GenAI Adoption, Academic Integrity, and Responsible Use Among First-Year Accounting Students

Journal of Strategic Behavior Accounting

Authors
Dava Hisyam Mahardika[1], Irene Sofia Herlani[2],
Uzy Faktihati Arista Putri[3], Sephanya Rifalia[4],
Helanda Nurul[5], Nabila Kurnia Nurhaini[6],
Aditya Rizky Herlambang[7], Ikolo Robert Oghenero[8]

Affiliations
[1,2,3,4,5,6,7] Department of Accounting, Universitas Negeri Surabaya, Indonesia
[8]Department of Office and Information Management, Southern Delta University, Nigeria

Corresponding Author Email
dikamahar946@gmail.com

Abstract
Generative artificial intelligence (GenAI) has rapidly become part of students' learning experiences, yet little is known about how first-year university students perceive and use these technologies responsibly. This study investigates GenAI adoption among first-year undergraduate students by examining four key dimensions: learning benefits, risks and dependencies, academic integrity intentions, and responsible use. A quantitative survey was conducted with 260 first-year students from Indonesian universities using a validated 25-item Likert-scale questionnaire. Data were analysed through descriptive statistics, Pearson correlation, one-way ANOVA, and multiple linear regression. The findings reveal that students generally hold positive perceptions of GenAI while remaining aware of its potential risks. Academic integrity intentions emerged as the strongest predictor of responsible GenAI use, whereas learning benefits showed a smaller but significant positive effect. Students who used GenAI more frequently also reported greater perceived learning benefits, while no significant gender differences were identified. These findings emphasise that promoting academic integrity alongside AI literacy is essential for encouraging responsible GenAI use and offer practical insights for higher education institutions seeking to integrate AI into teaching and learning responsibly.

Keywords
generative AI; academic integrity; responsible use; learning benefits; first-year students; higher education.

1. Introduction

Generative artificial intelligence (GenAI), particularly large language model (LLM)-based applications such as ChatGPT, Gemini, and Microsoft Copilot, has emerged as a transformative technology in higher education. Unlike earlier educational technologies that primarily support content delivery or information retrieval, GenAI can generate human-like text, code, analyses, and other forms of content through natural language interaction. These capabilities have reshaped how students access information, engage with learning activities, and develop academic competencies (Ouyang and Jiao, 2021). As GenAI adoption continues to expand across universities, higher education institutions face increasing challenges in establishing effective policies and pedagogical practices that promote its ethical and responsible use. This challenge is particularly evident in developing countries, where institutional governance and AI-related educational policies continue to evolve.

First-year undergraduate students constitute a particularly relevant group for examining GenAI adoption because the transition from secondary school to university is accompanied by substantial academic, cognitive, and social adjustment (Tinto, 1987). During this period, students are expected to develop greater independence in learning while adapting to new academic expectations and institutional standards. At the same time, the widespread availability of GenAI introduces both opportunities and challenges, requiring students to integrate AI into their learning practices without compromising academic integrity or critical thinking. Examining how these overlapping transitions shape students' perceptions and use of GenAI is therefore essential for understanding responsible AI adoption in higher education.

The issue is particularly relevant in business and accounting education, where students are expected to develop analytical reasoning, evidence-based decision-making, professional judgement, and ethical responsibility. GenAI can support these learning processes by facilitating problem-solving, improving access to information, and enhancing academic productivity. However, excessive dependence on AI may reduce students' engagement in the reflective and analytical thinking required to develop these competencies (Hmelo-Silver, 2004). Consequently, understanding how first-year students adopt and use GenAI responsibly is essential for ensuring that AI serves as a learning support tool rather than a substitute for the intellectual development expected of future accounting and business professionals.

Recent studies have increasingly examined the adoption of GenAI in higher education. Nevertheless, the existing literature remains limited in two important respects. First, empirical evidence is concentrated in North America, Europe, and East Asia, leaving developing countries underrepresented. Second, relatively few studies have focused specifically on first-year university students, whose early academic experiences may shape subsequent patterns of AI adoption and responsible use. Addressing these gaps, the present study investigates first-year Indonesian university students, a population situated within one of the world's largest higher education systems.

This study addresses the gap by examining four theoretical constructs: learning benefits (LB), risks and dependencies (R&D), academic integrity intentions (AII), and responsible usage (RU). These are the exact questions for the study:

RQ1: What are the levels of perceived learning benefits, risks and dependencies, academic integrity intentions, and responsible use among first-year students?

RQ2: How do GenAI usage frequency and gender relate to these four constructs?

RQ3: To what extent do learning benefits and academic integrity intentions predict responsible use of GenAI?

The findings offer theoretical contributions to the technology acceptance and academic integrity literatures, as well as practical implications for curriculum design, academic policy and institutional governance in AI-integrated educational environments.

2. Literature Review

2.1 GenAI and the student learning experience

The adoption of generative artificial intelligence (GenAI) in higher education can be understood through established technology acceptance theories, particularly the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). These frameworks suggest that students are more likely to adopt new technologies when they perceive them as useful, easy to use, and supported by favourable social and institutional conditions. In educational settings, these perspectives explain the growing integration of GenAI into learning activities; however, technology acceptance alone is insufficient to explain responsible AI use. The educational value of GenAI depends not only on students' willingness to adopt the technology but also on their commitment to academic integrity and their ability to use AI in ways that support meaningful learning and long-term competency development. From this perspective, human capital theory complements TAM and UTAUT by emphasising that GenAI should enhance, rather than replace, the development of critical thinking, problem-solving, and professional competencies (Zawacki-Richter et al., 2019). Accordingly, this study integrates these complementary perspectives to examine how learning benefits, risks and dependencies, academic integrity intentions, and responsible use collectively shape GenAI adoption among first-year university students.

Empirically, GenAI has been documented across a range of educational applications: personalised explanations and tutoring (Wollny et al., 2021), academic writing support and feedback (Gao et al., 2022), problem-solving scaffolding and code assistance. Students report significant time savings, improved understanding of complex concepts and greater confidence in completing academic tasks. These benefits are particularly salient for first-year students who are still building foundational academic skills and may lack the social capital to seek peer or instructor support.

However, the same properties that make GenAI educationally useful also generate substantive risks. Sweller's (1988) cognitive load theory provides a foundational warning: when learners delegate cognitive tasks to external agents, the very act of effortful processing that consolidates deep learning is bypassed. In the GenAI context, this manifests as cognitive offloading — the systematic externalisation of thinking to AI, potentially producing surface-level performance without durable skill acquisition. Students who rely on GenAI to generate answers rather than to scaffold their own reasoning may perform well on AI-assisted tasks whilst failing to develop the critical thinking, creative problem-solving and self-regulatory skills that constitute the core purpose of higher education.

2.2 Academic integrity in the AI era

Academic integrity encompasses the institutional and personal commitment to honesty, trust, fairness, respect and responsibility in all scholarly work (ICAI, 2021). The introduction of GenAI has fundamentally disrupted the ecology of academic misconduct: AI-generated content is frequently indistinguishable from original student work, plagiarism detection tools are inadequate, and the very concept of 'original work' is contested when AI can produce sophisticated text in seconds (Cotton et al., 2023).

Theoretical perspectives on academic dishonesty suggest that misconduct is driven by a combination of individual moral identity, situational opportunity and perceived detection risk (Bandura, 1986; McCabe et al., 2012). In the GenAI context, the opportunity costs of dishonesty are near-zero whilst detection probabilities remain low, creating structural conditions that increase misconduct risk even among students with generally positive integrity values. The Theory of Planned Behaviour (Ajzen, 1991) further suggests that the critical predictor of behaviour is not values per se but the strength and salience of behavioural intentions: students who have formed strong, explicit intentions to uphold academic integrity are significantly more likely to do so in practice than those who hold vague positive attitudes.

2.3 Responsible AI use and human capital development

Responsible use of GenAI in academic contexts can be operationalised along several dimensions: verifying AI-generated information against credible sources, disclosing AI assistance when required, using AI as a supplement rather than a substitute for one's own intellectual effort, and exercising critical judgement about the accuracy and appropriateness of AI outputs. These behaviours collectively constitute a form of AI literacy that is increasingly recognised as a key graduate attribute (Zawacki-Richter et al., 2019).

From a human capital economics perspective (Becker, 1964), responsible AI use has implications that extend well beyond individual assessment outcomes. Investment in human capital — through effortful learning generates skills and knowledge that carry long-term productivity returns. When AI substitutes for this effortful learning, the human capital formation process is interrupted: students may complete their degrees with credentials that overstate their authentic competencies. Responsible use behaviours are therefore not merely ethical preferences but economically consequential choices that shape the value of education as a human capital investment.

3. Research Methodology

3.1 Research design and participants

This study employed a quantitative cross-sectional survey design to examine GenAI adoption among first-year undergraduate accounting students in Indonesia. Participants were selected using purposive sampling based on the objectives of the study. Eligible respondents were first-year undergraduate accounting students (Semester 1 or 2) enrolled at Indonesian universities who had prior experience using or were familiar with at least one GenAI application, such as ChatGPT, Gemini, or Microsoft Copilot. The questionnaire was administered online through Google Forms in December 2025, and participation was entirely voluntary. Before completing the survey, all respondents received information about the purpose of the study and provided informed consent electronically. To ensure confidentiality, no personally identifiable information was collected, and only complete responses were retained for the final analysis.

A total of 260 valid responses were retained after screening for completion and consistency (n = 175 female, 67.3%; n = 85 male, 32.7%). The sampling approach was purposive, targeting first-year students with at least some prior exposure to or awareness of GenAI tools. All respondents confirmed first-year status (Semester 1 or 2) prior to completing the survey.

3.2 Survey instrument

The survey instrument comprised 25 items organised into four theoretically derived constructs: Learning Benefits (LB), Risks and Dependencies (R&D), Academic Integrity Intentions (AII), and Responsible Use (RU). Each construct was measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was developed by adapting measurement items from previous studies on GenAI adoption, technology acceptance, academic integrity, and responsible AI use, with minor modifications to ensure their relevance to first-year undergraduate accounting students in Indonesia.

Before the main data collection, the instrument was reviewed to improve the clarity and appropriateness of the item wording. Representative items included "GenAI helps me understand course materials more effectively" for Learning Benefits, "I am concerned that excessive reliance on GenAI may weaken my critical thinking" for Risks and Dependencies, "I would avoid using GenAI in ways that violate academic integrity" for Academic Integrity Intentions, and "I verify AI-generated information before incorporating it into my academic work" for Responsible Use. The complete construct structure and the number of items for each construct are presented in Table 1.

Table 1 Survey instrument structure

Construct	Description	Items
Learning Benefits (LB)	Perceived cognitive, motivational and efficiency gains from GenAI use in academic tasks	9
Risks and Dependencies (R&D)	Concerns about over-reliance, impaired critical thinking and information inaccuracy	5
Academic Integrity Intentions (AII)	Intentions to uphold academic honesty and avoid AI-facilitated misconduct	5
Responsible Use (RU)	Behavioural intentions to verify, disclose and appropriately limit AI assistance	6

Learning Benefits items assessed perceptions of cognitive support, motivational enhancement, time efficiency and adaptive explanation — capturing the degree to which students perceive GenAI as a genuinely useful learning partner. Risks and Dependencies items measured concerns about critical thinking impairment, information accuracy, and the risk of intellectual passivity. Academic Integrity Intentions items assessed the strength of students' commitment to avoiding AI-assisted misconduct, particularly under conditions of low detection risk. Responsible Use items measured intentions to verify AI outputs, declare use when required, and limit AI to a supplementary rather than substitutive role.

3.3 Reliability analysis

Internal consistency was assessed using Cronbach's alpha for each construct. As presented in Table 2, all four constructs exceeded the recommended threshold of $\alpha \geq 0.70$ (Hair et al., 2019), with coefficients ranging from 0.777 to 0.918, indicating acceptable to excellent reliability. The questionnaire was developed by adapting theoretically established measures from previous studies on GenAI adoption, technology acceptance, academic integrity, and responsible AI use, with minor wording revisions to improve clarity and contextual relevance for first-year undergraduate accounting students in Indonesia. These results support the reliability of the instrument for subsequent statistical analyses.

Table 2 Reliability analysis results

Construct	Cronbach's α	Classification
Learning Benefits (LB)	0.918	Excellent
Risks and Dependencies (R&D)	0.848	Good
Academic Integrity Intentions (AII)	0.777	Acceptable
Responsible Use (RU)	0.865	Good

3.4 Data analysis

Data were analysed using Python with the pandas, SciPy, and scikit-learn libraries. Descriptive statistics were first calculated to summarise respondents' demographic characteristics and the distribution of each construct. Pearson correlation analysis was then performed to examine the relationships among the four study constructs. A one-way analysis of variance (ANOVA) was used to determine whether perceived learning benefits differed across groups based on GenAI usage frequency, while an independent-samples t-test was conducted to compare learning benefit perceptions between male and female students. Finally, multiple linear regression analysis was employed to examine the extent to which learning benefits, risks and dependencies, and academic integrity intentions predicted responsible GenAI use. Statistical significance was evaluated at the 5% level ($p < .05$) for all analyses.

3.5 Ethical considerations

This study was conducted in accordance with the ethical principles for research involving human participants. Prior to completing the questionnaire, all participants were informed about the purpose of the study, the voluntary nature of their participation, their right to withdraw at any time without penalty, and the confidential treatment of their responses. Electronic informed consent was obtained from every participant before data collection commenced. No personally identifiable information was collected, and all responses were anonymised and used solely for academic research purposes. Because the study involved an anonymous, minimal-risk online survey, formal institutional ethical approval was not required under the applicable research guidelines.

4. Findings

4.1 Descriptive statistics

All four constructs returned mean scores above the scale midpoint of 3.00, indicating consistently positive orientations among respondents. Full results are presented in Table 3. Responsible use returned the highest mean ($M = 4.19$, $SD = 0.65$), followed by academic integrity intentions ($M = 4.08$, $SD = 0.67$), risks and dependencies ($M = 4.03$, $SD = 0.75$), and learning benefits ($M = 4.02$, $SD = 0.71$).

Table 3 Descriptive statistics (n = 260)

Construct	Mean	SD	Min	Max
Learning Benefits (LB)	4.02	0.71	1.33	5.00
Risks and Dependencies (R&D)	4.03	0.75	1.00	5.00
Academic Integrity Intentions (AII)	4.08	0.67	1.20	5.00
Responsible Use (RU)	4.19	0.65	1.17	5.00

The relatively similar mean scores for learning benefits and risks and dependencies suggest that respondents recognised both the potential educational value of GenAI and its associated risks. In addition, the comparatively higher mean score for responsible use (M = 4.19) indicates a generally positive orientation towards using GenAI responsibly in academic settings. These findings provide an initial descriptive overview of respondents' perceptions, while further statistical analyses are presented in the following sections.

4.2 GenAI usage frequency

Respondents reported varying frequencies of GenAI use for academic purposes. Nearly one-third (29.2%) reported using GenAI almost every day, while an equal proportion used it once or twice per week. A further 26.9% reported using GenAI three to five times per week, whereas 11.5% used it once or twice per month and 3.1% had never used GenAI. Overall, 85.4% of respondents reported using GenAI at least once a week, indicating that these technologies were widely used among first-year undergraduate accounting students. The complete distribution is presented in Table 4.

Table 4. GenAI usage frequency distribution (n = 260)

Frequency category	n (%)	Cumulative %
Almost every day	76 (29.2%)	29.2%
3–5 times per week	70 (26.9%)	56.2%
1–2 times per week	76 (29.2%)	85.4%
1–2 times per month	30 (11.5%)	96.9%
Never	8 (3.1%)	100.0%

4.3 Correlation analysis

Pearson correlation analysis showed that all four constructs were positively and statistically significantly related ($p < .001$). Table 5 shows the outcomes. The most significant correlation was seen between academic integrity intentions and responsible usage ($r = .706$), suggesting that students with higher integrity intents also express greater responsible use intentions. There was also a substantial correlation ($r = .593$) between learning advantages and intents to uphold academic integrity. This suggests that perceived educational usefulness and ethical commitment are not separate things, but are instead related in a meaningful way.

Table 5. Pearson correlation matrix

Construct	LB	R&D	AII	RU
Learning Benefits (LB)	1.000	0.222**	0.593**	0.585**
Risks and Dependencies (R&D)	0.222**	1.000	0.409**	0.352**
Academic Integrity Int. (AII)	0.593**	0.409**	1.000	0.706**
Responsible Use (RU)	0.585**	0.352**	0.706**	1.000

The relatively weaker correlation between risks and dependencies and the other constructs, whilst still significant, suggests that risk awareness is a partially independent cognitive dimension one that does not necessarily co-vary with perceived benefits or ethical intentions. This finding is relevant for understanding how risk awareness functions in the adoption process.

4.4 Effect of usage frequency on learning benefits

A one-way ANOVA was performed to determine if reported learning benefits varied significantly among groups based on GenAI usage frequency. The analysis demonstrated a statistically significant main effect [$F(4, 255) = 7.049$, $p < .001$], demonstrating a meaningful correlation between usage frequency and perceived educational utility. A post-hoc analysis of group means indicated a distinct monotonic trend: non-users exhibited significantly lower learning benefit scores ($M = 2.88$) in contrast to all regular user groups (M range: 3.81–4.11). The students who used GenAI virtually every day or three to five times a week said they got the most benefit from it ($M = 4.11$ and $M = 4.07$, respectively).

4.5 Gender differences

An independent-samples t-test revealed no statistically significant difference between male ($M = 4.03$, $SD = 0.72$) and female ($M = 4.02$, $SD = 0.71$) students regarding perceived learning gains [$t(258) = 0.110$, $p = .912$, $d = 0.014$]. The effect magnitude was insignificant. our data suggests that the perceived educational benefit of GenAI is similarly experienced across genders within our group, along with previous studies indicating that gender disparities in AI adoption views have significantly diminished among younger demographics.

4.6 Predictors of responsible use

A multiple linear regression analysis was conducted to examine whether learning benefits, risks and dependencies, and academic integrity intentions predicted responsible GenAI use. The overall model was statistically significant, $F(3, 256) = 102.40$, $p < .001$, explaining 54.7% of the variance in responsible use ($R^2 = 0.547$, adjusted $R^2 = 0.542$). Academic integrity intentions emerged as the strongest predictor ($\beta = 0.505$, $p < .001$), followed by learning benefits ($\beta = 0.238$, $p < .001$). In contrast, risks and dependencies did not significantly predict responsible use ($\beta = 0.072$, $p = .072$). The complete regression results are presented in Table 6.

Table 6. Multiple regression: predictors of responsible use

Predictor	β	r	t	p
Academic Integrity Intentions (AII)	0.505	0.706	8.71	< .001
Learning Benefits (LB)	0.238	0.585	4.02	< .001
Risks and Dependencies (R&D)	0.072	0.352	1.80	.072
$R^2 = 0.547$; Adjusted $R^2 = 0.542$; $F(3, 256) = 102.4$, $p < .001$				

5. Discussions and Conclusions

5.1 Discussions

The findings of this study contribute to a more comprehensive understanding of how first-year undergraduate accounting students perceive and use Generative Artificial Intelligence (GenAI) during the early stages of higher education. Taken together, the results indicate that responsible GenAI use is shaped by multiple interrelated factors, including students' recognition of its educational value, awareness of its potential risks, commitment to academic integrity, and experience gained through continued engagement with the technology. These findings are particularly relevant for accounting and business education, where analytical reasoning, professional judgement, ethical decision-making, and responsible technology use constitute essential graduate competencies.

The relatively similar mean scores for learning benefits (M = 4.02) and risks and dependencies (M = 4.03) indicate that first-year accounting students simultaneously recognised the educational opportunities and potential challenges associated with GenAI. Rather than discouraging adoption, awareness of potential risks appeared to coexist with favourable perceptions of GenAI as a learning resource. This pattern is consistent with technology acceptance research, which suggests that users may continue to adopt emerging technologies despite recognising associated risks, provided that the perceived benefits remain sufficiently compelling (Venkatesh et al., 2003). Within accounting education, such balanced perceptions are particularly important because future professionals are expected not only to utilise technological innovations effectively but also to exercise sound professional judgement and ethical responsibility when incorporating AI-assisted tools into decision-making processes.

These findings may also be interpreted through the perspective of Human Capital Theory (Becker, 1964), which views knowledge and skills as strategic investments that enhance individual capability and long-term professional value. Students who recognise both the strengths and limitations of GenAI are more likely to regard the technology as a complement to their own knowledge rather than a substitute for independent learning. Such perspectives may encourage the continued development of critical thinking, analytical reasoning, problem-solving, and professional judgement while allowing students to benefit from AI-assisted learning. Consequently, educational practices should support not only AI literacy but also the cultivation of independent learning habits that enable students to evaluate and apply AI-generated information critically and responsibly.

The regression analysis further demonstrated that academic integrity intentions represented the strongest predictor of responsible GenAI use ($\beta = 0.505$), followed by perceived learning benefits ($\beta = 0.238$), whereas risks and dependencies did not remain statistically significant in the full regression model. This finding suggests that students who demonstrate stronger intentions to uphold academic integrity are also more likely to report responsible patterns of GenAI use. The result aligns with the Theory of Planned Behaviour (Ajzen, 1991), which proposes that behavioural intentions constitute an important determinant of subsequent behaviour. Nevertheless, because this study employed a cross-sectional design based on self-reported responses, these relationships should be interpreted as statistical associations rather than evidence of causal effects or observed behavioural outcomes.

The prominence of academic integrity intentions has important implications for institutional governance within higher education. Rather than relying predominantly on surveillance-based approaches, universities may achieve more sustainable outcomes by fostering a culture of academic integrity that encourages responsible AI use. Although plagiarism detection software continues to play an important role in identifying potential academic misconduct, the present findings suggest that educational interventions designed to strengthen students' ethical awareness and responsible decision-making may provide greater long-term benefits. Integrating academic integrity, AI ethics, and responsible AI literacy into first-year accounting and business curricula may therefore help students establish appropriate habits for using GenAI as a learning support tool while preserving independent judgement, professional responsibility, and academic standards.

The results also demonstrated significant differences in perceived learning benefits across levels of GenAI usage frequency. Students who engaged with GenAI more frequently reported significantly greater learning benefits than those who used the technology infrequently or not at all. This finding is consistent with Experiential Learning Theory (Kolb, 1984), which emphasises that learning develops through repeated cycles of experience, reflection, conceptualisation, and active experimentation. Regular engagement with GenAI may enable students to develop a more sophisticated understanding of both its capabilities and limitations, thereby supporting more effective and responsible use. Accordingly, educational institutions may obtain greater educational value by integrating GenAI into structured learning activities under appropriate academic guidance rather than adopting exclusively restrictive approaches. Learning activities requiring students to evaluate AI-generated responses critically, verify information using credible sources, justify their conclusions, and reflect upon the limitations of AI-generated content may strengthen AI literacy, metacognitive awareness, and independent judgement while reinforcing the analytical and ethical competencies expected of future accounting professionals.

No statistically significant gender differences were identified in students' perceptions of the learning benefits associated with GenAI. This finding suggests that male and female first-year accounting students reported broadly comparable evaluations of GenAI as a learning resource. The result is broadly consistent with previous research indicating that the gender-related digital divide has narrowed among Generation Z students, particularly for AI applications characterised by accessible conversational interfaces rather than advanced technical or programming requirements (Venkatesh et al., 2003). Consequently, educational initiatives designed to promote responsible GenAI use may be implemented across student populations without substantial differentiation based on gender.

Overall, the findings suggest that GenAI should be understood not solely as a potential source of academic misconduct but as an educational technology whose effectiveness depends largely on students' ethical intentions, critical engagement, and the quality of institutional support. For accounting and business education, these findings support the development of integrated educational strategies that combine AI literacy, academic integrity, experiential learning, and ethical decision-making throughout the first year of study. Such an approach may better prepare future accounting professionals to employ GenAI responsibly while maintaining the analytical competence, professional judgement, and ethical standards required within an increasingly technology-enabled professional environment.

5.2 Conclusions

This study demonstrates that first-year undergraduate accounting students generally perceive GenAI positively while recognising its potential risks. Academic integrity intentions emerged as the strongest predictor of responsible GenAI use, highlighting the importance of ethical considerations in AI adoption. These findings contribute to the growing literature by providing evidence from the context of first-year accounting students in Indonesia. Although the cross-sectional design and self-reported data limit causal interpretation, the results offer practical implications for integrating AI literacy, academic integrity, and responsible AI governance into accounting and business education.

6. Limitations of Research

This study has several limitations that should be acknowledged. First, the cross-sectional design captures attitudes and intentions at a single point in time; longitudinal research is needed to examine whether integrity intentions in fact predict responsible use behaviour over the course of a degree programme. Second, the sample is drawn from a single national context (Indonesia) using purposive sampling, which limits generalisability. Replication in other emerging-economy university systems particularly those in South-East Asia, sub-Saharan Africa and Latin America would test the robustness of these findings. Third, the study relies exclusively on self-reported data, which is subject to social desirability bias; students may report higher responsible use and integrity intentions than they actually enact. Future research should complement survey data with behavioural observation, log data or experimental designs.

Future research should also examine the mediating and moderating mechanisms in the academic integrity–responsible use relationship. Specifically, whether institutional integrity culture, instructor modelling of responsible AI use, and explicit AI literacy instruction moderate the strength of this relationship are important questions for educational theory and practice.

References

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

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

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

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Gao, C. A., Howard, F. M., Markov, N. S., Dyer, E. C., Ramesh, S., Luo, Y., & Pearson, A. T. (2022). Comparing scientific abstracts generated by ChatGPT to original abstracts using an artificial intelligence output detector, plagiarism detector, and blinded human reviewers. *bioRxiv*. https://doi.org/10.1101/2022.12.23.521610

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*(3), 235–266. https://doi.org/10.1023/B:EDPR.0000034022.16470.f3

International Center for Academic Integrity. (2021). *The fundamental values of academic integrity* (3rd ed.). https://www.academicintegrity.org/the-fundamental-values-of-academic-integrity

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Prentice Hall.

McCabe, D. L., Butterfield, K. D., & Treviño, L. K. (2012). *Cheating in college: Why students do it and what educators can do about it*. Johns Hopkins University Press.

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence, 2*, 100020. https://doi.org/10.1016/j.caeai.2021.100020

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition*. University of Chicago Press.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wollny, S., Schneider, J., Di Mitri, D., Weidlich, J., Rittberger, M., & Drachsler, H. (2021). Are we there yet? A systematic literature review on chatbots in education. *Frontiers in Artificial Intelligence, 4*, 654924. https://doi.org/10.3389/frai.2021.654924

Zawacki-Richter, O., Marin, 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*(1), 39. https://doi.org/10.1186/s41239-019-0171-0