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Measuring ethical AI Use in higher education: Reliability and validity of the AI academic integrity scale for postgraduate students

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Abstract

This study developed and validated a psychometrically sound instrument to assess ethical artificial intelligence (AI) use among postgraduate students, addressing the critical gap in reliable measurement tools for AI academic integrity in higher education. A quantitative design employed two Egyptian postgraduate student samples (N_1=629, N_2=884) for exploratory and confirmatory factor analyses. The AI Academic Integrity Scale was developed through a comprehensive literature review and subjected to rigorous psychometric validation, including reliability assessment using multiple coefficients. Results revealed a robust three-factor structure: Ethical Use of AI, Awareness of Misuse Risks, and Academic Writing Support, explaining 39.997% of the total variance. Confirmatory factor analysis demonstrated an excellent model fit (χ^2/df=2.484, GFI=.974, CFI=.958, RMSEA=.041). The final 17-item instrument showed satisfactory reliability across subscales (McDonald's ω=.695-.708, Cronbach's α=.692-.707), with factor loadings ranging from .502 to .688. The AI Academic Integrity Scale is a reliable tool that identifies the ethical engagement of AI technologies in postgraduate education, offering a comprehensive assessment of both challenges and opportunities within academic contexts. The instrument assesses postgraduate students' ethical AI engagement, aiding policy development and targeted interventions, promoting responsible AI integration while maintaining academic integrity in AI-enhanced educational environments.

Keywords: Academic Integrity, Artificial Intelligence Ethics, Postgraduate Education, Psychometric Validation.

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1. Introduction

The integration of artificial intelligence (AI) technologies has emerged as a transformative force in higher education, particularly among postgraduate students who increasingly rely on these tools for academic pursuits [1, 2]. This rapid adoption has created a complex educational landscape where innovative technological applications intersect with fundamental questions of academic integrity and ethical practice. While AI offers unprecedented opportunities for personalized learning experiences, research enhancement, and skill development [3, 4], it simultaneously introduces significant challenges regarding assessment authenticity, intellectual ownership, and equitable access [5, 6].

The tension between educational benefits and academic integrity concerns represents a critical challenge for higher education institutions worldwide [7, 8]. On one hand, AI technologies facilitate enhanced student engagement, improved productivity, and greater accessibility to educational resources [9-11]. On the other hand, these same technologies raise serious concerns about plagiarism, diminished originality, and the potential erosion of critical thinking skills among students [12-14]. This fundamental tension necessitates developing robust institutional policies and ethical frameworks that maximize AI's educational potential while preserving academic integrity [15, 16].

Conventional academic integrity assessment methods have proven inadequate for addressing the unique challenges presented by advanced AI systems. Traditional plagiarism detection tools demonstrate limited effectiveness in identifying sophisticated AI-generated content, particularly when advanced prompting or paraphrasing techniques are employed [17, 18]. The ability of modern AI tools to closely mimic human writing and circumvent established detection methods creates substantial barriers to maintaining academic standards [16, 19]. Without reliable, validated assessment instruments specifically designed for AI-related academic integrity, educational institutions struggle to develop appropriate policies and implement effective training for both faculty and students [20].

Despite growing recognition of these challenges, there remains a significant gap in the literature regarding validated measurement tools for assessing ethical AI use in higher education settings. While researchers have documented the increasing prevalence of AI in academic contexts [21, 22] few studies have developed and validated psychometric instruments specifically designed to measure ethical AI usage among postgraduate students. This research gap hampers institutional efforts to formulate evidence-based policies and undermines attempts to foster responsible AI integration within academic communities [23-25].

The present study addresses this critical research gap by developing and validating the AI Academic Integrity Scale for Postgraduate Students. This psychometric instrument aims to provide educational institutions with a reliable tool for assessing ethical AI use among postgraduate learners, thereby facilitating more informed approaches to policy development, educational intervention, and curriculum design. By establishing the reliability and validity of this measurement tool, this research contributes to the broader scholarly discourse on maintaining academic integrity in an increasingly AI-enhanced educational landscape [2, 26-28].

2. Literature Review

The ethical use of AI in academic contexts is best conceptualized through multidisciplinary theoretical perspectives that emphasize fairness, transparency, and accountability [29, 30]. Recent studies have demonstrated the practical benefits of AI integration in specific educational contexts, such as language learning applications that enhance student performance [4]. These perspectives integrate philosophical, legal, and pedagogical frameworks to address the unique challenges presented by AI-enhanced learning environments. Traditional academic integrity theories remain relevant but require significant adaptation, particularly regarding transparency and proper attribution when using AI tools [31, 32]. The tension between technological innovation and academic ethics is addressed through theoretical models, including algorithm vigilance [33], which emphasizes continuous monitoring of AI systems, and frameworks that balance human oversight with technological advancement [34, 35]. These models collectively stress that ethical AI use requires integrating traditional academic values with new guidelines that promote responsible innovation while preserving the core principles of academic integrity.

Ethical AI use in higher education is conceptually defined as the transparent, responsible application of AI technologies that enhances learning while preserving academic integrity [36, 37]. The distinction between appropriate and inappropriate AI use among postgraduate students centers on intent, disclosure, and originality. Appropriate use supports understanding and research with proper attribution, while inappropriate use involves misrepresentation and bypassing intellectual development [38]. As AI technologies advance, academic integrity frameworks are evolving beyond traditional notions of authorship and plagiarism toward collaborative guidelines that emphasize student responsibility for AI-generated content and the ethical integration of AI into academic workflows [39-41]. This evolution reflects the growing recognition that AI tools fundamentally alter the academic landscape, necessitating new approaches to assessment and integrity verification.

The theoretical foundation for measuring ethical AI use in higher education draws upon several interconnected constructs. Fairness, accountability, transparency, autonomy, and socio-technical responsibility emerge as the most relevant dimensions for assessment [42-44]. Psychometric approaches increasingly integrate behavioral ethics models, particularly the Academic Integrity Model (AIM), which conceptualizes ethical behavior as emerging from human-AI interactions [42, 45]. These frameworks inform the dimensional structure of academic integrity scales by balancing universal ethical principles with contextual considerations [46, 47]. The shift from broad principle-based frameworks toward more nuanced, context-sensitive models reflects the complex interplay between human agency and AI capabilities in academic settings, necessitating assessment tools that capture both ethical decision-making processes and localized educational norms.

3. Method

3.1. Research Design

The study employed a quantitative research methodology to examine the psychometric properties of the AI Academic Integrity Scale for Postgraduate Students. The research specifically focused on investigating the scale's validity and reliability within the context of higher education in Egypt. The study was conducted during the 2024-2025 academic year at the Faculties of Education at Al-Azhar University (Men's campus in Dakahlia and Women's campus in Cairo) and the Faculty of Education at Kafr El-Sheikh University, Egypt.

3.2. Participants

The study utilized two distinct samples to conduct comprehensive psychometric analyses of the scale. The first sample, used for exploratory factor analysis, consisted of 629 postgraduate students recruited using a convenience sampling approach from various academic departments within the participating faculties. This sample achieved a 100% response rate, providing complete and valid responses. The participants represented different postgraduate levels, with 44.8% enrolled in diploma programs, 28.3% in master's programs, and 26.9% in doctoral programs. The age range of participants was 22-39 years (M = 26.78, SD = 4.96). The sample included both male (43.2%) and female (56.8%) students. The majority of students (72.8%) resided in rural areas, while 27.2% lived in urban areas.

The second sample, utilized for confirmatory factor analysis and reliability assessment, comprised 884 postgraduate students recruited from the same institutions using similar sampling procedures. This sample exhibited demographic characteristics reflective of the broader postgraduate student population in Egyptian higher education institutions. Specifically, 43.7% (n = 386) were enrolled in diploma programs, 30.4% (n = 269) in master's programs, and 25.9% (n = 229) in doctoral programs. The gender distribution included 45.8% male (n = 405) and 54.2% female (n = 479) participants. The age range was 23–41 years (M = 27.32, SD = 5.18). Regarding residential distribution, 31.6% (n = 279) of participants resided in urban areas, while 68.4% (n = 605) came from rural backgrounds. This robust and diverse sample facilitated rigorous testing of the scale's factor structure and psychometric properties across different demographic subgroups.

3.3. Instruments

The primary research instrument was the AI Academic Integrity Scale for Postgraduate Students, initially consisting of 24 items designed to measure ethical AI use among postgraduate students. The scale employed a 5-point Likert-type response format ranging from 1 (strongly disagree) to 5 (strongly agree). The items were developed based on a comprehensive review of literature on academic integrity and ethical AI use in higher education settings, with particular attention to the unique challenges and considerations relevant to postgraduate education. To ensure cultural appropriateness and linguistic accuracy, the researchers implemented a rigorous translation and adaptation process for the Arabic version of the scale. This comprehensive approach involved forward translation by bilingual experts, synthesis of translations, back-translation, and careful review by an expert committee of educational psychology specialists.

3.4. Data Collection Procedures

Researchers created a digital version of a scale using Google Forms after obtaining ethical approvals from participating institutions. This online format facilitated efficient data collection and standardized administration across participants. The Google Form included an introductory section, instructions for completing the scale, and a digital consent form. The link was distributed to postgraduate students across three faculties, and faculty members were requested to share the survey link during classes. The digital format allowed participants to complete the scale at their convenience, ensuring all questions required responses before submission. Confidentiality was assured, and the Google Form did not collect identifying information beyond basic demographic data. The scale was administered in Arabic, the primary language of instruction at the participating institutions.

3.5. Data Analysis

The study employed a comprehensive statistical approach to analyze the psychometric properties of the AI Academic Integrity Scale. For Sample 1, comprising 629 participants, exploratory factor analysis (EFA) was conducted to investigate the scale's structure. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were performed to assess data suitability. For Sample 2, with 884 participants, confirmatory factor analysis (CFA) was used to validate the identified structure. Multiple fit indices were examined to evaluate model fit. Reliability assessment was conducted using Cronbach's alpha, McDonald's omega coefficients, and composite reliability estimates. Convergent and discriminant validity were examined through correlational analyses with theoretically related and unrelated constructs. Descriptive statistics summarized sample demographics and response patterns across scale items. Measurement invariance testing was performed across gender and academic level subgroups to ensure the scale functioned effectively across diverse student populations.

4. Results

Prior to conducting exploratory factor analysis (EFA), the KMO measure of sampling adequacy and Bartlett's test of sphericity were performed to assess data suitability. The KMO value of .889 indicated excellent sampling adequacy, while Bartlett's test yielded a significant result ($\chi^2 = 3706.780$, df = 276, $p < .001$), confirming the appropriateness of the data for factor analysis.

The EFA was conducted on the initial 24-item scale using principal component analysis with varimax rotation. The analysis revealed a three-factor solution that explained 39.997% of the total variance. Factor 1 accounted for 24.602% of the variance, while Factors 2 and 3 explained 9.624% and 5.771% of the variance, respectively. Based on the EFA results, 17 items with factor loadings greater than .50 were retained, with 7 items eliminated due to insufficient factor loadings or cross-loading on multiple factors.

Table 1.
Factor Loading Analysis of 17-Item AI Academic Integrity Scale.

Items	Factor Loading	M	SD	Item total correlation
Factor 1: Ethical Use of AI				
16. I use AI tools to enhance my own thinking rather than replace it	0.657	3.453	0.913	0.434**
11. I consult my institution's guidelines before using AI for academic work	0.639	3.518	0.978	0.329**
15. I regularly reflect on whether my AI usage aligns with academic integrity principles	0.633	3.804	0.909	0.509**
9. I ensure AI assistance doesn't compromise the authenticity of my academic voice	0.625	3.789	0.930	0.503**
14. I believe using AI without disclosure constitutes plagiarism	0.616	3.804	0.950	0.371**
12. I verify AI-generated content against reliable academic sources	0.555	3.390	0.904	0.305**
Factor 2: Awareness of Misuse Risks				
7. I am aware that AI tools may reproduce biases present in academic literature	0.669	3.812	0.964	0.444**
5. I understand how AI use might undermine the learning objectives of assignments	0.661	4.011	0.921	0.448**
2. I understand the potential consequences of unattributed AI use in my institution	0.637	4.046	0.925	0.447**
1. I recognize that submitting AI-generated essays as my own work constitutes academic misconduct	0.629	3.806	0.757	0.452**
8. I understand how AI might generate convincing but factually incorrect content	0.612	3.836	0.892	0.560**
4. I am aware that AI can be used to circumvent plagiarism detection systems	0.552	4.040	0.974	0.419**
Factor 3: Academic Writing Support				
23. I request AI assistance for grammar and syntax improvements	0.688	3.639	0.999	0.422**
22. I employ AI to help clarify complex concepts in my drafts	0.658	3.568	0.900	0.454**
21. I use AI tools to overcome writer's block in academic writing	0.604	4.013	1.074	0.453**
24. I use AI to generate alternative phrasings for my own ideas	0.551	3.638	0.819	0.499**
17. I use AI tools to check for unintentional plagiarism in my work	0.502	3.440	1.034	0.339**

Note: **p < .01.

The final 17-item scale comprised three distinct factors: Ethical Use of AI (6 items), Awareness of Misuse Risks (6 items), and Academic Writing Support (5 items). As shown in Table 1, factor loadings for the retained items ranged from .502 to .688, indicating robust item-factor relationships. Item-total correlations ranged from .305 to .560, demonstrating adequate discriminative power. The mean scores for individual items ranged from 3.390 to 4.046 (on a 5-point scale), suggesting generally positive perceptions regarding ethical AI use among participants.

To validate the three-factor structure identified through EFA, CFA was conducted using the second sample (N=884). The CFA model specified the three latent factors (Ethical Use of AI, Awareness of Misuse Risks, and Academic Writing Support) with their respective observed variables as identified in the EFA solution. Figure 1 illustrates the structural model with standardized factor loadings.

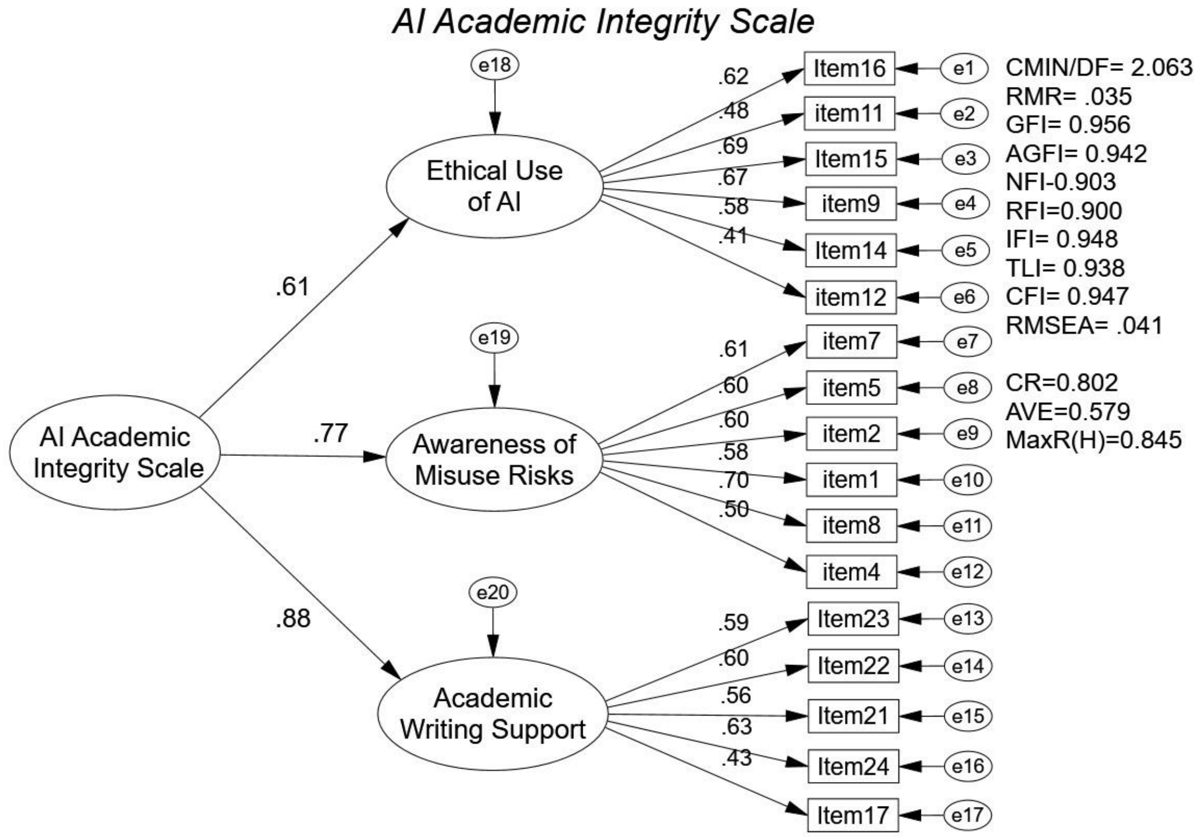

Figure 1.
CFA Model of 17-Item AI Academic Integrity Scale.

The CFA results indicated a good fit between the hypothesized model and the observed data. The chi-square test yielded $\chi^2/df = 2.484$, which is below the recommended threshold of 3.0, suggesting acceptable model fit. Additional fit indices provided further support for the model's adequacy: GFI = .974, AGFI = .961, NFI = .933, CFI = .958, and RMSEA = .041 (90% CI [.033, .049]). The RMSEA value fell below the .05 threshold, indicating excellent fit, while the CFI value exceeded the recommended cutoff of .95, demonstrating good fit. The PCLOSE value of .965 further supported the model's acceptability.

Convergent validity was supported by a CR of .752 and an average variance extracted (AVE) of .502, both exceeding the recommended thresholds of .70 and .50, respectively. These findings provide robust evidence for the three-factor structure of the AI Academic Integrity Scale for Postgraduate Students.

Reliability analysis was conducted to assess the internal consistency of the 17-item AI Academic Integrity Scale and its subscales. As presented in Table 2, the reliability coefficients were calculated using multiple approaches to ensure a comprehensive assessment. McDonald's omega (ω) coefficients were .708, .704, and .695 for the Ethical Use of AI, Awareness of Misuse Risks, and Academic Writing Support factors, respectively. Similarly, Cronbach's alpha (α) coefficients were .707, .702, and .692, while Guttman's lambda-2 (λ2) values were .708, .703, and .694 for the three subscales.

Table 2.
Reliability Coefficients of 17-Item AI Academic Integrity Scale.

Variable	McDonald's ω	Cronbach's α	Guttman's λ2
Ethical Use of AI	0.708	0.707	0.708
Awareness of Misuse Risks	0.704	0.702	0.703
Academic Writing Support	0.695	0.692	0.694

These reliability coefficients, all approaching or exceeding .70, demonstrate satisfactory internal consistency for the scale and its dimensions, particularly considering the multidimensional nature of the construct and the relatively small number of items per factor. The consistency across different reliability estimation methods further supports the scale's measurement stability.

The comprehensive psychometric evidence, including factor structure, model fit indices, and reliability coefficients, collectively supports the validity and reliability of the 17-item AI Academic Integrity Scale as a measurement tool for assessing ethical AI use among postgraduate students in the Egyptian higher education context.

5. Discussion

The present study aimed to develop and validate the AI Academic Integrity Scale for Postgraduate Students within the Egyptian higher education context. Through rigorous psychometric analysis, a three-factor structure emerged comprising *Ethical Use of AI, Awareness of Misuse Risks,* and *Academic Writing Support*. This structure demonstrates good model fit ($\chi^2/df = 2.484$, GFI = .974, CFI = .958, RMSEA = .041) and satisfactory reliability coefficients across all subscales (ω = .695–.708, α = .692–.707). These findings provide empirical support for the scale's utility in assessing ethical AI use among postgraduate students and offer several important theoretical and practical implications.

The validated three-factor structure aligns with and extends current theoretical frameworks on academic integrity in technology-enhanced learning environments. Particularly, the *Ethical Use of AI* dimension corresponds with the transparency and accountability principles emphasized in contemporary academic integrity models [36, 37]. Items loading on this factor, such as *"I use AI tools to enhance my own thinking rather than replace it"* and *"I ensure AI assistance doesn't compromise the authenticity of my academic voice,"* reflect the evolving conceptualization of integrity that acknowledges AI as a collaborative tool rather than merely a potential vector for misconduct. This finding supports the theoretical shift from traditional plagiarism frameworks toward more nuanced models of academic integrity that accommodate technological innovation while preserving educational values [39-41]. Similar multidimensional approaches to measuring AI-related concerns have emerged in other disciplines, as evidenced by the FAME scale [48], which examines *Fear, Anxiety, Mistrust, and Ethical issues* related to generative AI integration among health sciences students. Both scales recognize that responses to AI technologies in educational contexts extend beyond simple acceptance or rejection to encompass nuanced psychological and ethical dimensions.

The emergence of *Awareness of Misuse Risks* as a distinct factor highlights the importance of metacognitive understanding regarding AI limitations and ethical boundaries. This dimension resonates with algorithm vigilance frameworks proposed by Klimova et al. [33], which emphasize continuous critical evaluation of AI systems in educational contexts. The strong factor loadings for items related to understanding bias reproduction, factual inaccuracies, and plagiarism detection circumvention suggest that awareness of these risks constitutes a fundamental component of ethical AI use. This finding extends previous research by Cai et al. [1] and Zhou et al. [2] by empirically demonstrating that risk awareness represents a distinct cognitive dimension rather than merely a subset of general ethical considerations.

The *Academic Writing Support* factor represents a novel contribution to the literature by specifically addressing the legitimate academic applications of AI tools. This aligns with recent evidence showing positive educational outcomes from AI applications in language learning contexts [4]. Previous research has often focused predominantly on misconduct prevention rather than constructive implementation [21, 22]. The identification of this dimension empirically validates the theoretical position that ethical AI use involves not just avoiding misuse but actively leveraging AI capabilities to enhance learning outcomes within appropriate boundaries [3, 4]. This finding suggests that comprehensive academic integrity frameworks should explicitly acknowledge and provide guidelines for appropriate AI assistance in academic workflows.

From a practical perspective, the validated scale offers educational institutions a reliable assessment tool for evaluating ethical AI use among postgraduate students. The scale's multidimensional structure allows for nuanced measurement across different aspects of AI integration, potentially informing targeted interventions and policy development. For instance, lower scores on the *Ethical Use* dimension might indicate a need for clearer institutional guidelines and explicit instruction on appropriate AI attribution practices [41]. Similarly, deficiencies in the *Awareness of Misuse Risks* dimension could signal the importance of educational initiatives focused on critical evaluation of AI-generated content [33]. Such targeted approaches represent a significant advancement over generalized academic integrity policies that may not adequately address the unique challenges presented by AI technologies [15, 16].

The scale's validation in the Egyptian higher education context provides valuable insights regarding the cultural dimensions of AI ethics in academic settings. These contextual insights are particularly relevant given the recent transformations in higher education research practices following global disruptions such as the COVID-19 pandemic [49] which has reshaped how faculty and students approach academic work and research production. The consistently high mean scores across items (ranging from 3.390 to 4.046 on a 5-point scale) suggest generally positive perceptions regarding ethical AI use among Egyptian postgraduate students. This finding contrasts with some international studies reporting ambivalent or negative attitudes toward AI integration in higher education [12, 14]. The relatively high scores on items related to following institutional guidelines and consulting academic sources indicate a strong orientation toward authority and established norms, potentially reflecting cultural values prevalent in Egyptian educational institutions. These contextual insights highlight the importance of considering cultural factors when developing academic integrity frameworks in diverse educational settings.

The demographic composition of our samples further enriches the understanding of ethical AI use across different student populations. The balanced representation of academic levels (diploma, master's, and doctoral programs) allows for meaningful comparisons that could inform level-specific interventions. Similarly, the substantial participation from both urban and rural backgrounds (approximately 30% urban and 70% rural) provides valuable insights into potential geographical disparities in AI access and utilization. Future research could explore whether these demographic factors moderate relationships between scale dimensions and relevant educational outcomes, such as academic performance and integrity violations.

Despite its significant contributions, this study has several limitations that warrant acknowledgment. First, the cross-sectional design precludes causal inferences about the relationships between scale dimensions and behavioral outcomes. Longitudinal studies would be valuable for assessing the predictive validity of the scale regarding actual ethical AI use over time. Second, the reliance on self-report measures introduces potential social desirability bias, particularly concerning sensitive academic integrity issues. Future research might incorporate behavioral measures or scenario-based assessments to complement self-report data. Additionally, while the sample size was robust for psychometric analysis, all participants were recruited from Egyptian institutions, potentially limiting generalizability to other cultural and educational contexts.

These limitations suggest several promising directions for future research. Cross-cultural validation studies would help establish the scale's applicability across diverse educational settings and identify potential cultural variations in ethical AI conceptualizations. Longitudinal research designs could examine how ethical AI attitudes and behaviors evolve over the course of postgraduate education and in response to institutional interventions. Mixed-methods approaches incorporating qualitative interviews or focus groups would provide deeper insights into students' decision-making processes regarding AI use in academic contexts. Finally, extending the scale to undergraduate populations would facilitate comprehensive assessment across all levels of higher education.

The development and validation of the AI Academic Integrity Scale address a critical gap in the literature regarding measurement tools for ethical AI use in higher education. As AI technologies continue to transform educational practices, empirically validated assessment instruments become increasingly essential for maintaining academic integrity while maximizing the benefits of technological innovation. The three-factor structure identified in this study, encompassing ethical use principles, risk awareness, and appropriate academic applications, provides a comprehensive framework for understanding and evaluating postgraduate students' engagement with AI technologies. This multidimensional conceptualization moves beyond simplistic notions of academic misconduct toward a more nuanced understanding that acknowledges both the challenges and opportunities presented by AI in educational contexts. By providing a reliable and valid assessment tool, this research contributes to the development of evidence-based policies and interventions that foster responsible AI integration within academic communities.

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