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The Effect of AI Usage Strategy and Self-Regulated Learning on Students' Academic Integrity: The Moderating Role of AI Ethics Perception

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Abstract

The emergence of generative artificial intelligence (AI) poses new challenges to students' academic integrity. This study aims to analyze the effect of AI usage strategy and self-regulated learning (SRL) on academic integrity, and to examine the moderating role of AI ethics perception. This quantitative study employed a survey design involving 158 active students of the Accounting Education Study Program at Universitas Negeri Surabaya, selected through purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that AI usage strategy and SRL have a positive and significant effect on academic integrity, while AI ethics perception is the strongest direct predictor and also moderates the relationship between SRL and academic integrity. The research model explains 73.2% of the variance in academic integrity. The effects of SRL and AI ethics perception are strong and stable, whereas the moderating effect is weak. These findings confirm that ethical disposition and self-regulation capacity are the main determinants of academic integrity in the generative AI era, implying that AI literacy curriculum development should emphasize ethical dimensions and the strengthening of learning autonomy.

Keywords: academic integrity, AI ethics perception, AI usage strategy, self-regulated learning

INTRODUCTION

The emergence of generative artificial intelligence (AI) has fundamentally reshaped the landscape of higher education. The launch of ChatGPT in late 2022 marked a turning point at which AI technology became capable of producing text and analysis that is difficult to distinguish from human work (Kasneci et al., 2023). This capability

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directly enters the core domain of academic activity, from writing assignments to completing examinations, thereby raising new challenges that educational institutions have not fully anticipated (Bates et al., 2020).

One of the most pressing challenges is the threat to academic integrity. Eaton (2023) introduced the concept of postplagiarism to describe an era in which generative AI blurs the boundary between original work and machine-produced work, so that conventional approaches to plagiarism become inadequate. This phenomenon is even more critical in accounting education, where integrity is a core professional value that must be internalized from the very beginning of study. Saduk and Chariri (2024) found that AI-assisted academic dishonesty among accounting students is influenced by pressure, opportunity, and rationalization. Similar findings were reported by Aysah et al. (2025) and Tameno et al. (2025), which show that academic cheating behavior among accounting students, including AI-assisted cheating, is influenced by a range of psychological and situational factors (Pratiwi & Munari, 2024).

The real issue is not merely whether students use AI, but how they use it. Tseng and Warschauer (2023) proposed an AI literacy framework that emphasizes the competencies of understanding, accessing, prompting, verifying, and critically and ethically integrating AI output. Students who use AI productively and reflectively are expected to be better able to maintain academic integrity than those who use it reproductively without critical thinking (Warschauer et al., 2023).

Beyond AI usage strategy, the capacity for self-regulated learning (SRL) also plays an important role. SRL refers to students' ability to manage their own learning process independently through goal setting, comprehension monitoring, and the management of learning resources (Zimmerman, 2002; Pintrich, 2004). Students with high SRL tend to use AI as a critical dialogue partner rather than as a substitute for their own thinking, and are therefore better able to preserve academic integrity (Ng et al., 2023).

A third and equally important dimension is students' perception of AI ethics. Jobin et al. (2019) identified globally convergent AI ethics principles covering transparency, justice, responsibility, and privacy; Floridi et al. (2018) added the principle of explicability. Chan (2024) demonstrated that students' perception of the ethics of AI use is a significant predictor of compliance with academic integrity. AI ethics perception is assumed not only to exert a direct effect, but also to strengthen the relationship between SRL and academic integrity.

Although these three variables have been examined separately, few studies have simultaneously tested the effect of AI usage strategy and SRL on academic integrity with AI ethics perception as a moderator, particularly in the context of accounting education in Indonesia. This study aims to analyze the effect of AI usage strategy and SRL on academic integrity, the moderating role of AI ethics perception in the relationship between

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SRL and academic integrity, and the simultaneous effect of both variables. The study is expected to contribute theoretically to the development of an academic integrity model in the generative AI era, and practically to the design of a value-based AI literacy curriculum.

LITERATURE REVIEW

Academic integrity is defined as a commitment to the values of honesty, trust, fairness, respect, responsibility, and courage in academic activities (International Center for Academic Integrity, 2021). Bertram Gallant (2017) argues that genuine integrity arises from the internalization of values through the educational process, not merely from compliance with external rules. In the context of generative AI, Eaton (2023) emphasizes that human beings remain responsible for the truthfulness of content produced through collaboration with machines.

This study is grounded in Social Cognitive Theory (Bandura, 1986). The theory views human behavior as the product of reciprocal determinism among three elements, namely personal-cognitive factors, behavior, and the environment. From this perspective, academic integrity, a commitment to honesty, trust, fairness, respect, responsibility, and courage (International Center for Academic Integrity, 2021), is not merely a matter of obeying rules but the outcome of value internalization through education (Bertram Gallant, 2017). The central question, therefore, is not whether students use AI but how they use it. The three research variables are positioned accordingly within that framework: AI usage strategy represents the behavioral factor, self-regulated learning represents self-regulatory capacity, and AI ethics perception represents the personal-cognitive factor.

AI usage strategy draws on the AI literacy framework of Tseng and Warschauer (2023), which covers the competencies of understanding, accessing, prompting, corroborating, and incorporating. Warschauer et al. (2023) distinguish productive AI use, which involves critical evaluation and integration, from reproductive use, which surrenders the cognitive process entirely to AI. Students who apply productive strategies are expected to better maintain academic integrity. Based on this discussion, the first hypothesis is formulated (H1): AI usage strategy has a positive and significant effect on students' academic integrity.

Self-regulated learning is an active process in which students plan, monitor, and evaluate their own learning (Zimmerman, 2002). Pintrich's (2004) model encompasses the regulation of cognition, motivation, behavior, and context. Through meta-analysis, Richardson et al. (2012) confirmed SRL as a strong predictor of academic performance, and this finding is supported in the Indonesian student context (Maulidiyah et al., 2024). In the context of AI, students with high SRL are better able to control their use of AI responsibly (Ng et al., 2023). Based on this discussion, the second hypothesis is

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formulated (H2): self-regulated learning has a positive and significant effect on students' academic integrity.

AI ethics perception refers to students' understanding of and attitude toward the ethical principles of AI use (Jobin et al., 2019; Floridi et al., 2018). Chan (2024) showed that AI ethics perception influences students' academic behavior. A strong AI ethics perception is assumed to strengthen the relationship between SRL and academic integrity, so that students with both high self-regulation and a strong ethical perception display the most optimal integrity. Based on this discussion, the third hypothesis is formulated (H3): AI ethics perception moderates and strengthens the relationship between self-regulated learning and academic integrity; and the fourth hypothesis (H4): AI usage strategy and self-regulated learning simultaneously have a significant effect on students' academic integrity.

RESEARCH METHOD

This study employed a quantitative approach with a cross-sectional survey design. The population comprised active students of the Undergraduate Accounting Education Study Program at Universitas Negeri Surabaya. Sampling used a purposive technique with the criterion of active students who had used generative AI for academic purposes. The minimum sample size was determined using the inverse square root method (Kock & Hadaya, 2016) with an assumed minimum path coefficient of 0.2, yielding a minimum sample size of 155 respondents. The main data collected and meeting the criteria totaled 158 respondents.

The research instrument was a questionnaire using a five-point Likert scale measuring four variables: AI usage strategy, self-regulated learning, AI ethics perception, and academic integrity. Prior to the main data collection, the instrument was pilot-tested on 30 respondents separate from the main sample to avoid data contamination. The pilot test, conducted using SPSS, yielded adequate validity (item-total correlation) and reliability, with Cronbach's Alpha ranging from 0.786 to 0.890. Each variable was modeled as a first-order reflective latent construct.

The main data analysis used Partial Least Squares Structural Equation Modeling (PLS-SEM) following the recommendation of Hair et al. (2019) for complex models with moderate sample sizes and non-normal data, supported by PLS-SEM analysis software. The evaluation covered the measurement model (outer loadings, average variance extracted, composite reliability, and the heterotrait-monotrait ratio) and the structural model (R-square, path coefficients through bootstrapping, and the f-square effect size). The moderating effect was tested using the two-stage approach (Henseler & Chin, 2010). A robustness check was conducted by re-analyzing the data after eliminating multivariate outliers using Mahalanobis distance ($p < 0.001$).

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RESULTS AND DISCUSSION

The study involved 158 student respondents. Evaluation of the measurement model shows that, of the 48 initial items, 29 items were retained in the final model while still representing all conceptual dimensions. Table 1 shows that the constructs of AI usage strategy, AI ethics perception, and academic integrity meet the criterion of AVE ≥ 0.50, whereas the SRL construct (0.493) sits exactly at the threshold and remains acceptable because the composite reliability of all constructs is ≥ 0.80 (Fornell & Larcker, 1981). All Cronbach's Alpha and CR values satisfy the reliability requirement, and the HTMT values between constructs are below 0.90.

Table 1. Results of Convergent Validity and Reliability Testing

Variable	AVE	CR	Cronbach's Alpha	Remarks
AI Usage Strategy	0.516	0.865	0.813	Valid & Reliable
Self-Regulated Learning	0.493	0.828	0.740	Valid & Reliable
AI Ethics Perception	0.514	0.904	0.879	Valid & Reliable
Academic Integrity	0.509	0.900	0.873	Valid & Reliable

Source: Processed primary data (2026)

Evaluation of the structural model shows an R-square value for academic integrity of 0.732, meaning that 73.2% of the variance in academic integrity can be explained by the three predictor variables, which is considered substantial. The results of hypothesis testing through bootstrapping are presented in Table 2.

Table 2. Results of Hypothesis Testing

Hypothesis / Path	Coefficient (β)	t-statistic	p-value	Remarks
H1: AI Strategy → Integrity	0.276	3.543	< 0.001	Accepted
H2: SRL → Integrity	0.252	3.392	0.001	Accepted
AI Ethics Perception → Integrity	0.447	7.160	< 0.001	Significant
H3: SRL × AI Ethics → Integrity	0.092	2.099	0.036	Accepted

Source: Processed primary data (2026). Effect size f-square: SRL = 0.145; AI Ethics Perception = 0.312; AI Strategy = 0.109; interaction = 0.0358.

Table 2 shows that all four hypotheses are supported. AI usage strategy has a positive and significant effect on academic integrity (β = 0.276; t = 3.543; p < 0.001), so

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H1 is accepted. Notably, this result implies that what determines integrity is not the use of AI itself but the way students treat its output. Those accustomed to verifying and critically filtering AI results, rather than copying them wholesale, essentially retain control of and responsibility for the content of their work, precisely as Eaton (2023) emphasized regarding human responsibility in collaborating with machines. This pattern reinforces the distinction drawn by Warschauer et al. (2023) between productive and reproductive use, and shows that AI literacy in the sense of Tseng and Warschauer (2023) serves as more than technical skill: it acts as a behavioral safeguard against academic dishonesty. In the language of Social Cognitive Theory, this is the manifestation of the behavioral factor that helps shape academic actions with integrity. Nevertheless, the moderate magnitude of the coefficient suggests that strategic skill alone is not sufficient without the support of personal and regulatory factors.

Self-regulated learning is also shown to have a positive and significant effect ($\beta = 0.252$; $t = 3.392$; $p = 0.001$), meaning that H2 is accepted. The ability to set targets, monitor one's own comprehension, and organize learning resources independently apparently has a direct impact on behavior grounded in integrity, in line with Zimmerman (2002), the meta-analytic confirmation of Richardson et al. (2012), and evidence from Indonesian students (Maulidiyah et al., 2024). A plausible explanation is that students with strong self-regulation possess an internal locus of control that leads them to treat AI as a critical interlocutor rather than a shortcut (Ng et al., 2023), thereby narrowing the opportunity to cheat. This finding also complements studies of academic cheating among accounting students that have so far highlighted pressure, opportunity, and rationalization (Saduk & Chariri, 2024; Pratiwi & Munari, 2024): whereas those studies map the triggers of cheating, the present result identifies SRL as an internal restraint within the student.

Among the three predictors, AI ethics perception emerges as the strongest direct predictor ($\beta = 0.447$; $t = 7.160$; $p < 0.001$), with a coefficient nearly twice that of the other two. Such dominance conveys a fairly clear message: in facing generative AI, students' ethical stance matters more than technical proficiency in using AI or the capacity for self-regulation. Once the principles of transparency, justice, responsibility, and explicability are genuinely internalized (Jobin et al., 2019; Floridi et al., 2018), the decision to maintain integrity is driven more by value-based conviction than by fear of breaking rules, consistent with Bertram Gallant's (2017) view that genuine integrity grows out of value internalization. This result reinforces the findings of Chan (2024) and, within the Social Cognitive Theory framework, underscores the central role of personal-cognitive factors in reciprocal determinism. Consequently, safeguarding academic integrity in the AI era cannot rest solely on skills training or tighter regulation; it must reach the formation of students' ethical attitudes toward technology.

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As for the moderating role of AI ethics perception in the SRL–integrity relationship, it is indeed significant but weak (β = 0.092; t = 2.099; p = 0.036), so H3 is accepted. The positive direction indicates that students with both high SRL and a strong ethical perception display the most optimal integrity; however, the small effect size suggests that the contribution of SRL to integrity is relatively stable across different levels of ethical perception. In other words, the strength of AI ethics perception operates largely through its dominant direct path rather than by amplifying the effect of SRL. This finding should therefore be read with caution: although statistically significant, its moderating role is too limited to serve as the main foundation for designing interventions.

Overall, the model is able to explain 73.2% of the variance in academic integrity (R-square = 0.732), which is substantial according to the benchmark of Hair et al. (2019), so H4 is also supported: AI usage strategy and self-regulated learning jointly influence academic integrity. Re-analysis after the removal of multivariate outliers still shows all hypotheses to be supported, indicating that the findings are sufficiently robust. The remaining 26.8% of unexplained variance implies the presence of other factors outside the model, including the situational and psychological triggers of cheating identified in previous studies (Aysah et al., 2025; Tameno et al., 2025), which may open avenues for further model development. Taken together, these three paths ultimately affirm the core idea of Social Cognitive Theory: academic integrity in the generative AI era arises from the interplay among personal-cognitive factors, behavior, and self-regulation, with ethical attitude as the most prominent driver.

CONCLUSION

This study concludes that AI usage strategy, self-regulated learning, and AI ethics perception simultaneously have a positive effect on the academic integrity of Accounting Education students at Universitas Negeri Surabaya, with AI ethics perception serving as the strongest predictor as well as a moderator of the relationship between self-regulated learning and academic integrity. Self-regulated learning and AI ethics perception are strong and stable determinants, whereas the moderating effect, although significant, is weak. These findings confirm that ethical disposition and self-regulation capacity are the main determinants of academic integrity in the generative AI era. The implication is that the development of an AI literacy curriculum needs to emphasize the strengthening of ethical dimensions and students' learning autonomy, rather than merely the technical skills of using AI. Further research is recommended to broaden the population across study programs and universities, and to consider a longitudinal design in order to strengthen the generalizability of the findings.

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