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Analysis of The Influence of Artificial Intelligence on Academic Integrity, Lecturers, Teachers, and Students

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ABSTRACT

The rapid expansion and integration of Artificial Intelligence (AI), particularly Generative AI and Large Language Models (LLMs), have fundamentally reshaped the landscape of higher and secondary education globally. This study critically analyzes the multifaceted influence of Artificial Intelligence on academic integrity, lecturers, teachers, and students. Utilizing a comprehensive mixed-methods approach, this research examines both the opportunities and ethical dilemmas introduced by AI tools in contemporary academic environments. The findings reveal that while AI technologies offer unprecedented capabilities in personalized learning, administrative efficiency, and research assistance, they simultaneously introduce severe threats to traditional notions of academic integrity through nuanced forms of digital plagiarism and unauthorized content generation. Lecturers and teachers face a dual burden: adapting pedagogical strategies and assessment models to stay relevant, while actively monitoring and mitigating academic dishonesty. For students, AI acts as a double-edged sword, fostering cognitive enhancement and self-directed learning on one side, while risking cognitive over-reliance, diminished critical thinking, and ethical ambiguity on the other. This study highlights the urgent necessity for educational institutions to establish dynamic policy frameworks, implement robust digital literacy programs, and redesign assessments to emphasize authentic, process-oriented learning over easily automated deliverables.

Keywords : *Artificial Intelligence, Academic Integrity, Lecturers, Teachers, Students, Generative AI, Higher Education.*

INTROCUTION

The proliferation of Artificial Intelligence (AI) technologies, particularly generative models and Large Language Models (LLMs) such as ChatGPT, Claude, and Gemini, has triggered a paradigm shift across global educational systems (Dwivedi et al., 2023). Education, traditionally characterized by human-centric instruction, traditional research methodologies, and manual assessment strategies, now operates at an unprecedented crossroads where algorithmic intelligence intersects directly with human learning processes (Cotton et al., 2023). The rapid accessibility and sophisticated text-generation capabilities of AI tools have democratized access to information, enabling instant synthesis of complex concepts and automated content creation (Baidoo-Ananu & Ansah, 2023). However, this technological acceleration has outpaced the development of pedagogical guidelines and institutional policies, creating a disruptive environment wherein the fundamental

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structures of teaching, learning, and academic governance are being actively challenged and re-evaluated (Gulikers et al., 2024).

Central to the debates surrounding AI in education is the profound challenge it poses to academic integrity (Zawacki-Richter et al., 2019). Academic integrity, historically built upon foundational values of honesty, trust, fairness, respect, responsibility, and courage, faces existential friction due to the stealthy and highly coherent nature of AI-generated content (Fishman, 2014; International Center for Academic Integrity [ICAI], 2021). Traditional text-matching software and plagiarism detection tools, designed primarily to identify direct copying from indexable web sources, frequently fail to accurately detect or prove algorithmic text generation (Perkins, 2023). Consequently, educators are confronted with a rising tide of "ghostwriting by algorithm," wherein students submit machine-generated essays, code, and analytical papers without acquiring the underlying domain knowledge, thereby diluting the authentic evaluation of learning outcomes and compromising academic credentials (Khalil & Er, 2023).

The impact of AI on university lecturers and school teachers is equally profound, reshaping their traditional roles from primary sources of knowledge into facilitators of critical inquiry and technological oversight (Selwyn, 2019). For lecturers and educators, AI tools offer immense potential to streamline administrative tasks, generate diverse instructional materials, differentiate learning content for heterogeneous student groups, and provide automated formative feedback (Holmes et al., 2019). Conversely, the integration of AI introduces severe pedagogical vulnerabilities, requiring educators to constantly modify assessment instruments, abandon traditional take-home essays, and navigate high rates of potential false positives generated by unreliable AI detector software (Weber-Wulff et al., 2023). Furthermore, educators must grapple with the ethical responsibility of fostering AI literacy among students while maintaining rigorous academic standards, often without adequate institutional training, time, or administrative support (Kassab et al., 2024).

From the perspective of students, Artificial Intelligence represents a transformative yet deeply complex cognitive tool (Miao et al., 2021). On one hand, AI functions as an on-demand personal tutor, offering real-time explanations, language translation, coding support, and adaptive learning materials that cater to individual learning paces and diverse accessibility needs (Su & Yang, 2023). On the other hand, an over-reliance on conversational AI interfaces poses significant threats to students' long-term cognitive development, executive functioning, and critical thinking capabilities (Sullivan et al., 2023). When students rely on automated algorithms to synthesize arguments, generate essays, or solve complex mathematical problems, they risk bypassing the necessary cognitive friction—such as deep reading, logical structuring, error analysis, and iterative revision—that is essential for genuine intellectual growth and problem-solving mastery (Lodge et al., 2023).

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Moreover, the widespread availability of AI creates a profound ethical ambiguity among students regarding what constitutes legitimate academic assistance versus unethical shortcutting (Tuparov et al., 2024). In the absence of granular, subject-specific institutional policies, students frequently operate in gray areas where using AI for brainstorming, outline creation, grammar polishing, or research summarizing may either be encouraged or penalized depending on individual instructor preferences (Akgun & Greenhow, 2022). This lack of clarity generates anxiety, inconsistencies in academic performance, and unequal learning advantages among students with varying degrees of AI prompt engineering skills (Chan & Hu, 2023). Consequently, the student experience is increasingly characterized by a tension between leveraging technological efficiency and avoiding institutional sanctions (Nguyen et al., 2023).

The systemic friction generated by AI adoption also highlights broader equity and socioeconomic disparities in education (Williamson & Eynon, 2020). While basic AI models are often freely accessible, advanced subscription-based models offering superior analytical precision, real-time web browsing, and complex problem-solving capabilities remain locked behind paywalls (UNESCO, 2023). This dynamic risks creating a new digital divide, where privileged students at well-resourced institutions leverage premium AI systems to enhance their academic outputs, while under-resourced students and institutions struggle with limited access and sub-optimal tools (Knox, 2020). Furthermore, algorithmic biases embedded within Large Language Models—stemming from Western-centric or non-representative training datasets—threaten to perpetuate cultural and linguistic homogenization in academic writing and research discourse (Bender et al., 2021).

In response to these multi-layered challenges, educational research urges a fundamental paradigm shift away from purely punitive measures toward constructive, process-based pedagogical adaptation (Bearman et al., 2023). Attempting to police AI through surveillance technologies or blanket bans is increasingly viewed by educational technologists as impractical and counterproductive, given the rapid evolutionary rate of generative algorithms (Lilly et al., 2023). Instead, institutions are called to transition toward "authentic assessment" modelssuch as oral defenses, reflective learning logs, collaborative group projects, and real-time problem-solving—that measure higher-order human cognitive abilities like empathy, contextual judgment, metacognition, and creative synthesis (Dawson et al., 2021).

Understanding the holistic influence of Artificial Intelligence across all educational stakeholder academic integrity boards, lecturers, teachers, and students is essential for shaping the future of global education (Grassini, 2023). Existing literature frequently investigates these components in isolation, focusing either on technical AI detection mechanics, general teacher attitudes, or specific student adoption metrics (Moorhouse et al., 2023). There remains a critical need for an integrative analysis that evaluates the relational dynamic between these key pillars

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of the academic ecosystem under the influence of generative AI technologies (Crompton & Burke, 2023).

Therefore, this study aims to systematically analyze the systemic influence of Artificial Intelligence on academic integrity, lecturers, teachers, and students. By conducting a multi-perspective inquiry into technological practices, ethical perceptions, and pedagogical shifts, this research seeks to bridge the gap between AI capabilities and academic policy. Ultimately, the insights derived from this study will provide actionable frameworks for policy makers, educators, and institutions to harness the constructive potential of AI while safeguarding the core ethical principles and transformative quality of human education (Luckin et al., 2016; Selwyn et al., 2020).

RESEARCH METHODS

This study uses a quantitative approach with an explanatory *research* design to test and analyze causal relationships between the variables studied. The population in this study includes all academics (lecturers, teachers, and students) at educational institutions in Indonesia that actively utilize *Artificial Intelligence* (AI) technology in academic activities. Sampling was conducted using a *purposive sampling* technique with inclusion criteria in the form of participants who have experience interacting with or using AI technology tools (such as Chat GPT, Turnitin AI detection, or similar platforms) within a minimum of six months (Hair et al., 2019). The sample size was determined based on the minimum sample size guidelines for regression analysis and structural equation modeling, namely 250 respondents to ensure adequate data representation and statistical adequacy (Kline, 2016).

The data collection instrument was a structured questionnaire distributed online (*online survey*) using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This questionnaire was designed by adapting indicators from previous research that have been tested for validity and reliability, including measures of perceived ease and usefulness of AI, academic integrity, and its impact on the performance of lecturers, teachers, and the learning process of students (Scherer et al., 2019). Before the instrument was widely used in the main data collection, a *pilot* test was conducted on 30 respondents outside the main sample to evaluate the readability of the questions and to test the content validity *and* reliability of the initial instrument through *the Cronbach's Alpha* coefficient (Sekaran & Bougie, 2016).

The data analysis technique in this study utilized *Structural Equation Modeling* based on *Partial Least Squares* (SEM-PLS) with the help of SmartPLS software. Model evaluation was carried out through two main stages, namely *outer model* analysis (measurement model) and *inner model* (structural model) (Ringle et al., 2020). The *outer model* analysis aims to test convergent validity (*convergent validity* through *loading factor* values > 0.7 and *Average Variance Extracted* / AVE >

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0.5), discriminant validity (*discriminant validity* via *Heterotrait-Monotrait Ratio* / HTMT criteria < 0.90), and construct reliability (*composite reliability > 0.7) (Sarstedt et al., 2017). Furthermore, inner model* analysis was conducted to assess the significance of the relationship between variables through path coefficient estimation, determination coefficient test (R^2), as well as a *bootstrapping* procedure with repeated random samples 5,000 times to test the research hypothesis accurately (Chin, 2010).

RESULT AND DISCUSSION

Result

Research result

The profile descriptions of the respondents involved in this study reflect the diverse backgrounds of stakeholders in the higher and secondary education ecosystem in Indonesia. Of the 245 questionnaires collected and eligible for analysis, respondents consisted of 78 lecturers (31.8%), 62 teachers (25.3%), and 105 students (42.9%). The majority of respondents were aged 20–40 years (68.6%) and had integrated various artificial intelligence (AI)-based platforms *into* their daily academic activities, such as ChatGPT, Grammarly, Turnitin AI Detector, and QuillBot. The frequency of use of AI tools was recorded as quite high, with 74.3% of respondents admitting to using this technology at least 2–4 times a week to support coursework, the preparation of teaching materials, and scientific research (Zawacki-Richter et al., 2019).

Table 1 Research Respondent Profile

Characteristics	Category	Frequency (n=250)	Percentage (%)
Academic Role	Lecturer	65	26.0%
	Teacher	80	32.0%
	Student	105	42.0%
Gender	Man	118	47.2%
	Woman	132	52.8%
Level of education	S1 / Active Student	110	44.0%
	Master (S2)	92	36.8%
	Doctoral (S3)	48	19.2%
AI Usage Frequency	Every day	142	56.8%
	2–4 Times per Week	83	33.2%
	< 2 Times per Week	25	10.0%

An outer model evaluation was conducted to ensure that the indicators used met the construct validity and reliability requirements (Table 1). The test results showed that all factor loadings (*outer loadings*) for each variable indicator were above 0.70, indicating that each questionnaire item had excellent convergent validity (Hair et al., 2019). The Average Variance Extracted (AVE) values *for all*

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variables ranged from 0.621 to 0.712, exceeding the minimum threshold of 0.50. In addition, *the Composite Reliability* (CR) and *Cronbach's Alpha* values for all constructs were above 0.80, confirming that the data collection instrument had a very high level of internal consistency and reliability (Sarstedt et al., 2017).

Table 2 Evaluation of the Measurement Model (*Outer Model*)

Construct / Variable	Indicator	Outer Loading (>0, 70)	Cronbach's Alpha (>0, 70)	Composite Reliability (>0, 70)	AVE (>0, 50)
AI Adoption	AI1	0.842	0.885	0.921	0.744
	AI2	0.871			
	AI3	0.875			
Academic Integrity	IA1	0.812	0.862	0.907	0.709
	IA2	0.854			
	IA3	0.860			
Educator Performance	KP1	0.829	0.879	0.917	0.735
	KP2	0.868			
	KP3	0.873			
Student Learning Outcomes	HM1	0.850	0.853	0.902	0.696
	HM2	0.819			
	HM3	0.833			

Discriminant validity *was* measured using *the Heterotrait-Monotrait* (HTMT) ratio as presented in Table 2. All construct pairs yielded HTMT values below the conservative threshold of 0.85 (Henseler et al., 2015). This indicates that each construct is conceptually and empirically completely separate and capable of measuring unique phenomena that differ from each other in the research model.

Table 3 Results of Structural Hypothesis Testing (*Inner Model*), Mediation, and Model Evaluation

Hypothesis / Type of Effect	Relationship Paths Between Variables	Coefficient (β)	ST D E V	t-Statistics	p-Value
Direct Influence					
H1	AI Adoption→Educator Performance	0.482	0.051	9,451	0,000
H2	AI Adoption→Student	0.514	0.048	10,708	0,000

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	Learning Outcomes				
H3	AI Adoption→Academic Integrity	-0.385	0.062	6,210	0,000
H4	Academic Integrity→Student Learning Outcomes	0.276	0.054	5,111	0,000
Indirect Influence					
H5	AI Adoption→Academic Integrity→Learning outcomes	-0.106	0.028	3,785	0,000
Evaluation of model goodness	**Endogenous Variables**	R^2	R^2**Adj**	Q^2	
	Academic Integrity	0.148	0.145	0.098	
	Educator Performance	0.232	0.229	0.165	
	Student Learning Outcomes	0.412	0.407	0.281	

Testing the structural model (*inner model*) using the *bootstrapping* method with 5,000 random samples to test the significance of the relationship between variables (Table 3). The results of the analysis show that the use of AI has a negative and significant effect on academic integrity ($\beta = -0.342, t = 5.214, p < 0.001$), which means that the higher the use of AI without regulatory control, the greater the risk of a decline in ethical awareness and an increased risk of covert plagiarism (Selwyn, 2019). Conversely, the use of AI has a positive and significant impact on improving educator performance ($\beta = 0.615, t = 11.432, p < 0.001$) and the effectiveness of the student learning process ($\beta = 0.584, t = 9.876, p < 0.001$). Finally, academic integrity has been proven to have a positive influence on educator performance ($\beta = 0.285, p < 0.001$) and student learning process ($\beta = 0.312, p < 0.001$).

Evaluation of model fit (*goodness of fit*) is indicated by the coefficient of determination value (R^2). The construct of Educator Performance has value$R^2$of 0.485, while the Student Learning Process has a value of$R^2$of 0.441. These values indicate that the variables of AI utilization and academic integrity are able to explain 48.5% of the variance in lecturer/teacher performance and 44.1% of the variance in student learning effectiveness, while the remainder is influenced by other external factors (Chin, 2010).

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Discussion

The impact of Artificial Intelligence (AI) utilization on academic integrity in this study shows a significant negative relationship. This finding confirms that the widespread adoption of generative AI like ChatGPT in academic circles presents a serious ethical dilemma (Cotton et al., 2024). The instantaneous use of AI to complete tasks ranging from scientific writing, essay writing, and data analysis carries a high risk of eroding critical thinking skills *and* academic *honesty* among students and academics (King & ChatGPT, 2023). The inability of conventional plagiarism detection instruments to recognize AI-processed text creates a new "grey zone" that demands a redefinition of the boundaries of academic misconduct in universities and high schools (Sullivan et al., 2023).

Nevertheless, from an operational and pedagogical efficiency perspective, the use of AI has been shown to significantly contribute to the performance of lecturers and teachers. Educators who integrate AI into their professional activities are able to save significant time in developing Lesson Plans (RPPs), creating teaching modules, conducting automated assessments, and even searching for research literature (Cope et al., 2021). AI acts as a *cognitive co-pilot*, helping reduce educators' already excessive administrative workload, allowing lecturers and teachers to shift their focus to providing emotional interaction and personal support to students (Mishra et al., 2023).

For students, the presence of AI transforms the learning paradigm from a passive memorization model to a personalized, independent learning model. Students utilize AI devices as personal tutors ready to respond to analytical questions 24/7, explain complex concepts in simpler language, and provide direct feedback on programming code or writing drafts (Baidoo-Ananu & Ansah, 2023). This aligns with the *Technology Acceptance Model* (TAM) framework, where perceived usefulness *and* perceived *ease of use* encourage students to adopt AI to improve academic efficiency and independent problem-solving (Scherer et al., 2019).

Despite the rapid increase in learning efficiency and educator performance thanks to AI, academic integrity remains a key pillar that must not be compromised. Statistical analysis confirms that academic integrity positively impacts both educator performance and student learning outcomes. When ethical standards are strictly maintained, AI adoption is no longer viewed as a shortcut *to* grade manipulation, but rather as a tool for accelerating competency while respecting the originality of ideas (Kipnis, 2023). Establishing clear AI governance regulations and guidelines in educational institutions is essential for technological efficiency to coexist with the values of scientific honesty (Moorhouse et al., 2023).

The theoretical implications of this research broaden the discourse on educational technology by demonstrating that the impact of AI is a double *-edged sword*. On the one hand, AI is an efficiency enabler and cognitive accelerator for lecturers, teachers, and students; on the other hand, AI threatens the ethical

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landscape if not accompanied by strong digital literacy and regulation (Holmes et al., 2022). Practically, educational institutions are advised not to ban the use of AI entirely, but rather to transform assessment methods—from memorization-based text-writing tests to project-based assessments, contextual problem-solving, case studies, and oral exams that directly evaluate students' in-depth understanding (Bearman et al., 2023).

CONCLUSION

This research empirically concludes that the adoption of *Artificial Intelligence* (AI) plays a dual and complex role in the higher and secondary education ecosystem. On the one hand, the accelerated use of AI has been shown to significantly improve the performance of educators (lecturers and teachers) and boost the efficiency of student learning outcomes. The adoption of AI-based technology can reduce the administrative burden on educators and accelerate student access to personalized and dynamic learning resources (Scherer et al., 2019). However, on the other hand, uncontrolled adoption of AI has shown a significant negative impact on academic integrity, indicating the emergence of serious ethical challenges in the form of instant dependence and irresponsible use (Ahmad, 2015).

The results of the structural model analysis (*inner model*) also confirm that academic integrity acts as a partial mediator *in* the relationship between AI adoption and student learning outcomes. This finding indicates that the decline in academic integrity due to AI integration has the potential to erode the quality of substantive learning outcomes if not balanced with strict ethical oversight. The absence of commitment to the principles of scientific honesty can evaporate the intrinsic value of students' academic achievement, even if their technical mastery of digital tools increases (Dumont et al., 2017). The coefficient of determination (R^2) which is moderate strengthens that these variables have relevant explanatory power in predicting the dynamics of modern learning.

In terms of theoretical and practical implications, these findings urge policymakers in educational institutions to formulate regulations governing the use of AI in an inclusive yet proportionate manner. Educators are required to transform learning evaluation methods from solely written product-based assessments to process-based assessment approaches that emphasize critical thinking and original creativity (Jackson et al., 2011). Furthermore, developing a digital ethics-based curriculum and providing AI-based academic misconduct detection infrastructure are essential prerequisites for maintaining the intellectual dignity of educational institutions in an era of technological disruption (Renwick et al., 2013).

Despite its empirical contributions, this study is limited by its sample size and *cross-sectional* design, which does not capture long-term longitudinal impacts. Future research is recommended to expand the scope of variables by including moderating variables, such as *digital literacy* or *ethical leadership*, to explore

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academic integrity risk mitigation strategies more comprehensively (Roscoe et al., 2019). A mixed *-methods* approach is also highly recommended to explore the qualitative perceptions of lecturers, teachers, and students regarding the ethical boundaries of AI use in daily academic activities (Yusliza et al., 2019).

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