
From threat to tool: AI self-efficacy and user profiles in higher education

Herianto Herianto

Eko Wahyudi

Andi Jusmiana

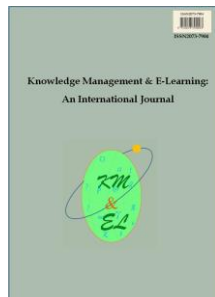
Habib Ratu Perwira Negara

Ansyari Ansyari

Universitas Negeri Yogyakarta, Indonesia

Sarah Samben

Universitas Negeri Malang, Indonesia



Knowledge Management & E-Learning: An International Journal (KM&EL)
ISSN 2073-7904

Recommended citation:

Herianto, H., Wahyudi, E., Jusmiana, A., Negara, H. R. P., Ansyari, A., & Samben, S. (2026). From threat to tool: AI self-efficacy and user profiles in higher education. *Knowledge Management & E-Learning*, 18(3), 372–392. <https://doi.org/10.34105/j.kmel.2026.18.017>

From threat to tool: AI self-efficacy and user profiles in higher education

Herianto Herianto* 

Department of Educational Research and Evaluation
Universitas Negeri Yogyakarta, Indonesia
E-mail: herianto3pasca.2022@student.uny.ac.id

Eko Wahyudi 

Department of Educational Research and Evaluation
Universitas Negeri Yogyakarta, Indonesia
E-mail: ekowahyudi.pep@gmail.com

Andi Jusmiana 

Department of Educational Research and Evaluation
Universitas Negeri Yogyakarta, Indonesia
E-mail: andijusmiana.2023@student.uny.ac.id

Habib Ratu Perwira Negara 

Department of Educational Research and Evaluation
Universitas Negeri Yogyakarta, Indonesia
E-mail: habib0024pasca.2023@student.uny.ac.id

Ansyari Ansyari 

Department of Educational Research and Evaluation
Universitas Negeri Yogyakarta, Indonesia
E-mail: ansyari.2022@student.uny.ac.id

Sarah Samben 

Department of Biology Education
Universitas Negeri Malang, Indonesia
E-mail: sarahsamben02@gmail.com

*Corresponding author

Abstract: Generative artificial intelligence (GenAI) has brought both challenges and opportunities for teachers in higher education. This study does not focus on restrictive methods; instead, it explores how educators can actively promote academic integrity. We contend that AI self-efficacy, characterized as a student's confidence in their capacity to employ AI ethically and efficiently, constitutes a

substantial determinant. This paper delineates significant findings derived from a survey administered by 177 university students. A moderation analysis indicates that the adverse correlation between AI usage frequency and academic integrity is markedly diminished among students exhibiting high AI self-efficacy. Moreover, a cluster analysis clearly delineates three distinct AI user profiles: Confident and Cautious Users, Pragmatic High Users, and Dependent Users. Demographic studies reveal a significant correlation between these profiles and the students' academic disciplines. The results suggest that the focus of instruction should transition from a "one-size-fits-all" approach to tailored interventions designed to enhance student empowerment. This article outlines practical implications and customized strategies for each student profile.

Keywords: GenAI; AI self-efficacy; Academic integrity; Student profiles; Higher education

Biographical notes: Herianto Herianto is doctoral student in Educational Research and Evaluation at Universitas Negeri Yogyakarta, Indonesia. He concurrently serves as a lecturer in the Department of Mathematics Education at Institut Turatea Indonesia. His research interests encompass educational measurement and assessment, mathematics education, and innovative learning strategies.

Eko Wahyudi is doctoral student in Educational Research and Evaluation at Universitas Negeri Yogyakarta, Indonesia. In addition to his studies, he is a physics teacher at SMAN 1 Ketapang in West Kalimantan. His scholarly focus includes physics education, educational assessment and evaluation, and the integration of technology in assessment.

Andi Jasmiana is doctoral student in Educational Research and Evaluation at Universitas Negeri Yogyakarta, Indonesia. She is also a lecturer in the Department of Mathematics Education at Universitas Perjuangan Republik Indonesia. Her primary research areas are educational measurement and assessment, mathematics education, and the professional development of teachers.

Habib Ratu Perwira Negara is doctoral student in Educational Research and Evaluation at Universitas Negeri Yogyakarta, Indonesia. Furthermore, he is a lecturer at Universitas Bumigora. His research highlights educational measurement, assessment practices, and pedagogical innovations within mathematics education.

Ansyari Ansyari is doctoral student in Educational Research and Evaluation at Universitas Negeri Yogyakarta, Indonesia. He concurrently serves as a lecturer in the Faculty of Teacher Education and Training at Universitas Madako. His academic interests are primarily rooted in general educational research and non-formal education systems.

Sarah Samben is a doctoral student in Biology Education at Universitas Negeri Malang, Indonesia. She holds a position as a lecturer in the Department of Biology Education at Universitas Perjuangan Republik Indonesia. Her research is centered on exploring and developing innovations in biology education across both secondary and tertiary levels.

1. Introduction

Higher education instructors are currently confronted with a fundamental challenge that is altering conventional assessment paradigms: How can educators effectively assess student learning and critical thinking when artificial intelligence (AI) can generate a coherent study, a comprehensive literature review, or even functional code solutions in mere seconds? (Bond et al., 2020). The pervasive deployment of large language models has given rise to numerous challenges, prompting many institutions to adopt a predominantly defensive stance. These measures encompass the utilization of technological tools for plagiarism identification and the imposition of more stringent academic regulations (Kelly et al., 2023; O’Dea, 2024). Nevertheless, the approach of employing “technology police” has demonstrated limited efficacy and frequently serves to intensify the problem. The classroom environment can become characterized by distrust, thereby engendering a state of discord between teachers and students (Esnaashari et al., 2025). These dynamic changes, a space meant for working together, are transformed into one filled with doubt. This pedagogical approach has the potential to adversely impact the relationship between teachers and students, as it tends to shift the balance of authority, thereby transforming the teacher from a facilitator of learning to a mere supervisor (Abate et al., 2025; Morris & Evans, 2023).

This strategy is generally ineffective because the advancement of artificial intelligence is exceeding the capacity of detection technologies to keep pace. This has resulted in a scenario where the competition to develop new technologies has essentially become a technical arms race from which no side can emerge victorious (Cotton et al., 2024; Guo et al., 2024). The efficacy of detection methods is often called into question when attempting to distinguish between content created by a proficient non-native speaker and that produced by AI, thereby raising concerns of bias and inequity (Liang et al., 2023). Consequently, a significant number of institutional resources, including financial resources for software licenses and faculty time allocated to investigating alleged violations, are expended on monitoring. A more effective allocation of these resources would be directed towards significant advancements in education (Bearman et al., 2023). This emphasis on limitations disregards a more profound and transformative inquiry: Considering the prevailing circumstances of transformation, it is imperative to leverage this period as an opportunity to reevaluate and enhance our pedagogical approaches. The objective is to ensure that our students are adequately prepared to thrive in a future where the utilization of AI is not merely an option but an indispensable component of their professional pursuits (Ahmad, 2019; McDiarmid & Zhao, 2023). The failure to instruct students in these competencies can be likened to the absence of calculator use in a mathematical classroom; it results in students being less prepared to tackle real-world problems (Chen & Wang, 2025).

This study posits that the most sustainable and significant solution to this problem resides not in advanced monitoring technologies but in the deliberate reconfiguration of the classroom educational experience (Kinshuk et al., 2016). Recent empirical evidence also emphasizes that integrating AI ethically and structurally is paramount for fostering sustainable learning environments in higher education, rather than relying on reactive measures (Ranjan et al., 2024). Consequently, we propose a significant transformation: shifting from merely overseeing and regulating students’ external behaviors (particularly their interactions with AI) to a program designed to understand and influence their internal psychological traits, especially their self-evaluations regarding their ability to engage with this technology (Laupichler et al., 2023; Wu et al., 2025). The motivation for our research

arises from a substantial gap in the swiftly growing body of literature on the topic. A substantial body of research has meticulously documented the range of AI tools utilized and their pervasiveness among students (Farrokhnia et al., 2024). However, there is a paucity of research investigating the complex issues surrounding the precise motivations for their utilization (Tirado-Olivares et al., 2023). Moreover, extant literature frequently conceptualizes students as a homogeneous entity (Chan, 2023), overlooking the exploration of potential distinct user typologies or profiles associated with their demographic or academic backgrounds.

By addressing these issues, the objective of this study is to transcend the realm of anecdotal evidence and construct a robust, empirically substantiated framework for educators (Henderson et al., 2022). This research aims to provide a comprehensive understanding of students' interactions with AI, encompassing the underlying motivations and individual characteristics. By achieving this, the objective is to empower educators to formulate tailored interventions that cater to the unique needs of diverse student profiles, rather than relying on the frequently ineffective "one-size-fits-all" policies (Carli et al., 2019; Crompton & Burke, 2023; Rousell & Sinclair, 2025).

2. Literature review

2.1. Generative AI and the threat to academic integrity

The increased accessibility of generative AI challenges academic integrity, complicating the discernment between original student work and computer-generated content (Bretag, 2018; Striepe et al., 2023). Institutional responses have largely been reactive. Many have imposed limitations or detection tools, but this approach is often ineffective, creating a '*technical arms race*' and classroom distrust (Cotton et al., 2024; Dalalah & Dalalah, 2023; Tlili et al., 2023). Others have focused on redesigning assessments (e.g., oral tests, portfolios) to be AI-proof, but this poses significant practical difficulties, especially in large classes (De Winter, 2024).

The present study is chiefly concerned with an examination of the instructional and pedagogical methodology. This viewpoint suggests that educational institutions should not merely prohibit the technology, but rather, proactively instruct students on the ethical, critical, and effective utilization of AI as a pedagogical tool (Kasneci et al., 2023; Lodge et al., 2023; Tan et al., 2024). A notable absence in extant literature within this field is its inclination to remain at a conceptual level (Chan & Lee, 2023) and its frequent presupposition that all students constitute a homogeneous group with identical learning requirements (Zhai et al., 2022). Although recent studies have begun to explore the ethical dimensions and risk perceptions associated with ChatGPT adoption (Ma, 2026), a paucity of comprehensive empirical research exists that delineates the psychological factors distinguishing between advantageous and detrimental AI usage (Chen et al., 2024; Fu & Qiao, 2023). Furthermore, there remains a critical need to categorize students into distinct typologies or profiles to facilitate more targeted and efficacious educational interventions (Johnson et al., 2018). The objective of this study is to address this knowledge gap.

2.2. Building a framework for response: SoTL and self-efficacy

The study is situated within the Scholarship of Teaching and Learning (SoTL) framework, which advocates for the pedagogical methodologies by educators to promote ongoing enhancement (Boyer, 1990; Canning & Masika, 2022; Hutchings et al., 2001). In the contemporary context of rapidly evolving technological advancements, particularly in the domain of artificial intelligence, the SoTL approach is gaining significant prominence. It demands the transcendence of anecdotal evidence and relies on systematic data to inform modifications in the classroom that are grounded in empirical evidence regarding student learning outcomes (Felten et al., 2013; How, 2020). A SoTL practitioner might pose the following question: “*In what circumstances, and with what type of assignment design, can this AI be utilized to enhance student learning?*” Rather than posing the question, “*Is this AI good or bad?*”, the practitioner might seek to understand the potential of AI to support learning and assessment in higher education (Trigwell, 2021).

The present study employs Bandura’s (1986) Social Cognitive Theory, particularly its core principle of self-efficacy, to analyze the internal “*conditions*” of students that affect their interaction with AI. This theory posits that human behavior is shaped by two sets of factors: firstly, external factors, including technological accessibility; and secondly, internal components, including personal beliefs (Bandura, 1999). Zimmerman (2000) proposes that self-efficacy, defined as the belief in one’s capabilities, functions as a pivotal predictor of an individual’s problem-solving strategies, work ethic, and resilience in adverse circumstances. AI self-efficacy is defined as the extent to which students believe in their ability to utilize AI in a manner that is both ethical and effective. The effective utilization of AI necessitates its application in pursuit of higher-order learning objectives, such as synthesis, critical analysis, or creative ideation, rather than its mere utilization for the expeditious attainment of responses (Schunk, 1991). The term “*ethical*” in this context signifies the ability to discern the presence of AI, to halt instances of plagiarism, and to evaluate AI-generated content with a discerning eye, seeking any underlying biases (Pajares, 1996).

According to Bandura (1986), self-efficacy beliefs are not innate qualities; rather, they are developed from four primary sources. The most potent of these is mastery experiences, defined as personal triumphs in a specific domain (Usher & Pajares, 2008). The sources encompass vicarious experiences, defined as observing peers adeptly execute the designated task; social persuasion, understood as receiving encouragement from credible sources; and physiological and emotional states, encompassing the interpretation of one’s own anxiety or enthusiasm regarding a given task (Bandura, 2006). This method gives teachers a lot of power because it shows that students’ AI self-efficacy is not something they are born with, but something they can learn and improve over time (van Dinther et al., 2011). This paper subsequently analyzes pedagogical implications that specifically address these four sources, focusing on the creation of structured mastery experiences that cultivate substantial and genuine student confidence.

This theoretical foundation supports the conceptual framework that directs our research, illustrated in Fig. 1.

The model delineates a clear correlation between the prevalence of AI utilization and academic integrity (McCabe & Trevino, 1993). The primary thesis of this research contends that this correlation is not consistent among all students. It is posited that AI self-efficacy functions as a substantial moderating variable (Baron & Kenny, 1986). The strength and direction of the relationship between AI usage and academic integrity will

depend on how confident students are in their ability to use AI in a morally sound and effective manner. It is evident that the model under consideration articulates the primary point and establishes the foundation for evaluating the various hypotheses.

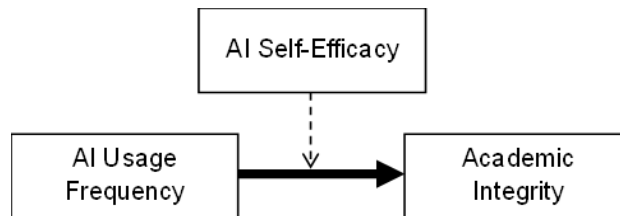


Fig. 1. Theoretical framework (Notes: The solid arrow shows the correlation (RQ3) between the frequency with which college students use AI and their honesty. The dashed arrow shows how AI self-efficacy is expected to affect this relationship (RQ4).)

2.3. The present study

Based on the theoretical framework and the identified gaps in the literature regarding student heterogeneity, this study aims to address the following research questions:

RQ1: Do students demonstrate different types of AI usage based on how often they use it, how confident they are in their AI skills, and how honest they are in their academic work?

RQ2: Is there a notable correlation between students' demographic attributes (such as field of study) and their AI user profiles?

RQ3: Is there a substantial negative correlation between the frequency of students' AI utilization and their academic integrity?

RQ4: Does AI self-efficacy have a significant influence on this relationship?

3. Methods

3.1. Research design, participants, and procedure

This study employed a cross-sectional survey method to gather data at a singular moment, offering a comprehensive overview of the interrelationships among the variables of interest (Creswell & Creswell, 2017). The present study involved 177 active university students from diverse disciplines in Indonesia (see Table 1), selected through convenience sampling (Etikan, 2016). This context is particularly relevant as Indonesia, like many non-Western nations, is experiencing rapid adoption of generative AI in higher education, presenting unique challenges and opportunities for educators that are relevant to an international audience.

A survey was disseminated online by a social media site and a network of students. The initial page of the questionnaire proffered a detailed elucidation of the study's objective and assured the participants that their information would be strictly confidential. The participants then provided their informed consent prior to advancing to the subsequent phase of the study.

Table 1Respondent characteristics ($N = 177$)

Characteristic	Category	Frequency	%
Gender	Female	111	62.7
	Male	66	37.3
Field of study	Social Sciences and Humanities	84	47.5
	STEM	60	33.9
	Health Sciences	33	18.6
	Year 1	21	11.9
Year of study	Year 2	56	31.6
	Year 3	63	35.6
	Year 4 +	37	20.9

3.2. Measures

The questionnaire we used had three main parts, and each one went through a strict process to make sure the data was accurate. To ensure a high response rate and minimize respondent fatigue, we opted for parsimonious scales while prioritizing psychometric robustness (Burisch, 1984). A panel of seven experts was assembled, including three specialists in educational psychology, two in learning technology, and two in assessment and measurement, to perform content validation (Rusticus, 2023). The participation of this multidisciplinary panel guaranteed that the measures were both psychometrically robust and contextually pertinent to the convergence of technology, pedagogy, and student behavior. We used Aiken's V index (Aiken, 1985) to look at the experts' ratings, and then we used Cronbach's Alpha (Cronbach, 1951) to check their internal reliability.

3.2.1. AI usage frequency

This was measured using a single item asking participants, "*How frequently do you use generative AI tools (e.g., ChatGPT) for your university assignments?*" Responses were recorded on a 5-point Likert scale ranging from 1 (Never) to 5 (Always).

3.2.2. AI self-efficacy

A 5-item scale was developed for this study to assess students' confidence in using AI ethically. Sample items include: "*I am confident in my ability to verify the accuracy of AI-generated information*" and "*I can effectively use AI to brainstorm ideas without copying*" (see Appendix I for the full list of items). The validation results showed great content validity (Aiken's $V > 0.80$) and good internal reliability ($\alpha = 0.85$).

3.2.3. Academic integrity

Adapted from McCabe and Trevino (1993), this 5-item scale measured students' adherence to academic honesty standards. A sample item includes: "*I would never submit work generated by AI as my own without attribution.*" Responses ranged from 1 (Strongly Disagree) to 5 (Strongly Agree). The same expert panel (Aiken's $V > 0.80$) also confirmed

that this adaptation had a high level of internal consistency ($\alpha = 0.78$) (see Appendix II for the full list of items).

3.3. Data analysis

The analysis was conducted using RStudio (R-4.5.1) and a systematic analysis method (Chambers, 2008). The initial phase of the study involved the creation of descriptive statistics, which were utilized to illustrate the distribution of the primary variables.

In order to respond to RQ1, a person-centered methodology was employed, utilizing K-Means Cluster analysis (Hofmans et al., 2017; Wu et al., 2022). To interpret the clusters, we standardized the scores (z-scores) for AI usage, self-efficacy, and academic integrity. The clusters were labeled based on their dominant characteristics: (1) Confident and Cautious Users (low usage, high efficacy/integrity), (2) Dependent Users (moderate usage, low efficacy/integrity), and (3) Pragmatic High Users (high usage, moderate efficacy/integrity).

To ascertain the significance of the relationship between cluster membership and field of study (RQ2), we employed a chi-square test (Agresti & Tarantola, 2018). We then employed Pearson correlation analysis (Cohen et al., 2003) to directly address RQ3. Finally, to evaluate RQ4, we employed a moderation regression analysis (Hayes & Rockwood, 2017). A series of diagnostic tests was performed on the regression model, and the results demonstrated that the assumptions of normality, linearity, and homoscedasticity were not significantly violated (see Fig. A1 in Appendix III) (McKean & Sheather, 2009).

4. Results

4.1. Three AI user profiles and their relationship with demographics

The cluster analysis (RQ1) successfully identified three statistically distinct AI user profiles, which we have classified based on their distinctive attributes, as detailed in Table 2. The predominant category is the Confident and Cautious Users (38.4%), who don't use AI very often but are very sure of themselves and honest. The Dependent Users group is the second largest, making up 37.3% of the total. They use AI to a small extent, but they don't have much confidence in themselves or their integrity. The Pragmatic High users make up the smallest group, with only 24.3% of the total. They utilize AI extensively and remain honest, which is facilitated by their moderate self-efficacy.

Table 2

Summary of student AI user profiles

Profile	%	AI usage frequency	AI self-efficacy	Academic integrity
Confident and cautious	38.4	Low (2.79)	High (4.49)	High (2.31)
Dependent users	37.3	Moderate (3.58)	Low (3.41)	Low (1.71)
Pragmatic high users	24.3	High (4.23)	Moderate (4.02)	High (2.40)

A chi-square test indicated a significant correlation between these characteristics and the students' field of study, $\chi^2(4, n = 177) = 11.06, p = 0.026$, thus answering RQ2. Table 3 shows how these data are spread out. The results show that STEM students make up a large percentage of the Confident and Cautious group (48.3%), while students in the

Social Sciences and Humanities make up a large percentage of the Dependent Users group (47.6%).

Table 3

Distribution of AI user profiles categorised by field of study

Field of study	Confident and cautious	Dependent users	Pragmatic high users	Total
Social sciences and humanities	28 (33.3%)	40 (47.6%)	16 (19.0%)	84
STEM	29 (48.3%)	17 (28.3%)	14 (23.3%)	60
Health sciences	11 (33.3%)	9 (27.3%)	13 (39.4%)	33
Total	68 (38.4%)	66 (37.3%)	43 (24.3%)	177

Fig. 2 shows what these clusters look like. This plot shows where each student falls based on their AI self-efficacy and academic integrity scores. The colors show which profile they were given. The clusters are clearly separated from each other, which supports the statistical identification of these groups and makes their defining features clear right away.

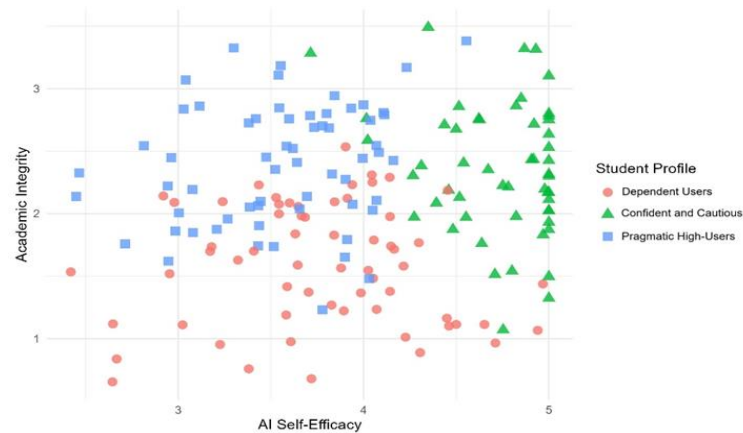


Fig. 2. Visualization of the three student AI user profiles

4.2. Descriptive statistics and correlations

The descriptive statistics and correlations for the core research variables are presented in Table 4. A substantial negative correlation was identified between the frequency of AI utilization and academic integrity ($r = -0.23, p < 0.01$), answering RQ3. This suggests that, in general, using AI more often is linked to lower academic integrity.

Table 4

Descriptive statistics and correlations of core variables

Variable	Mean	SD	AI usage frequency	AI self-efficacy	Academic integrity
AI usage frequency	3.41	1.00	1.00	-0.02	-0.23
AI self-efficacy	3.98	0.67	-0.02	1.00	0.14
Academic integrity	2.10	0.62	-0.23**	0.14	1.00

Note. ** $p < .01$

4.3. The moderating effect of AI self-efficacy

A moderation regression analysis was conducted to evaluate RQ4. The findings presented in Table 5 indicate a significant interaction effect between the frequency of AI utilization and AI self-efficacy on academic integrity ($\beta = 0.13$, $p = .048$). This validates that AI self-efficacy functions as a substantial moderator.

Table 5

Results of moderation regression in predicting academic integrity

Variable	B	SE	β	p
Constant	2.100	0.045	–	< .001
AI usage (X)	–0.135	0.046	–0.222	0.002
AI self-efficacy (M)	0.130	0.068	0.141	0.058
X * M	0.125	0.063	0.134	0.048

Note: B = Unstandardized coefficient; SE = Standard error; β = Standardized coefficient.

The nature of this interaction is visualized in Fig. 3. To further probe the significant interaction, a simple slopes analysis was conducted. The results indicated that for students with low AI self-efficacy (–1 SD), there was a significant negative relationship between AI usage and academic integrity ($p < .05$). However, for students with high AI self-efficacy (+1 SD), this relationship became non-significant. This demonstrates that high self-efficacy effectively buffers the potential negative impact of frequent AI usage on integrity.

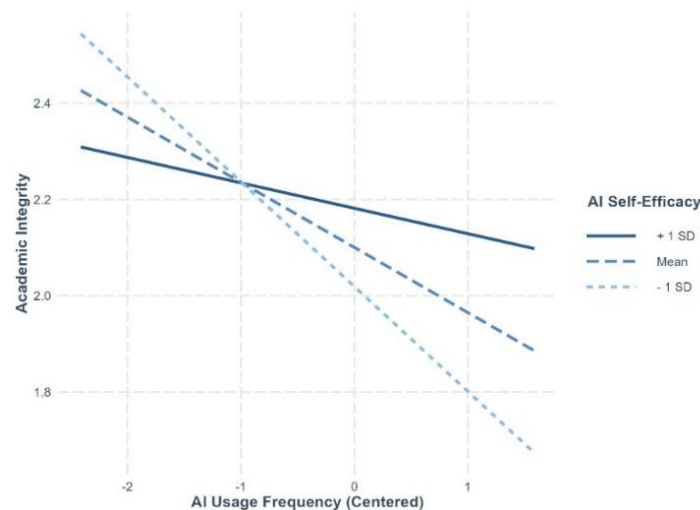


Fig. 3. Moderating effect of AI self-efficacy (Notes: The simple slopes analysis indicates that for students exhibiting low AI self-efficacy (–1 SD), the correlation between AI usage and academic integrity is both negative and significant. The relationship is not statistically significant for students with high AI self-efficacy (+1 SD).)

In conclusion, the statistical analyses offer significant corroboration for our research questions. The exploratory analysis identified three distinct student profiles (RQ1), with membership significantly correlated to their academic field of study (RQ2). A definitive negative correlation was identified between the frequency of AI utilization and academic integrity (RQ3). Nonetheless, this correlation was significantly influenced by the

students' AI self-efficacy, thereby substantiating the proposed moderation model (RQ4). When viewed collectively, these findings offer a nuanced perspective on student engagement with AI, contesting the oversimplified belief that AI usage is inherently problematic. The next part will look at what these complicated interactions mean.

5. Discussion

The moderating effect of AI self-efficacy shifts the discourse from a technologically deterministic viewpoint (where the tool causes harm) to a human-centric paradigm (Gebru et al., 2022; Seralidou et al., 2025). This finding supports Bandura's (1986) theory, suggesting the problem is not the AI itself, but the user's psychological framework. This strongly aligns with recent discourse indicating that students' adoption of ChatGPT is a complex process influenced by internal risk perceptions and ethical considerations, rather than just an inherent drive for academic dishonesty (Ma, 2026). This moves the focus from "*technological surveillance*" to "*pedagogical development*" (Gouseti et al., 2025), implying that a superior learning design, not detection software, is the most effective long-term solution (Bandura, 2006). Ultimately, ethical AI integration serves not merely as a regulatory framework, but as a foundational catalyst for sustainable learning and continuous student growth (Ranjan et al., 2024).

The delineation of three distinct user profiles contradicts the prevailing "*one-size-fits-all*" paradigm in institutional policies (Carli et al., 2019; Msoroka & Amundsen, 2017). This diagnostic comprehension is crucial. For instance, the high proportion of Dependent Users (47.6%) among Social Sciences and Humanities students suggests a "perfect storm": high-stakes writing assignments coupled with low student confidence may make AI misuse highly appealing (Baidoo-anu & Ansah, 2023). This risks students graduating without essential competencies (Perkins & Roe, 2024).

Conversely, the predominance of Confident and Cautious STEM students (48.3%) may be linked to the verifiable nature of their tasks (e.g., debugging code, checking calculations), which allows AI to be used as a tool without supplanting the user's final judgment (Kasperski & Blau, 2023; Nadelson et al., 2017). This verifiable context fosters control and confidence. The Pragmatic High-Users profile, characterized by high use and high integrity, represents an ideal pedagogical goal (Al Issa & Maheshwari, 2025). Ultimately, these cluster findings provide a "*map*" for educators, confirming that the student population is diverse and requires differentiated interventions.

5.1. Differentiated pedagogical implications

The recognition of these distinct student profiles facilitates the transcendence of standardized policies and the advancement toward more flexible, personalized instruction. Fig. 4 illustrates the potential application of these data in formulating a constructive model for responding to students. This approach assists educators in identifying the unique needs of each student and facilitates the responsible integration of AI by associating each student's profile with a particular set of interventions.

The objective of instructing Confident and Cautious Users, a pedagogical approach prevalent in STEM disciplines, is to promote deliberate exploration (Lo, 2024). While they possess a high degree of confidence in their abilities, they may be reluctant to fully adopt AI technology. An approach to make it easier for individuals and AI to work together is to

give them tasks that require AI help. In a programming class, students may be required to use an AI to create a first code block and then write a report detailing how they identified, fixed, and improved bugs in that code, thereby demonstrating their understanding of it (Fuchs, 2023).

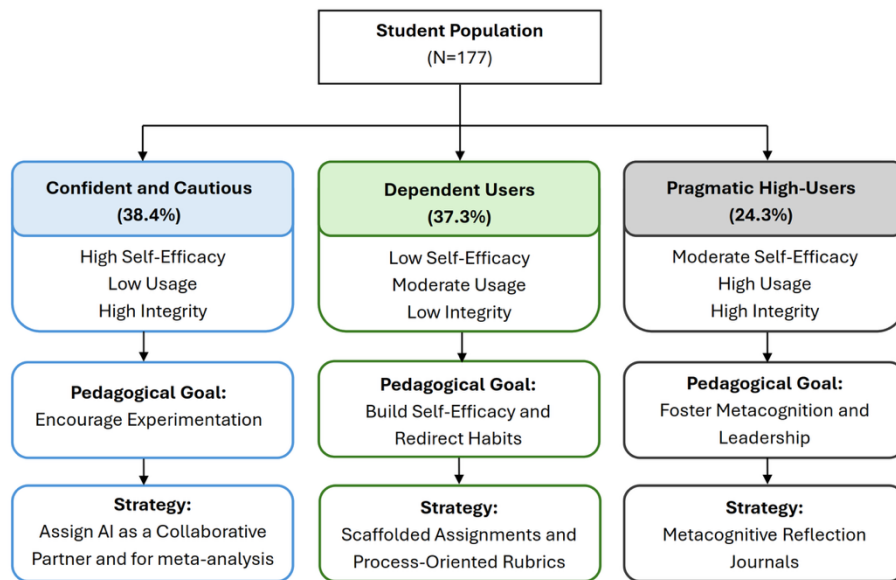


Fig. 4. The pedagogical response framework for various AI user profiles

The notion presents a substantially modified approach for Dependent Users, characterized by diminished self-efficacy and integrity. The most effective learning method is a scaffolded assignment design that clearly aims to provide “*mastery experiences*” (Hmelo-Silver et al., 2007). A foundational academic writing course may allocate a period of four weeks for students to engage in writing and study. During the initial week, students may require assistance from AI tools to assist with the generation of titles and the provision of an overview. The evaluation of these students would be based solely on their completion of the task, not on the quality of their work. This outcome would be characterized as a modest and low-risk achievement. It is reasonable to hypothesize that the chores will become more arduous in the coming weeks. For instance, the AI system might be tasked with producing an introductory paragraph that would subsequently be assessed during a peer-review session dedicated to the analysis of “*vicarious experiences*.” Ultimately, the students would be tasked with the complete rewriting of the text in their own words (Rahimi & Mosalli, 2025).

The Pragmatic High users initiative aims to assist these individuals in leveraging their existing competencies to assume leadership and mentorship roles. The intervention must prioritize metacognition and the rigorous assessment of AI (Pang et al., 2025). In such cases, a synergistic approach that utilizes a process-oriented assessment rubric (Hao et al., 2025) and a metacognitive reflection journal (Fan et al., 2025) is imperative. It is imperative to elucidate and enhance their cognitive processes. For example, a rubric for an academic study assignment might say that a “*process appendix*” is worth one-third of the total grade. This appendix lists a number of things that students need to do. Initially,

students are directed to incorporate screenshots of significant prompts employed during their engagements with the AI system. In addition, they are expected to provide a concise explanation elucidating the rationale behind each inquiry. Finally, students are prompted to compose a brief reflective journal entry that responds to the following question: “*What aspect of this argument is exclusively my own, and how did the AI system enhance it?*” This method not only supports their approach but also encourages a more thoughtful and purposeful use of technology.

5.2. Limitations and future research directions

This study has several limitations. First, while the sample size ($N = 177$) is sufficient for the exploratory nature of this study, it warrants caution in generalizing findings to all higher education contexts. Second, the reliance on self-report data may be subject to social desirability bias, although we attempted to mitigate this through anonymity. Third, the sample being drawn from a single national context (Indonesia) limits the direct generalizability of the findings to other cultural settings. However, we contend that the study’s value lies in its innovative pedagogical model (the three user profiles), which provides an empirically based framework that educators in other national contexts can adapt, test, and apply, rather than a universally generalizable statistic.

Future research should address these limitations by adopting longitudinal methodologies to examine how student profiles evolve. Experimental pre-test/post-test designs are also imperative to evaluate the efficacy of the proposed pedagogical interventions (e.g., scaffolded assignments) in enhancing AI self-efficacy and academic integrity across diverse institutional contexts, thereby addressing generalizability concerns.

6. Conclusion

The upcoming improvements in generative AI shouldn’t scare us; instead, they should be seen to spark new ideas in teaching methods. In this digital age, it’s important to think about the main goals of higher education and the methods used to reach them. The present study demonstrates that a transition from reactive policies based on fear to proactive pedagogies driven by comprehension is possible. This transition can be achieved by focusing on students’ internal factors, such as AI self-efficacy, and recognizing that their interactions with technology can vary. The present study proposes an evidence-based model that delineates the state of self-efficacy and the corresponding user profiles. This approach assists educators in effectively integrating AI into their teaching practices and transforming it into a valuable collaborative tool. Given the unique needs of each student, educators face the formidable challenge of balancing the use of technology in the classroom. This will give students the knowledge they need to do well in college and the digital skills they need to do well in the future.

Author Statement

The authors declare that there is no conflict of interest.

Acknowledgements

The authors extend their appreciation to the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia (KEMDIKTISAINTEK RI), the Centre for Higher Education Funding and Assessment (PPAPT), the Education Fund Management Institution (LPDP), and the Indonesian Education Scholarship (BPI) for funding this research work through the project.

ORCID

Herianto Herianto  <https://orcid.org/0000-0001-6698-512X>

Eko Wahyudi  <https://orcid.org/0009-0002-6451-6033>

Andi Jusmiana  <https://orcid.org/0000-0001-9976-9642>

Habib Ratu Perwira Negara  <https://orcid.org/0000-0002-0980-430X>

Ansyari Ansyari  <https://orcid.org/0009-0009-3951-8353>

Sarah Samben  <https://orcid.org/0009-0004-6443-7604>

References

- Abate, S. G., Mengistie, T. A., & Ayenalem, K. A. (2025). Shaping teacher attitudes: Key factors and implications for professional development policies and practices. *Teacher Development*. <https://doi.org/10.1080/13664530.2025.2537087>
- Agresti, A., & Tarantola, C. (2018). Simple ways to interpret effects in modeling ordinal categorical data. *Statistica Neerlandica*, 72(3), 210–223. <https://doi.org/10.1111/stan.12130>
- Ahmad, T. (2020). Scenario based approach to re-imagining future of higher education which prepares students for the future of work. *Higher Education, Skills and Work-based Learning*, 10(1), 217–238. <https://doi.org/10.1108/HESWBL-12-2018-0136>
- Aiken, L. R. (1985). Three coefficients for analyzing the reliability and validity of ratings. *Educational and Psychological Measurement*, 45(1), 131–142. <https://doi.org/10.1177/0013164485451012>
- Al Issa, H. E., & Maheshwari, G. (2026). Shaping the future of education: A cluster analysis of generative AI's transformative impact. *Interactive Technology and Smart Education*, 23(1), 113–165. <https://doi.org/10.1108/ITSE-01-2025-0013>
- Baidoo-anu, D., & Ansah, L. O. (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/10.61969/jai.1337500>
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall. <https://doi.org/10.1017/S0813483900008238>
- Bandura, A. (1999). Social cognitive theory: An agentic perspective. *Asian Journal of Social Psychology*, 2(1), 21–41. <https://doi.org/10.1111/1467-839X.00024>
- Bandura, A. (2006). Toward a psychology of human agency. *Perspectives on Psychological Science*, 1(2), 164–180. <https://doi.org/10.1111/j.1745-6916.2006.00011.x>
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations.

- Journal of Personality and Social Psychology*, 51(6), 1173–1182.
<https://doi.org/10.1037/0022-3514.51.6.1173>
- Bearman, M., Ryan, J., & Ajjaw, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education*, 86, 369–385.
<https://doi.org/10.1007/s10734-022-00937-2>
- Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education*, 17: 2. <https://doi.org/10.1186/s41239-019-0176-8>
- Boyer, E. L. (1990). *Scholarship reconsidered: Priorities of the professoriate*. The Carnegie Foundation for the Advancement of Teaching. Retrieved from <https://www.umces.edu/sites/default/files/al/pdfs/BoyerScholarshipReconsidered.pdf>
- Bretag, T. (2018). *Academic integrity*. Oxford University Press.
<https://doi.org/10.1093/acrefore/9780190224851.013.147>
- Burisch, M. (1984). Approaches to personality inventory construction: A comparison of merits. *American Psychologist*, 39(3), 214–227.
<https://psycnet.apa.org/doi/10.1037/0003-066X.39.3.214>
- Canning, J., & Masika, R. (2022). The scholarship of teaching and learning (SoTL): The thorn in the flesh of educational research. *Studies in Higher Education*, 47(6), 1084–1096. <https://doi.org/10.1080/03075079.2020.1836485>
- Carli, G., Tagliaventi, M. R., & Cutolo, D. (2019). One size does not fit all: The influence of individual and contextual factors on research excellence in academia. *Studies in Higher Education*, 44(11), 1912–1930.
<https://doi.org/10.1080/03075079.2018.1466873>
- Chambers, J. (2008). Basic data and computations. In J. Chambers (Ed.), *Software for Data Analysis: Programming with R* (pp. 139–236). Springer. https://doi.org/10.1007/978-0-387-75936-4_6
- Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20: 38. <https://doi.org/10.1186/s41239-023-00408-3>
- Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, 10: 60.
<https://doi.org/10.1186/s40561-023-00269-3>
- Chen, B., & Wang, M. (2025). Integrated STEM curriculum design: A conceptual framework and visible thinking approach. *Knowledge Management & E-Learning*, 17(4), 538–556. <https://doi.org/10.34105/j.kmel.2025.17.025>
- Chen, J., Yuan, D., Dong, R., Cai, J., Ai, Z., & Zhou, S. (2024). Artificial intelligence significantly facilitates development in the mental health of college students: A bibliometric analysis. *Frontiers in Psychology*, 15: 1375294.
<https://doi.org/10.3389/fpsyg.2024.1375294>
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. Routledge.
<https://doi.org/10.4324/9780203774441>
- 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>
- Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. SAGE. Retrieved from <https://edge.sagepub.com/creswellrd5e>

- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20: 22. <https://doi.org/10.1186/s41239-023-00392-8>
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16(3), 297–334. <https://doi.org/10.1007/BF02310555>
- Dalalah, D., & Dalalah, O. M. A. (2023). The false positives and false negatives of generative AI detection tools in education and academic research: The case of ChatGPT. *The International Journal of Management Education*, 21(2): 100822. <https://doi.org/10.1016/j.ijme.2023.100822>
- de Winter, J. C. F. (2024). Can ChatGPT pass high school exams on English language comprehension? *International Journal of Artificial Intelligence in Education*, 34(3), 915–930. <https://doi.org/10.1007/s40593-023-00372-z>
- Esnaashari, S., Gardner, L., & Rehm, M. (2025). Students' perceptions of educational tool use in a blended learning environment: An activity theory perspective. *Communications of the Association for Information Systems*, 56, 128–154. <https://doi.org/10.17705/1CAIS.05605>
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2015). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. <https://doi.org/10.11648/j.ajtas.20160501.11>
- Fan, F., Wang, S., Maihemuti, M., Nie, X., & Yang, L. T. (2025). Enhancing students' metacognition with innovative IA-based metacognitive reflective learning tool. *IEEE Transactions on Learning Technologies*, 18, 699–715. <https://doi.org/10.1109/TLT.2025.3580536>
- Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, 61(3), 460–474. <https://doi.org/10.1080/14703297.2023.2195846>
- Felten, P., Bagg, J., Bumbry, M., Hill, J., Hornsby, K., Pratt, M., & Weller, S. (2013). A call for expanding inclusive student engagement in SoTL. *Teaching and Learning Inquiry*, 1(2), 64–74. <https://doi.org/10.20343/teachlearningqu.1.2.63>
- Fu, M., & Qiao, W. (2023). Analysis and countermeasures of psychological characteristics in college students' psychological education based on artificial intelligence. *Applied Artificial Intelligence*, 37(1): 2204262. <https://doi.org/10.1080/08839514.2023.2204262>
- Fuchs, K. (2023). Exploring the opportunities and challenges of NLP models in higher education: Is Chat GPT a blessing or a curse? *Frontiers in Education*, 8: 1166682. <https://doi.org/10.3389/feduc.2023.1166682>
- Gebri, B., Zeleke, L., Blankson, D., Nabil, M., Nateghi, S., Homaifar, A., & Tunstel, E. (2022). A review on human-machine trust evaluation: Human-centric and machine-centric perspectives. *IEEE Transactions on Human-Machine Systems*, 52(5), 952–962. <https://doi.org/10.1109/THMS.2022.3144956>
- Gouseti, A., James, F., Fallin, L., & Burden, K. (2025). The ethics of using AI in K-12 education: A systematic literature review. *Technology, Pedagogy and Education*, 34(2), 161–182. <https://doi.org/10.1080/1475939X.2024.2428601>
- Guo, S., Zheng, Y., & Zhai, X. (2024). Artificial intelligence in education research during 2013–2023: A review based on bibliometric analysis. *Education and Information Technologies*, 29, 16387–16409. <https://doi.org/10.1007/s10639-024-12491-8>
- Hao, S., Pan, H., & Zhang, D. (2025). A process-oriented approach to assessing high school students' mathematical problem-solving competence: Insights from multidimensional eye-tracking analysis. *Education Sciences*, 15(6): 761.

- <https://doi.org/10.3390/educsci15060761>
- Hayes, A. F., & Rockwood, N. J. (2017). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy*, 98, 39–57. <https://doi.org/10.1016/j.brat.2016.11.001>
- Henderson, R., Hewagallage, D., Follmer, J., Michaluk, L., Deshler, J., Fuller, E., & Stewart, J. (2022). Mediating role of personality in the relation of gender to self-efficacy in physics and mathematics. *Physical Review Physics Education Research*, 18: 010143. <https://doi.org/10.1103/PhysRevPhysEducRes.18.010143>
- Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist*, 42(2), 99–107. <https://doi.org/10.1080/00461520701263368>
- Hofmans, J., Vantilborgh, T., & Solinger, O. N. (2018). K-centres functional clustering: A person-centered approach to modeling complex nonlinear growth trajectories. *Organizational Research Methods*, 21(4), 905–930. <https://doi.org/10.1177/1094428117725793>
- How, Z. J. (2020). A systematic review of scholarship of teaching and learning research in higher education institutes from 2014–2019. In S. C. Tan & S. A. Chen (Eds.), *Transforming Teaching and Learning in Higher Education* (pp. 11–43). Springer Singapore. https://doi.org/10.1007/978-981-15-4980-9_2
- Hutchings, P., Huber, M. T., & Ciccone, A. (2001). *The scholarship of teaching and learning reconsidered: Institutional integration and impact*. The Carnegie Foundation for the Advancement of Teaching. Retrieved from https://api.pageplace.de/preview/DT0400.9781118086421_A23915442/preview-9781118086421_A23915442.pdf
- Johnson, R., Johnson, C. W., Vijayan, S., Tata, D., & Villegas, R., Jr. (2018). Diagnosis, prescription, intervention, evaluation, advanced academic training, and college student success. *Journal of College Student Retention: Research, Theory & Practice*, 22(4), 699–720. <https://doi.org/10.1177/1521025118779803>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... Kasneci, 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>
- Kasperski, R., & Blau, I. (2023). Social capital in high-schools: Teacher-student relationships within an online social network and their association with in-class interactions and learning. *Interactive Learning Environments*, 31(2), 955–971. <https://doi.org/10.1080/10494820.2020.1815220>
- Kelly, A., Sullivan, M., & Strampel, K. (2023). Generative artificial intelligence: University student awareness, experience, and confidence in use across disciplines. *Journal of University Teaching and Learning Practice*, 20(6): 12. <https://doi.org/10.53761/1.20.6.12>
- Kinshuk, Chen, N. S., Cheng, I. L., & Chew, S. W. (2016). Evolution is not enough: Revolutionizing current learning environments to smart learning environments. *International Journal of Artificial Intelligence in Education*, 26(2), 561–581. <https://doi.org/10.1007/s40593-016-0108-x>
- Laupichler, M. C., Aster, A., Perschewski, J. O., & Schleiss, J. (2023). Evaluating AI courses: A valid and reliable instrument for assessing artificial-intelligence learning through comparative self-assessment. *Education Sciences*, 13(10): 978. <https://doi.org/10.3390/educsci13100978>

- Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology, 14*, 1285392. <https://doi.org/10.3389/fpsyg.2023.1285392>
- Lo, N. P. (2024). From theory to practice: Unveiling the synergistic potential of design and maker education in advancing learning. *SN Computer Science, 5*, 360. <https://doi.org/10.1007/s42979-024-02726-3>
- Lodge, J. M., Thompson, K., & Corrin, L. (2023). Mapping out a research agenda for generative artificial intelligence in higher education. *Australasian Journal of Educational Technology, 39*(1), 1–8. <https://doi.org/10.14742/ajet.8695>
- Ma, W. W. K. (2026). Assessing the adoption of ChatGPT as a learning tool for college students: An ethical perspective. *Knowledge Management & E-Learning, 18*(2), 168–189. <https://doi.org/10.34105/j.kmel.2026.18.008>
- McCabe, D. L., & Trevino, L. K. (1993). Academic dishonesty: Honor codes and other contextual influences. *The Journal of Higher Education, 64*(5), 522–538. <https://doi.org/10.1080/00221546.1993.11778446>
- McDiarmid, G. W., & Zhao, Y. (2023). Time to rethink: Educating for a technology-transformed world. *ECNU Review of Education, 6*(2), 189–214. <https://doi.org/10.1177/20965311221076493>
- McKean, J. W., & Sheather, S. J. (2009). Diagnostic procedures. *WIREs Computational Statistics, 1*(2), 221–233. <https://doi.org/10.1002/wics.12>
- Morris, A. E., & Evans, B. (2023). Experiences of African American Spanish learners in the US: Mitigating racialization and fostering belonging through an inclusive curriculum. *Journal of Spanish Language Teaching, 10*(2), 138–154. <https://doi.org/10.1080/23247797.2023.2294633>
- Nadelson, L. S., McGuire, S. P., Davis, K. A., Farid, A., Hardy, K. K., Hsu, Y. C., ... Wang, S. (2017). Am I a STEM professional? Documenting STEM student professional identity development. *Studies in Higher Education, 42*(4), 701–720. <https://doi.org/10.1080/03075079.2015.1070819>
- O'Dea, X. (2024). Generative AI: Is it a paradigm shift for higher education? *Studies in Higher Education, 49*(5), 811–816. <https://doi.org/10.1080/03075079.2024.2332944>
- Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research, 66*(4), 543–578. <https://doi.org/10.3102/00346543066004543>
- Pang, Y., Hashim, H., & Said, N. E. M. (2025). Cognitive amplification: Harnessing artificial intelligence to augment metacognitive learning strategies. *Dirasat: Human and Social Sciences, 53*(1): 7967. <https://doi.org/10.35516/Hum.2025.7967>
- Perkins, M., & Roe, J. (2024). Decoding academic integrity policies: A corpus linguistics investigation of AI and other technological threats. *Higher Education Policy, 37*, 633–653. <https://doi.org/10.1057/s41307-023-00323-2>
- Rahimi, A. R., & Mosalli, Z. (2025). Language learners' surface, deep, and organizing approaches to ChatGPT-assisted language learning: What contextual, individual, and ChatGPT-related factors contribute? *Smart Learning Environments, 12*: 16. <https://doi.org/10.1186/s40561-025-00368-3>
- Ranjan, S., Joshith, V. P., Kavitha, K., & Chittakath, S. (2024). The AI-knowledge management nexus for sustainable learning: A PLS-SEM study. *Knowledge Management & E-Learning, 16*(4), 811–837. <https://doi.org/10.34105/j.kmel.2024.16.037>
- Rousell, D., & Sinclair, M. P. (2025). Desiring-futures in education policy: Assemblage theory, artificial intelligence, and UNESCO's futures of education. *Educational Review, 77*(6), 1754–1777. <https://doi.org/10.1080/00131911.2024.2362176>

- Rusticus, S. (2023). Content validity. In F. Maggino (Ed.), *Encyclopedia of Quality of Life and Well-being Research* (pp. 1384–1385). Springer. https://doi.org/10.1007/978-3-031-17299-1_553
- Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist*, 26(3/4), 207–231. <https://doi.org/10.1080/00461520.1991.9653133>
- Seralidou, E., Kioskli, K., Fotis, T., & Polemi, N. (2025). AI_TAF: A human-centric trustworthiness risk assessment framework for AI systems. *Computers*, 14(7): 243. <https://doi.org/10.3390/computers14070243>
- Striepe, M., Thomson, S., & Sefcik, L. (2023). Understanding academic integrity education: Case studies from two Australian universities. *Journal of Academic Ethics*, 21, 1–17. <https://doi.org/10.1007/s10805-021-09429-x>
- Tan, S., Rudolph, J., & Tan, S. (2024). Riding the generative AI tsunami: Addressing the teaching and learning crisis in higher education. In J. Rudolph et al. (Eds.), *The Palgrave Handbook of Crisis Leadership in Higher Education* (pp. 135–154). Palgrave Macmillan Cham. https://doi.org/10.1007/978-3-031-54509-2_8
- Tirado-Olivares, S., Navío-Inglés, M., O'Connor-Jiménez, P., & Cózar-Gutiérrez, R. (2023). From human to machine: Investigating the effectiveness of the conversational AI ChatGPT in historical thinking. *Education Sciences*, 13(8): 803. <https://doi.org/10.3390/educsci13080803>
- 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: 15. <https://doi.org/10.1186/s40561-023-00237-x>
- Trigwell, K. (2021). Scholarship of teaching and learning. In L. Hunt, & D. Chalmers (Eds.), *University Teaching in Focus: A Learning-centred Approach* (pp. 286–303). Routledge.
- Usher, E. L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of Educational Research*, 78(4), 751–796. <https://doi.org/10.3102/0034654308321456>
- Van Dinther, M., Dochy, F., & Segers, M. (2011). Factors affecting students' self-efficacy in higher education. *Educational Research Review*, 6(2), 95–108. <https://doi.org/10.1016/j.edurev.2010.10.003>
- Wu, W., Sun, L., Li, H., Zhang, J., Shen, J., Li, J., & Zhou, Q. (2022). Approaching person-centered clinical practice: A cluster analysis of older inpatients utilizing the measurements of intrinsic capacity. *Frontiers in Public Health*, 10: 1045421. <https://doi.org/10.3389/fpubh.2022.1045421>
- Wu, X. Y., Radloff, J. D., Yeter, I. H., Wang, L., & Chiu, T. K. F. (2025). Designing artificial intelligence chatbots for self-regulated learning from a systematic review based on Habermas's three interests. *Interactive Learning Environments*. <https://doi.org/10.1080/10494820.2025.2563086>
- Zhai, X., He, P., & Krajcik, J. (2022). Applying machine learning to automatically assess scientific models. *Journal of Research in Science Teaching*, 59(10), 1765–1794. <https://doi.org/10.1002/tea.21773>
- Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-regulation* (pp. 13–39). Academic Press. <https://doi.org/10.1016/B978-012109890-2/50031-7>

Appendix I

AI self-efficacy scale

(Rated on a 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree)

1. I am confident in my ability to verify the accuracy of AI-generated information.
2. I can effectively use AI to brainstorm ideas without copying the content directly.
3. I feel capable of distinguishing between ethical and unethical uses of AI in my coursework.
4. I am confident I can prompt AI tools to help me learn rather than just produce answers.
5. I possess the skills to critically evaluate the quality of output generated by AI.

Appendix II

Academic integrity scale (adapted from McCabe & Trevino, 1993)

(Rated on a 5-point Likert scale: 1 = Strongly Disagree to 5 = Strongly Agree) Note: Items are reverse-scored where appropriate so that higher scores indicate higher integrity.

1. I would never submit work generated by AI as my own without attribution.
2. I consider using AI to write my entire essay to be a form of cheating.
3. I always verify AI-generated citations before including them in my work.
4. It is important to me that my work reflects my own understanding, even if I use AI for assistance.

Appendix III

Regression diagnostics

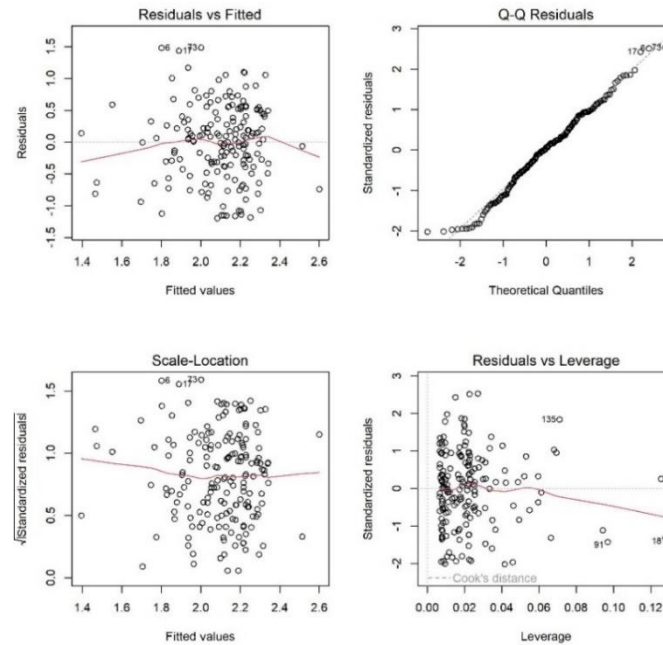


Fig. A1. Diagnostic plots for the moderation regression model (Note: The Residuals vs. Fitted plot does not show any clear pattern, which supports linearity and homoscedasticity. The Normal Q-Q plot shows that the residuals mostly follow the theoretical line, which backs up the idea that they are normal.)