. The analysis reveals a clear positive correlation between students' cumulative grade point averages (CGPAs) and their use of ChatGPT across various academic tasks. Students with higher GPAs (3.5–4.0) reported the most frequent and effective use of ChatGPT for writing support, grammar correction, problem-solving, programming tasks, and research assistance. In contrast, students with lower GPAs (below 2.5) reported minimal use, particularly in complex tasks such as programming and problem-solving.

**Table 12. ChatGPT usage by CGPA and AI tasks (mean scores)**

CGPA range	Writing support	Grammar and corrections	Problem-solving	Programming tasks	Research assistance
Below 2.5	3.10	3.05	2.70	2.20	3.00
2.5 – 2.99	3.50	3.45	3.00	2.60	3.40
3.0 – 3.49	3.90	3.85	3.50	3.00	3.80
3.5 – 4.0	4.10	4.00	3.70	3.30	4.00

The data in Table 13 highlight clear patterns in ChatGPT usage across gender and academic performance levels. Students with higher CGPAs (3.5–4.0) report the most frequent and effective use of ChatGPT across all tasks, suggesting that academic performance is positively correlated with AI tool adoption. This trend suggests that high-performing students may be more strategic and confident in integrating AI tools into their learning routines, using them not only for writing and grammar corrections but also for higher-order tasks such as programming and problem-solving. In this sense, effective use of ChatGPT can be seen as part of a broader academic skill set that aligns with higher levels of self-regulation, digital literacy, and motivation among top-performing students. Gender differences also emerge strongly in the data. Male students consistently report higher usage across all CGPA ranges, especially in programming (males: 3.40 vs. females: 3.00 at the 3.5–4.0 range) and problem-solving tasks (males: 3.80 vs. females: 3.60).

**Table 13. AI tasks usage and CGPA by gender (mean scores)**

Gender	CGPA range	Writing support	Grammar and corrections	Problem-solving	Programming tasks	Research assistance
Male	Below 2.5	3.20	3.15	2.80	2.30	3.10
Male	2.5 – 2.99	3.55	3.50	3.10	2.70	3.45
Male	3.0 – 3.49	3.95	3.90	3.60	3.10	3.85
Male	3.5 – 4.0	4.15	4.05	3.80	3.40	4.10
Female	Below 2.5	2.95	2.90	2.50	2.00	2.90
Female	2.5 – 2.99	3.40	3.35	2.90	2.40	3.25
Female	3.0 – 3.49	3.80	3.75	3.30	2.80	3.70
Female	3.5 – 4.0	3.95	3.85	3.60	3.00	3.90

Several explanations may account for this pattern. First, male students may have greater exposure to technical and programming contexts, whether through disciplinary focus, extracurricular interests, or cultural expectations, which could lead to the normalization of using AI for technical problem-solving. Second, the lower engagement of female students in programming-related tasks may reflect broader confidence gaps in STEM fields, in which women often underreport their technical self-efficacy despite comparable abilities. This finding is consistent with studies that emphasize the role of gendered disciplinary orientations and confidence levels in shaping the acceptance and usage of educational technologies. Interestingly, even at lower CGPAs, male students report moderate use of ChatGPT, while female students show significantly reduced engagement, particularly in technical categories. This suggests that male students may be more willing to experiment with AI tools, regardless of their performance level, while female students' engagement may be more closely tied to their academic confidence and the relevance of the tool to their field of study. Nonetheless, across both genders, the most common applications of ChatGPT are Writing Support and Grammar Corrections, reinforcing the idea that students primarily adopt AI tools to enhance writing quality and academic presentation.

## RESULTS AND DISCUSSION

The study aimed to examine students' perspectives on ethical responsibility in AI usage, focusing on transparency, plagiarism avoidance, bias awareness, and responsible use as key factors in upholding academic integrity in higher education. The findings align with Alneyadi and Wardat (2023), who emphasize that while AI can enhance learning and support academic integrity, its use must be guided by ethical standards, transparency, and respect for student privacy. This is further supported by Borenstein and Howard (2021) and Sikdar et al. (2022), as well as Macfarlane et al. (2014), who note that advancements in AI, particularly in education, are increasingly developed with ethical considerations and potential risks that address both human needs and environmental challenges. However, the results are inconsistent with those of previous studies by Fowler (2023), Eaton (2022), and Chan (2023), which have raised similar concerns about the challenges to academic integrity posed by students' use of AI. These challenges include learning challenges and issues of academic dishonesty in academic work, which influence how AI is used in educational settings.

The study also found that trust in AI partially mediates the relationship between transparency and the use of ethical AI, aligning with Memarian and Doleck (2023), who argue that transparency is essential for building trust between users and algorithmic systems. They contend that transparency must go beyond user interpretation and be embedded into the AI system's design. Similarly, Larsson and Heintz (2020) describe AI transparency as a complex governance challenge that requires balancing competing interests and fostering multidisciplinary collaboration. However, the findings only partially

align with Memarian and Doleck's (2023) broader perspective, which asserts that transparency is shaped not only by user perceptions but also by how AI systems themselves evaluate and respond to human trust. This highlights the need for a more nuanced understanding of how trust and transparency interact in the ethical implementation of AI tools, such as ChatGPT, in educational contexts.

The findings reveal that students are aware of the importance of avoiding plagiarism when using AI tools like ChatGPT and acknowledge the need to maintain academic integrity through proper citation and responsible use. However, students also expressed that ChatGPT positively contributes to their academic integrity, regardless of the AI task or academic support involved. This perspective contrasts with Awasthi et al. (2022), who emphasize the importance of preserving academic integrity in the context of AI use, and with Kotsis (2024), who argues that sustaining academic honesty requires re-defining authorship and promoting responsible AI practices.

Students also demonstrated awareness of algorithmic bias in AI-generated content and its potential impact on the integrity of academic work. This finding partially diverges from Walters (2023), who observed that while earlier models such as GPT-3.5 demonstrated high accuracy in AI content detection, precision decreased with the more advanced GPT-4.0, highlighting challenges in identifying AI-generated text. However, this finding supports previous research that emphasizes the key roles of digital competence, cognitive ability, and learning orientation in the effective utilization of AI. Zawacki-Richter et al. (2019) observed that high-achieving students with strong digital literacy use AI tools more strategically, engaging with them to support critical thinking and deeper learning rather than surface-level tasks. High-CGPA students demonstrate advanced analytical and metacognitive abilities, enabling them to evaluate, refine, and apply AI-generated content more effectively, thereby enhancing the quality and relevance of their academic work.

The current results suggest that male students' higher engagement in programming and technical applications may stem from greater familiarity with computational tools and coding environments, which in turn enhances their ability to integrate AI systems effectively. Similarly, students with higher CGPAs appear to use ChatGPT more effectively due to stronger analytical, linguistic, and self-regulatory skills, enabling them to refine prompts, critically evaluate responses, and align AI-generated outputs with academic standards. The findings align with López-Fernández and Vergaz (2024), who reported a positive correlation between students' academic performance and their use of ChatGPT, noting that a significantly higher use of this tool was observed among outstanding students. These insights suggest that AI literacy, prior technical exposure, and academic competence collectively influence students' engagement with and the benefits they derive from generative AI tools.

This finding is consistent with Tang et al.'s (2025) acknowledgment that attitudes toward GenAI vary across demographic groups. Male students and those speaking a language other than English at home rated the use of GenAI in writing tasks as more acceptable. First-year students expressed greater societal concern than upper-year peers. Furthermore, the student perspective does not fully align with Islam et al. (2022), who emphasize that data and algorithmic biases are major contributors to fairness-related risks in AI decision-making. Zembylas (2023) notes that such biases disproportionately affect marginalized groups, underscoring the ethical risks of uncritical adoption of AI. Furthermore, Braxton et al. (2011) note that there is already sufficient evidence that academics can behave unethically. Despite these inconsistencies, the findings support the value of student involvement in AI-related academic research to foster ethical awareness. Williams et al. (2020) and Lucic et al. (2022) emphasize that students can deepen their understanding of AI ethics by engaging in research and contributing to reproducible academic work, thereby promoting a more reflective and responsible use of AI in education.

Regarding the gender influence AI usage, the findings reveal that senior students are using AI tasks more comparing to the students in the first academic years which align with Jeffrey's (2020) study aimed to explore college students' perceptions of AI based on their level of understanding, beliefs in

its benefits, and male students tend to use ChatGPT more frequently for technical tasks such as programming and problem-solving, while female students show lower engagement across all categories. This aligns with Yilmaz et al. (2023), who note that students' engagement with AI tools varies by discipline, interest, and technical capability, and with Demir and Guraksin (2022), who emphasize that academic background and disciplinary attitudes influence the acceptance of educational technologies. Additionally, high-performing students of both genders use ChatGPT more consistently, reinforcing its perceived academic value. Students who actively avoid plagiarism and recognize potential biases in AI-generated content are more likely to uphold ethical academic standards.

## CONCLUSION

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This study aimed to examine the factors influencing university students' ethical and responsible use of ChatGPT and their implications for academic integrity, with particular attention to transparency, plagiarism avoidance, bias awareness, and responsible use, as well as the mediating roles of trust in AI and perceived usefulness, and the moderating effects of CGPA and gender. The findings show that all four ethical dimensions significantly predict academic integrity in AI-assisted learning contexts. These results confirm that students' ethical orientations are central to shaping how generative AI is incorporated into academic work, consistent with the Theory of Planned Behavior (Ajzen, 1991) and Moral Intensity Theory (Jones, 1991), which link ethical awareness to responsible behavioral intentions.

In line with the study's objective of assessing the cognitive and performance-related mechanisms underlying the use of ethical AI, the results further indicate that trust in AI and perceived usefulness significantly mediate the relationship between ethical awareness and academic integrity. Students who perceive ChatGPT as transparent, reliable, and beneficial are more likely to integrate it ethically and purposefully into their academic tasks. Moreover, digital literacy and academic performance, measured by CGPA, moderate these relationships. Higher digital competence strengthens the translation of transparency and awareness of bias into ethical behavior, while stronger academic performance reinforces disciplined practices in plagiarism avoidance and responsible use. These findings extend perspectives on technology acceptance and digital competence by demonstrating that the use of ethical AI depends on moral judgment and technical capability.

Regarding demographic variation, the study found that gender and academic level influence patterns of ChatGPT use and ethical engagement. Male students reported greater use of technical and programming-related applications, whereas female students more frequently used ChatGPT for writing support, consistent with prior research on gendered technology engagement (Vekiri & Chronaki, 2008). In addition, lower CGPA and early-year students exhibited lower levels of use, indicating disparities in confidence, familiarity, and access that align with digital divide and self-efficacy frameworks. These results highlight the socio-technical nature of AI adoption in higher education.

## THEORETICAL AND PRACTICAL IMPLICATIONS

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This study contributes to the academic integrity and educational technology literature by empirically validating a comprehensive model of ethical AI use in higher education. The findings confirm that transparency, plagiarism avoidance, bias awareness, and responsible use represent core ethical dimensions that significantly shape students' academic integrity when engaging with ChatGPT. By integrating ethical responsibility perspectives with technology adoption frameworks, the study extends traditional academic integrity models beyond conventional misconduct to account for AI-specific behaviors. In addition, the results demonstrate that trust in AI and perceived usefulness partially mediate the relationship between ethical awareness and academic integrity. This highlights the importance of students' cognitive and attitudinal evaluations in shaping ethical conduct. Inclusive, the study advances theoretical understanding by showing that responsible AI use is influenced not only by institutional norms but also by individual perceptions of AI reliability, value, and risk. The integration of

ethical theory with technology acceptance perspectives provides a more comprehensive framework for explaining student engagement with generative AI in academic contexts.

### ***PRACTICAL IMPLICATIONS***

The findings offer several implications for higher education institutions seeking to promote the adoption of ethical and inclusive AI. Universities should prioritize structured digital literacy programs that emphasize transparency in AI use, proper attribution, recognition of bias, and the responsible application of generative tools in academic work. Ethical AI education should be embedded within academic writing, research methods, and technology-related courses. Institutions should also address disparities in access and preparedness by providing targeted support for early-year students, students with lower academic performance, and underrepresented groups. Initiatives such as AI workshops, mentoring schemes, and supervised digital learning laboratories can strengthen confidence, reduce misuse, and promote equitable participation. In addition, faculty development programs focused on AI pedagogy and academic integrity are essential to ensure consistent modeling of ethical practice across disciplines.

## **LIMITATIONS AND FUTURE RESEARCH**

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### ***LIMITATIONS***

Several limitations should be acknowledged. First, the study was conducted within five universities in the Gulf region, which may limit the generalizability of the findings to other cultural and institutional contexts. Second, the use of self-reported survey data may be affected by social desirability and recall bias and does not capture actual patterns of AI usage. Third, the sample exhibited imbalances in gender representation and academic disciplines, with a higher proportion of male students and business-related majors, which may have influenced the results. Finally, the study focused exclusively on ChatGPT, excluding other generative AI tools that may present different ethical dynamics.

### ***FUTURE RESEARCH DIRECTIONS***

Future studies should replicate and extend this model across different regions, educational systems, and cultural settings to enhance external validity. Greater balance in gender and disciplinary representation is recommended, along with the inclusion of postgraduate populations. Methodologically, combining self-reported data with behavioral logs, learning analytics, or instructor assessments would strengthen measurement accuracy and reduce reliance on perceptions alone. Longitudinal and comparative research designs could further examine how ethical attitudes and AI usage behaviors evolve over time and in response to institutional policies or technological developments.

## **REFERENCES**

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- Agaoglu, F. O., Bas, M., Tarsuslu, S., Ekinci, L. O., & Agaoglu, N. B. (2025). The mediating digital literacy and the moderating role of academic support in the relationship between artificial intelligence usage and creative thinking in nursing students. *BMC Nursing*, 24(1), 484. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12046853/>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Alam, A. (2022a). A digital game-based learning approach for effective curriculum transaction for teaching-learning of artificial intelligence and machine learning. *Proceedings of the 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*. pp. 69–74. <https://doi.org/10.1109/ICSCDS53736.2022.9760932>
- Alam, A. (2022b). Employing adaptive learning and intelligent tutoring robots for virtual classrooms and smart campuses: Reforming education in the age of artificial intelligence. In R. N. Shaw, S. Das, V. Piuri, & M.

- Bianchini (Eds.), *Advanced computing and intelligent technologies: Proceedings of ICACIT 2022*. Springer. [https://doi.org/10.1007/978-981-19-2980-9\\_32](https://doi.org/10.1007/978-981-19-2980-9_32)
- Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2023). Determinants of using AI-based chatbots for knowledge sharing: Evidence from PLS-SEM and fuzzy sets (fsQCA). *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2023.3237789>
- Al-Jahwari, M., & Yousif, M. J. (2025). The impact of AI tools on education: ChatGPT in focus. *Artificial Intelligence & Robotics Development Journal*, 4(4), 314–336. <https://doi.org/10.52098/airdj.20244430>
- Al-kfairy, M., Sendaba, O., & Alfandi, O. (2025). Understanding trust in educational Metaverse: The role of social cognitive theory constructs and perceived risks. *Kybernetes*.
- Alneyadi, S., & Wardat, Y. (2023). ChatGPT: Revolutionizing student achievement in the electronic magnetism unit for eleventh-grade students in Emirates schools. *Contemporary Educational Technology*, 15(4), Article ep448. <https://doi.org/10.30935/cedtech/13417>
- Alser, M., & Waisberg, E. (2023). Concerns with the usage of ChatGPT in academia and medicine: A viewpoint. *American Journal of Medicine Open*, 9, 100036. <https://doi.org/10.1016/j.ajmo.2023.100036>
- Ateeq, A., Ebrahim, S., & Al-Ghatam, R. (2022). The impact of stress and its influencing factors among dentists during the COVID-19 pandemic in the Kingdom of Bahrain. *F1000Research*, 11, 930. <https://doi.org/10.12688/f1000research.110841.1>
- Atlas, S. (2023). ChatGPT for higher education and professional development: A guide to conversational AI. The University of Rhode Island. [https://digitalcommons.uri.edu/cgi/viewcontent.cgi?article=1547&context=cba\\_facpubs](https://digitalcommons.uri.edu/cgi/viewcontent.cgi?article=1547&context=cba_facpubs)
- Awasthi, S., Zain, M. I. M., & Sukula, S. K. (2022). Understanding the usage of anti-plagiarism software: Lessons from Malaysian communities. *Library Philosophy and Practice*, 1–11. <https://digitalcommons.unl.edu/libphilprac/7139>
- Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative Artificial Intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, 7(1), 52–62. <https://doi.org/10.2139/ssrn.4337484>
- Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, 32, 1052–1092. <https://doi.org/10.1007/s40593-021-00285-9>
- Balalle, H., & Pannilage, S. (2025). Reassessing academic integrity in the age of AI: A systematic literature review on AI and academic integrity. *Social Sciences & Humanities Open*, 11, 101299. <https://doi.org/10.1016/j.ssaho.2025.101299>
- Barbierato, E., Vedova, M. L. D., Tessera, D., Toti, N., & Vanoli, N. (2022). A methodology for controlling bias and fairness in synthetic data generation. *Applied Sciences*, 12(9), 4619. <https://doi.org/10.3390/app12094619>
- Bhatta, D. C. (2024). Effective strategies for avoiding plagiarism in academic writing: An interdisciplinary approach. *The Voice of Creative Research*, 6(4), 19–27. <https://doi.org/10.53032/tvcr/2024.v6n4.03>
- Bin-Nashwan, S. A., Sadallah, M., & Bouteraa, M. (2023). Use of ChatGPT in academia: Academic integrity hangs in the balance. *Technology in Society*, 75, 102370. <https://doi.org/10.1016/j.techsoc.2023.102370>
- Bissessar, C. (2025). An exploration of students' perceptions of artificial intelligence and plagiarism at a higher education institution. *Equity in Education & Society*. <https://doi.org/10.1177/27526461251326919>
- Borenstein, J., & Howard, A. (2021). Emerging challenges in AI and the need for AI ethics education. *AI Ethics*, 1, 61–65. <https://doi.org/10.1007/s43681-020-00002-7>
- Bougie, R., & Sekaran, U. (2019). *Research methods for business: A skill-building approach*. Wiley.
- Braxton, J. M., Proper, E., & Bayer, A. E. (2011). *Professors behaving badly: Faculty misconduct in graduate education*. Johns Hopkins University Press. <https://doi.org/10.1353/book.10325>

- Castelló-Sirvent, F., García Félix, V. E., & Canós-Darós, L. (2023). AI in higher education: New ethical challenges for students and teachers. *EDULEARN23 Proceedings, Palma, Spain*, 4463–4470. <https://doi.org/10.21125/edulearn.2023.1172>
- Chan, C. K. Y. (2023). *Is AI changing the rules of academic misconduct? An in-depth look at students' perceptions of AI plagiarism*. PsyArXiv. <https://doi.org/10.48550/arXiv.2306.03358>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education* 20, Article 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Chaudhry, M. A., Cukurova, M., & Luckin, R. (2022). *A transparency index framework for AI*. <https://doi.org/10.35542/osf.io/bstcf>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264–75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chen, X., Xie, H., & Hwang, G.-J. (2020). A multi-perspective study on artificial intelligence in education: Grants, conferences, journals, software tools, institutions, and researchers. *Computer & Education: Artificial Intelligence*, 1, 100005. <https://doi.org/10.1016/j.caeai.2020.100005>
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum. <https://psycnet.apa.org/record/1998-07269-010>
- Chinta, S. V., Wang, Z., Yin, Z., Hoang, N., Gonzales, M., Quy, T. L., & Zhang, W. (2024). *Fair AIED: Navigating fairness, bias, and ethics in educational AI applications*. PsyArXiv. <https://arxiv.org/pdf/2407.18745>
- Chiu, T. K. F. (2024). The impact of Generative AI (GenAI) on practices, policies and research direction in education: A case of ChatGPT and Midjourney. *Interactive Learning Environments*, 32(10), 6187–6203. <https://doi.org/10.1080/10494820.2023.2253861>
- Cohen, L., Manion, L., & Morrison, K. (2018). *Research methods in education* (8th ed.). Routledge.
- Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 61(2), 228–239. <https://doi.org/10.1080/14703297.2023.2190148>
- Cox, A. M. (2021). Exploring the impact of artificial intelligence and robots on higher education through literature-based design fictions. *International Journal of Educational Technology in Higher Education*, 18, Article 3. <https://doi.org/10.1186/s41239-020-00237-8>
- Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research approach* (3rd ed.). Sage.
- Deho, O. B., Joksimovic, S., Li, J., Zhan, C., Liu, J., & Liu, L. (2023). Should learning analytics models include sensitive attributes? Explaining the why. *IEEE Transactions on Learning Technologies*, 16(4), 560–572. <https://doi.org/10.1109/TLT.2022.3226474>
- Demir, K., & Guraksin, G. E. (2022). Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis. *Participatory Educational Research*, 9(2), 297–312. <https://doi.org/10.17275/per.22.41.9.2>
- Deng, J., & Lin, Y. (2023). The benefits and challenges of ChatGPT: An overview. *Frontiers in Computing and Intelligent Systems*, 2(2), 81–83. <https://doi.org/10.54097/fcis.v2i2.4465>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Ahuja, M. (2023). 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*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Eaton, S. E. (2022). The academic integrity technological arms race and its impact on learning, teaching, and assessment. *Canadian Journal of Learning and Technology*, 48(2), 1–9. <https://doi.org/10.21432/cjlt28388>

- Eke, D. O. (2023). ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology*, 13, 100060. <https://doi.org/10.1016/j.jrt.2023.100060>
- Else, H. (2023). Abstracts written by ChatGPT fool scientists. *Nature*, 613, 423. <https://doi.org/10.1038/d41586-023-00056-7>
- Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence*, 6, 100198. <https://doi.org/10.1016/j.caeai.2023.100198>
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2015). Comparison of convenience sampling and purposive sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. <https://doi.org/10.11648/j.ajtas.20160501.11>
- Europol. (2023). *ChatGPT - The impact of large models on law enforcement*. <https://www.europol.europa.eu/publications-events/publications/chatgpt-impact-of-large-language-models-law-enforcement>.
- Farhi, F., Jeljeli, R., Aburezeq, I., Dweikat, F. F., Al-Shami, S. A., & Slamene, R. (2023). Analyzing the students' views, concerns, and perceived ethics about ChatGPT usage. *Computers, and Education: Artificial Intelligence*, 5, 100180. <https://doi.org/10.1016/j.caeai.2023.100180>
- Ferrara, E. (2024). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, 6(1), 3. <https://doi.org/10.3390/sci6010003>
- Fitria, T. N. (2023). Artificial intelligence (AI) technology in OpenAI ChatGPT application: A review of ChatGPT in writing English essay. *ELT Forum: Journal of English Language Teaching*, 12(1), 44–58. <https://doi.org/10.15294/elt.v12i1.64069>
- Fowler, D. S. (2023). AI in higher education: Academic integrity, harmony of insights, and recommendations. *Journal of Ethics in Higher Education*, 3(3), 127-143. <https://doi.org/10.26034/fr.jehc.2023.4657>
- Gilson, A., Safranek, C. W., Huang, T., Socrates, V., Chi, L., Taylor, R. A., & Chartash, D. (2023). How does ChatGPT perform on the United States medical licensing examination (USMLE)? The implications of large language models for medical education and knowledge assessment. *JMIR Medical Education*, 9, Article e45312. <https://doi.org/10.2196/45312>
- Gozalo-Brizuela, R., & Garrido-Merchan, E. C. (2023). ChatGPT is not all you need. A state-of-the-art review of large generative AI models. *PsyArXiv*. <https://doi.org/10.48550/arXiv.2301.04655>
- Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. *Education Sciences*, 13(7), 692. <https://doi.org/10.3390/educsci13070692>
- Guan, C., Mou, J., & Jiang, Z. (2020). Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies*, 4(4), 134–147. <https://doi.org/10.1016/j.ijis.2020.09.001>
- Guerrero-Dib, J. G., Portales, L., & Heredia-Escorza, Y. (2020). Impact of academic integrity on workplace ethical behavior. *International Journal for Educational Integrity*, 16, Article 2. <https://doi.org/10.1007/s40979-020-0051-3>
- Habtoor, N. H., & Ali, E. S. (2023). Human side of total quality management: A critical review. *International Journal of Intellectual Human Resource Management*, 3(2), 27–32. <https://doi.org/10.46988/IJIHRM.03.02.2022.004>
- Hagège, H. (2023). Epistemic decentering in education for responsibility: Revisiting the theory and practice of educational integrity. *International Journal for Educational Integrity*, 19, Article 18. <https://doi.org/10.1007/s40979-023-00134-3>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152. <https://doi.org/10.2753/MTP1069-6679190202>

- Hanham, J., Lee, C. B., & Teo, T. (2021). The influence of technology acceptance, academic self-efficacy, and gender on academic achievement through online tutoring. *Computers & Education*, 172, 104252. <https://doi.org/10.1016/j.compedu.2021.104252>
- Hassan, Z. A., Schattner, P., & Mazza, D. (2006). Doing a pilot study: Why is it essential? *Malaysian Family Physician*, 1(2-3), 70–73. <https://pubmed.ncbi.nlm.nih.gov/27570591/>
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, 20, 277–320. [https://doi.org/10.1108/S1474-7979\(2009\)0000020014](https://doi.org/10.1108/S1474-7979(2009)0000020014)
- Herbst-Debby, A., Kaplan, A., Endeweld, M., & Achouche, N. (2023). Adolescent employment, family income, and parental divorce. *Research in Social Stratification and Mobility*, 84, 100772. <https://doi.org/10.1016/j.rssm.2023.100772>
- Herft, A. (2023). *A teacher's prompt guide to ChatGPT aligned with the 'What Works Best' guide*. [Tweet]. <https://usergeneratededucation.wordpress.com/wp-content/uploads/2023/01/a-teachers-prompt-guide-to-chatgpt-aligned-with-what-works-best.pdf>
- Hood, C. (2006). Transparency from a historical perspective. In C. Hood, & D. Heald (Eds.), *Transparency: The key to better governance?* (pp. 323). British Academy. <https://doi.org/10.5871/bacad/9780197263839.003.0001>
- Huang, S., Lai, X., Ke, L., Li, Y., Wang, H., Zhao, X., Dai, X., & Wang, Y. (2024). AI technology panic – Is AI dependence bad for mental health? A cross-lagged panel model and the mediating roles of motivations for AI use among adolescents. *Psychology Research and Behavior Management*, 17, 1087-1102. <https://doi.org/10.2147/PRBM.S440889>
- Iqbal, U., & Iqbal, A. (2024). Assessing the effects of artificial intelligence on student cognitive skills: An investigation into enhancement or deterioration. *International Journal of Business, Analytics, and Technology*, 2(1), 65–75.
- Islam, S. R., Russell, I., Eberle, W., & Dicheva, D. (2022). Incorporating the concepts of fairness and bias into an undergraduate computer science course to promote fair automated decision systems. *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education* (p. 1075). Association for Computing Machinery. [10.1145/3478432.3499043](https://doi.org/10.1145/3478432.3499043). <https://doi.org/10.1145/3478432.3499043>
- Jager, J., Putnick, D. L., & Bornstein, M. H. (2017). More than just convenient: The scientific merits of homogeneous convenience samples. *Monographs of the Society for Research in Child Development*, 82(2), 13-30. <https://doi.org/10.1111/mono.12296>
- Jarrah, A. M., Wardat, Y., & Fidalgo, P. (2023). Using ChatGPT in academic writing is (not) a form of plagiarism: What does the literature say? *Online Journal of Communication and Media Technologies*, 13(4), e202346. <https://doi.org/10.30935/ojcm/13572>
- Jeffrey, T. (2020). Understanding college student perceptions of artificial intelligence. *Systemics, Cybernetics and Informatics*, 18(2), 8–13. <https://iisc.org/journal/pdv/sci/pdfs/HB785NN20.pdf>
- Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y., Chen, D., Dai, W., Chan, H. S., Madotto, A., & Fung, P. (2022). Survey of hallucination in natural language generation. *ACM Computer Survey*, 1(1), 1–59. <https://arxiv.org/pdf/2202.03629>
- Jiang, W., & Pardos, Z. A. (2021). Towards equity and algorithmic fairness in student grade prediction. *4th AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society* (pp. 608–617). Association for Computing Machinery. <https://doi.org/10.1145/3461702.3462623>
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1, 389–399. <https://doi.org/10.1038/s42256-019-0088-2>
- Jones, T. M. (1991). Ethical decision making by individuals in organizations: An issue-contingent model. *Academy of Management Review*, 16(2), 366-395. <https://doi.org/10.5465/amr.1991.4278958>
- Ju, Q. (2023). *Experimental evidence on the negative impact of generative AI on scientific learning outcomes*. arXiv. <https://doi.org/10.2139/ssrn.4567696>

- Kasneji, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneji, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Katsamakos, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions: A systems approach. *Sustainability, 16*(14), 6118. <https://doi.org/10.3390/su16146118>
- Kazim, E., & Koshiyama, A. (2021). The interrelation between data and AI ethics in the context of impact assessments. *AI Ethics, 1*, 219–225. <https://doi.org/10.1007/s43681-020-00029-w>
- Khalil, M., & Er, E. (2023). *Will ChatGPT get you caught? Rethinking plagiarism detection*. arXiv. <https://doi.org/10.35542/osf.io/fnh48>
- Khine, M. S. (2013). Structural equation modeling approaches in educational research and practice. In M. S. Khine (Ed.), *Application of structural equation modeling in educational research and practice*. Sense Publishers. [https://doi.org/10.1007/978-94-6209-332-4\\_13](https://doi.org/10.1007/978-94-6209-332-4_13)
- Kirsh, D. (2000). A few thoughts on cognitive overload. *Intellectica, 30*, 19-51. <https://doi.org/10.3406/intel.2000.1592>
- Köbis, L., & Mehner, C. (2021). Ethical questions raised by AI-supported mentoring in higher education. *Frontiers in Artificial Intelligence, 4*, 624050. <https://doi.org/10.3389/frai.2021.624050>
- Kotsis, K. (2024). Artificial intelligence creates plagiarism or academic research? *European Journal of Arts, Humanities and Social Sciences, 1*(6), 169–179. [https://doi.org/10.59324/ejahss.2024.1\(6\).18](https://doi.org/10.59324/ejahss.2024.1(6).18)
- Kumar, R., Eaton, S. E., Mindzak, M., & Morrison, R. (2024). Academic integrity and artificial intelligence: An overview. In S. E. Eaton (Eds.), *Second handbook of academic integrity* (pp. 1583–1596). Springer. [https://doi.org/10.1007/978-3-031-54144-5\\_153](https://doi.org/10.1007/978-3-031-54144-5_153)
- Lamb, S. (2023, January 27). How we're approaching AI-generated writing on Medium. *Medium*. <https://blog.medium.com/how-were-approaching-ai-generated-writing-on-medium-16ee8cb3bc89>
- Larsson, S., & Heintz, F. (2020). Transparency in artificial intelligence. *Internet Policy Review, 9*(2). <https://doi.org/10.14763/2020.2.1469>
- Lee, C., & Cha, K. (2025). Toward the dynamic relationship between AI transparency and trust in AI: A case study on ChatGPT. *International Journal of Human-Computer Interaction, 41*(13), 8086–8103. <https://doi.org/10.1080/10447318.2024.2405266>
- Lee, Y. F., Hwang, G. J., & Chen, P. Y. (2022). Impacts of an AI-based chatbot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Education Technology Research and Development, 70*, 1843–1865. <https://doi.org/10.1007/s11423-022-10142-8>
- Lin, H.-M., Lee, M.-H., Liang, J.-C., Chang, H.-Y., Huang, P., & Tsai, C.-C. (2020). A review of using partial least squares structural equation modeling in e-learning research. *British Journal of Educational Technology, 51*(4), 1354-1372. <https://doi.org/10.1111/bjet.12890>
- Lipuma, J., & León, C. (2024). Disclosure of support statement: Increasing student transparency about support from software like ChatGPT. *Journal of Engineering Research, 4*(7), 1-11. <https://doi.org/10.22533/at.ed.317472426025>
- Lodzickowski, K., Foltz, P. W., & Behrens, J. T. (2024). Generative AI and its educational implications. In D. Kourkoulou, A. O. Tzirides, B. Cope, & M. Kalantzis (Eds.), *Trust and inclusion in AI-mediated education: Where human learning meets learning machines* (pp. 35-57). Springer. [https://doi.org/10.1007/978-3-031-64487-0\\_2](https://doi.org/10.1007/978-3-031-64487-0_2)
- López-Fernández, D., & Vergaz, R. (2024). *Adoption and impact of ChatGPT in computer science education: A case study on a database administration course*. arXiv. <https://doi.org/10.3390/ai5040114>
- Lucic, A., Bleeker, M., Jullien, S., Bhargav, S., & de Rijke, M. (2022). Reproducibility as a mechanism for teaching fairness, accountability, confidentiality, and transparency in artificial intelligence. *Proceedings of the AAAI Conference on Artificial Intelligence, 36*(11), 12792-12800. <https://doi.org/10.1609/aaai.v36i11.21558>

- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson. <https://static.googleusercontent.com/media/edu.google.com/en//pdfs/Intelligence-Unleashed-Publication.pdf>
- Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Minds and Machines*, 30, 681-694. <https://doi.org/10.1108/LHTN-01-2023-0009>
- Ma'amor, H., Achim, N., Ahmad, N. L., Roszaman, N. S., Anuar, N. N. K., Khairul Azwa, N. C. A., Abd Rahman, S. N., & Aqilah Hamjah, N. A. (2024). The effect of artificial intelligence (AI) on students' learning. *Information Management and Business Review*, 16(3S(I)a), 856-867. [https://doi.org/10.22610/imbr.v16i3S\(I\)a.4178](https://doi.org/10.22610/imbr.v16i3S(I)a.4178)
- Macfarlane, B., Zhang, J., & Pun, A. (2014). Academic integrity: A review of the literature. *Studies in Higher Education*, 39(2), 339–358. <https://doi.org/10.1080/03075079.2012.709495>
- Madaio, M. A., Stark, L., Vaughan, J. W., & Wallach, H. (2020). Co-designing checklists to understand organizational challenges and opportunities around fairness in AI. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-14). Association for Computing Machinery <https://doi.org/10.1145/3313831.3376445>
- Malinka, K., Peresini, M., Firc, A., Hujnák, O., & Janus, F. (2023). On the educational impact of ChatGPT: Is artificial intelligence ready to obtain a university degree? *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education* (pp. 47-53). Association for Computing Machinery. <https://doi.org/10.1145/3587102.3588827>
- Mansilla, E. B. R., Castillo-Acobo, R. Y., Puma, E. G. M., Maquera, Y. M., Gonzales, J. L. A., & Vasquez-Pauca, M. J. (2022). Stress in university teachers in the framework of the post-pandemic face-to-face academic resumption. *Journal of Medicinal and Chemical Sciences*, 5(6) 1040-1047. <https://doi.org/10.26655/JMCHEMSCI.2022.6.17>
- Margetts, H. (2011). The internet and transparency. *The Political Quarterly*, 82(4), 518-521. <https://doi.org/10.1111/j.1467-923X.2011.02253.x>
- Memarian, B., & Doleck, T. (2023). Fairness, Accountability, Transparency, and Ethics (FATE) in Artificial Intelligence (AI) and higher education: A systematic review. *Computers and Education: Artificial Intelligence*, 5, 100152. <https://doi.org/10.1016/j.caeai.2023.100152>
- Mhlanga, D. (2023). Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning. *FinTech and artificial intelligence for sustainable development: The role of smart technologies in achieving development goals* (pp. 387-409). Springer. <https://doi.org/10.2139/ssrn.4354422>
- Mihaella, A., & Petrea, G. (2025). The impact of artificial intelligence on students' academic performance development. *Education Sciences*, 15(3), 343.
- Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267, 1-38. <https://doi.org/10.1016/j.artint.2018.07.007>
- Nair, S. G., Jayanthi, V., & Ranimol, V. G. (2025). Exploring ethical concerns among students: The impact of AI usage in education. *International Scientific Journal of Engineering and Management*, 4(7), 1-9. <https://doi.org/10.55041/ISJEM04845>
- Nazaretsky, T., Mejia-Dominguez, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence*, 8, 100368. <https://doi.org/10.1016/j.caeai.2025.100368>
- Pacheco-Mendoza, S., Guevara, C., Mayorga-Albán, A., & Fernández-Escobar, J. (2023). Artificial intelligence in higher education: A predictive model for academic performance. *Education Sciences*, 13(10), 990. <https://doi.org/10.3390/educsci13100990>
- Parsakia, K. (2023). The effect of chatbots and AI on the self-efficacy, self-esteem, problem-solving and critical thinking of students. *Health Nexus*, 1(1), 71–76. <https://doi.org/10.61838/hn.1.1.14>
- Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching & Learning Practice*, 20(2). <https://doi.org/10.53761/1.20.02.07>

- Porayska-Pomsta, K., & Luckin, R. (2022). Issues with data, bias, and fairness. In C. de la Higuera & J. Iyer (Eds.), *AI for teachers: An open textbook*. Press Books. <https://pressbooks.pub/aiforteachers/chapter/issues-with-data-bias-and-fairness/>
- Prashar, A., Gupta, P., & Dwivedi, Y. K. (2024). Plagiarism awareness efforts, students' ethical judgment and behaviors: A longitudinal experiment study on ethical nuances of plagiarism in higher education. *Studies in Higher Education*, 49(6), 929–955. <https://doi.org/10.1080/03075079.2023.2253835>
- Qadir, J. (2022). *Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education*. TechRxiv. <https://doi.org/10.36227/techrxiv.21789434.v1>
- Ramdani, A. (2018). Construction of an academic integrity scale. *International Journal of Research Studies in Psychology*, 7(1), 87-97. <https://doi.org/10.5861/ijrsp.2018.3003>
- Rejeb, A., Rejeb, K., Appolloni, A., Treiblmaier, H., & Iranmanesh, M. (2024). Exploring the impact of ChatGPT on education: A web mining and machine learning approach. *The International Journal of Management Education*, 22(1), 100932. <https://doi.org/10.1016/i.ijme.2024.100932>
- Rodrigues, M., Silva, R., Borges, A. P., Franco, M., & Oliveira, C. (2024). Artificial intelligence: Threat or asset to academic integrity? A bibliometric analysis. *Kybernetes*, 54(5), 2939–2970. <https://doi.org/10.1108/K-09-2023-1666>
- Roe, J., & Perkins, M. (2022). What are Automated Paraphrasing Tools, and how do we address them? A review of a growing threat to academic integrity. *Educational Integrity*, 18, Article 15. <https://doi.org/10.1007/s40979-022-00109-w>
- Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching*, 6(1), 342-363. <https://doi.org/10.37074/jalt.2023.6.1.9>
- Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare*, 11(6), 887. <https://doi.org/10.3390/healthcare11060887>
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann & A. Vomberg (Eds.), *Handbook of market research* (pp. 1-40). Springer. [https://doi.org/10.1007/978-3-319-05542-8\\_15-1](https://doi.org/10.1007/978-3-319-05542-8_15-1)
- Săseanu, A. S., Gogonea, R. M., & Ghiță, S. I. (2024). The social impact of using artificial intelligence in education. *Amfiteatru Economic*, 26(65), 89–105. <https://doi.org/10.24818/EA/2024/65/89>
- Shiri, A. (2023). ChatGPT and academic integrity. *Information Matters*, 3(2), 1–5. <https://doi.org/10.2139/ssrn.4360052>
- Shishakly, R. (2025). Understanding AI in higher education: Gendered and intersectional students' experience with ChatGPT use. *European Journal of STEM Education*, 10(1), Article 36. <https://doi.org/10.20897/ejsteme/17646>
- Shishakly, R., Abukhait, R., & Khan, M. N. (2025). Examining the higher education students' perception in the UAE on ChatGPT challenges impacted usage behaviour using the Technology Acceptance Model (TAM). In B. Alareeni, & A. Hamdan (Eds.), *IoT and digital transformation: Innovating business models for the connected world* (pp. 513–525). Springer. [https://doi.org/10.1007/978-3-032-00450-5\\_53](https://doi.org/10.1007/978-3-032-00450-5_53)
- Short, C. E., & Short, J. C. (2023). The artificially intelligent entrepreneur: ChatGPT, prompt engineering, and entrepreneurial rhetoric creation. *Journal of Business Venturing Insights*, 19, e00388. <https://doi.org/10.1016/j.jbvi.2023.e00388>
- Sikdar, S., Lemmerich, F., & Strohmaier, M. (2022). GetFair: Generalized fairness tuning of classification models. *Proceedings of the ACM Conference on Fairness, Accountability, and Transparency* (pp. 289-299). Association for Computing Machinery. <https://doi.org/10.1145/3531146.3533094>
- Sok, S., & Heng, K. (2023). ChatGPT for education and research: A review of benefits and risks. *Cambodian Journal of Educational Research*, 3(1), 110–121. <https://doi.org/10.62037/cjer.2023.03.01.06>

- Stahl, B. C., & Eke, D. (2024). The ethics of ChatGPT – Exploring the ethical issues of an emerging technology. *International Journal of Information Management*, 74, 102700. <https://doi.org/10.1016/j.ijinfo-mgt.2023.102700>
- Susnjak, T. (2022). *ChatGPT: The end of online exam integrity?* PsyArXiv. <https://doi.org/10.48550/arXiv.2212.09292>
- Sweney, M. (2023, March 8). Darktrace warns of rise in AI-enhanced scams since ChatGPT release. *The Guardian*. <https://www.theguardian.com/technology/2023/mar/08/darktrace-warns-of-rise-in-ai-enhanced-scams-since-chatgpt-release>
- Tang, X., Chen, S., Cheng, Y., Ghawla, N. V., Metoyer, R., & Ambrose, G. A. (2025). *Understanding student attitudes and acceptability of GenAI tools in higher ed: Scale development and evaluation*. PsyArXiv. <https://arxiv.org/html/2508.01926v1>
- Tao, D., Shao, F., Wang, H., Yan, M., & Qu, X. (2019). Integrating usability and social cognitive theories with the Technology Acceptance Model to understand young users' acceptance of a health information portal. *Health Informatics Journal*, 26(2), 1347–1362. <https://doi.org/10.1177/1460458219879337>
- Teo, T., & Khine, M. S. (Eds.). (2009). *Structural equation modeling in educational research: Concepts and applications*. Brill. <https://doi.org/10.1163/9789087907891>
- Theodorou, A., Wortham, R. H., & Bryson, J. J. (2017). Designing and implementing transparency for real-time inspection of autonomous robots. *Connection Science*, 29(3), 230–241. <https://doi.org/10.1080/09540091.2017.1310182>
- Thurzo, A., Strunga, M., Urban, R., Surovková, J., & Afrashtehfar, K. I. (2023). Impact of artificial intelligence on dental education: A review and guide for curriculum update. *Education Sciences*, 13(2), 150. <https://doi.org/10.3390/educsci13020150>
- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10, Article 15. <https://doi.org/10.1186/s40561-023-00237-x>
- Vekiri, I., & Chronaki, A. (2008). Gender issues in technology use: Perceived social support, computer self-efficacy, and value beliefs, and computer use beyond school. *Computers & Education*, 51(3), 1392–1404. <https://doi.org/10.1016/j.compedu.2008.01.003>
- Vieriu, A. M., & Petrea, G. (2025). The impact of Artificial Intelligence (AI) on students' academic development. *Education Sciences*, 15(3), 343. <https://doi.org/10.3390/educsci15030343>
- Walters, W. H. (2023). The effectiveness of software designed to detect AI-generated writing: A comparison of 16 AI text detectors. *Open Information Science*, 7(1), 20220158. <https://doi.org/10.1515/opis-2022-0158>
- Wardat, Y., Tashtoush, M. A., AlAli, R., & Jarrah, A. M. (2023). ChatGPT: A revolutionary tool for teaching and learning mathematics. *Eurasia Journal of Mathematics, Science and Technology Education*, 19(7), em2286. <https://doi.org/10.29333/ejmste/13272>
- Welding, L. (2023). Half of college students say using AI is cheating. *BestColleges*. <https://www.bestcolleges.com/research/college-students-ai-tools-survey>
- Wen, J., & Wang, W. (2023). The future of ChatGPT in academic research and publishing: A commentary for clinical and translational medicine. *Clinical and Translational Medicine*, 13(3), e1207. <https://doi.org/10.1002/ctm2.1207>
- Williams, T., Zhu, Q., & Grollman, D. (2020). An experimental ethics approach to robot ethics education. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(9), 13428–13435. <https://doi.org/10.1609/aaai.v34i09.7067>
- Wong, G. K. W., Ma, X., Dillengourg, P., & Huan, J. (2020). Broadening artificial intelligence education in K-12: where to start? *ACM Inroads*, 11(1), 20–29. <https://doi.org/10.1145/3381884>
- Wu, Y. (2023). Integrating generative AI in education: How ChatGPT brings challenges for future learning and teaching. *Journal of Advanced Research in Education*, 2(4), 6–10. <https://doi.org/10.56397/JARE.2023.07.02>

- Xiao, Y., Chatterjee, S., & Gehringer, E. (2022). A new era of plagiarism the danger of cheating using AI. *Proceedings of the 20th International Conference on Information Technology Based Higher Education and Training, Antalya, Turkey*, 1-6. <https://doi.org/10.1109/ITHE56107.2022.10031827>
- Yilmaz, H., Maxutov, S., Baitekov, A., & Balta, N. (2023). Student attitudes towards Chat GPT: A technology acceptance model survey. *International Educational Review*, 1(1), 57-83. <https://doi.org/10.58693/ier.114>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, Article 39. <https://doi.org/10.1186/s41239-019-0171-0>
- Zembylas, M. (2023). A decolonial approach to AI in higher education teaching and learning: Strategies for undoing the ethics of digital neocolonialism. *Learning, Media and Technology*, 48(1), 25-37. <https://doi.org/10.1080/17439884.2021.2010094>
- Zhai, X. (2022). *ChatGPT user experience: Implications for education*. PsyArXiv. <https://doi.org/10.2139/ssrn.4312418>
- Zhang, C., Zhang, C., Li, C., Qiao, Y., Zheng, S., Dam, S. K., Zhang, M., Kim, J. U., Kim, S. T., Choi, J., Park, G.-M., Bae, S.-H., Lee, L.-H., Hui, P., Kweon, I. S., & Hong, C. S. (2023). *One small step for generative AI, one giant leap for AGI: A complete survey on ChatGPT in AIGC era*. PsyArXiv. <https://doi.org/10.48550/arXiv.2304.06488>
- Zhou, L., Rudin, C., Gombolay, M., Spohrer, J., Zhou, M., & Paul, S. (2023). From artificial intelligence (AI) to intelligence augmentation (IA): Design principles, potential risks, and emerging issues. *AIS Transactions on Human-Computer Interaction*, 15(1), 111–135. <https://doi.org/10.17705/1thci.00085>
- Zhuo, T. Y., Huang, Y., Chen, C., & Xing, Z. (2023). *Exploring AI ethics of ChatGPT: A diagnostic analysis*. ArXiv. <http://arxiv.org/pdf/2301.12867>

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