

AI Plagiarism Intention: The Role of Individualism-Collectivism Culture Moderated by Performance-based Goal Orientation

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ABSTRACT

Artificial intelligence (AI) plagiarism has become a vital problem threatens academic integrity in higher education. Several studies have tried to uncover its causes from both individual and cultural factors. However, research on the influence of cultural factors on AI plagiarism is still scarce and inconsistent in its results. Drawing on the Theory of Planned Behavior, this study examined whether students' cultural orientation (i.e., individualism and collectivism) predicts AI plagiarism intention and whether performance-based goal orientation moderates this relationship. Cultural orientation was measured as students' tendency to endorse individualistic or collectivistic values, whereas AI plagiarism intention referred to students' willingness to use generative AI in ways that violate academic integrity standards. A total of 214 Indonesian university students participated in this study through convenience sampling and completed an online questionnaire. The proposed moderation model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicated that collectivism was positively associated with AI plagiarism intention, whereas individualism showed no significant relationship. Contrary to expectations, performance-based goal orientation did not significantly moderate the relationship between cultural orientation and AI plagiarism intention. Discussion is provided to elaborate these findings.

Keywords: AI plagiarism, academic misconduct, collectivism, individualism, performance motivation

1. INTRODUCTION

While technologies advancement present significant educational opportunities, they have also raised concerns regarding academic integrity, particularly the emergence of AI plagiarism. AI plagiarism is defined as unethical practice of using artificial intelligence technologies, particularly generative language models, to generate content that is plagiarized either from original human-authored work or directly from AI-generated content, without appropriate acknowledgement of the original sources or AI's contribution (Chan, 2025).

According to Turnitin's AI Writing Report, among 38.5 million submissions analyzed, approximately 9.6% contained at least 20% AI-generated content, while 3.5% contained between 80% and 100% AI-generated content (Turnitin, 2023). Additionally, nearly 89 % students acknowledged that they use ChatGPT to finish their overall assignments, making educators worry about the high risk of plagiarism (Forbes, 2023). Unlike conventional plagiarism, AI-assisted plagiarism occupies an ethical gray area because students do not directly copy another person's work but instead generate original-looking content using AI

systems. Consequently, distinguishing legitimate AI-assisted learning from academic misconduct has become increasingly challenging for educators and higher education institutions.(Eret & Ok, 2014; Peytcheva-Forsyth et al., 2018; Skjuve et al., 2024).

The emergence of AI plagiarism has prompted growing concern among higher education institutions worldwide and attract scholar to investigate deeper. Students' decisions to use AI are likely to depend not only on institutional regulations but also on their personal values, cultural beliefs, and motivational orientations (Cespedes & Tursunkhanova, 2026; Cihodaru-Ştefanache et al., 2026; Sozon et al., 2024; Torres-Diaz et al., 2025). One of cultural orientation that has been associated with plagiarism is individualism and collectivism. Individualism focuses more on personal achievements and independence, whereas collectivism cares more about group harmony and communal sharing (Singelis et al., 1995; Triandis & Gelfand, 1998). (Hutson, 2024) argued that Western societies, which are generally characterized by stronger individualistic values like the United States of America, tend to regard plagiarism as the unauthorized appropriation of intellectual property, whereas collectivistic cultures may place greater emphasis on knowledge sharing and collective achievement.

The relationship between cultural orientation and plagiarism still appears to be inconclusive. Research in Thailand college students with stronger individualistic orientations exhibit lower tolerance toward academic cheating (Thomas, 2017), whereas others have found that individualism is associated with a greater likelihood of engaging in plagiarism (Kasler et al., 2021; Martin, 2011). More recently, Zhang (2024) demonstrated that the predictive power of the Theory of Planned Behavior (TPB) varies across individualism–collectivism orientations, highlighting that cultural values function as important boundary conditions in explaining academic cheating rather than acting as simple direct predictors. These inconsistent findings suggest that additional psychological mechanisms are needed to explain when cultural orientation is translated into unethical academic intentions.

One motivational factor that may determine whether cultural values become behaviorally consequential is performance-based goal orientation. Students with strong performance-based goals prioritize obtaining high grades, demonstrating competence, and outperforming others. Under increasing academic competition, generative AI may be perceived as an efficient strategy for achieving these outcomes.(Elliot & Murayama, 2008; Krou et al., 2021). Moreover, students that appear to lack the competence to pass exams may be inclined to conduct academic dishonesty (Surahman & Wang, 2022).

The present study addresses three important gaps in the literature. First, it extends previous plagiarism research by focusing specifically on AI plagiarism, which differs conceptually and psychologically from traditional plagiarism. Second, it examines whether individualism and collectivism continue to predict AI plagiarism intention within the ethically ambiguous environment created by generative AI. Third, it introduces performance-based goal orientation as a theoretically grounded boundary condition that may explain when cultural values are translated into AI plagiarism intention. Little attention has been devoted to its potential role as

a boundary condition explaining when cultural values are translated into AI plagiarism intention. Examining performance-based goal orientation as a moderator is therefore theoretically relevant because it helps explain why students with similar cultural values may differ in their intentions to misuse generative AI, especially when it's been proven to predict student's attitude, performance, and behavior (Daumiller & Janke, 2019, 2020; Krou et al., 2021).

To fill in the gaps, this study is grounded in the Theory of Planned Behavior (TPB), which suggests that behavioral intention is the most proximal determinant of behavior and is primarily influenced by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991, 2011). Beyond these proximal determinants, TPB acknowledges that behavioral intentions are shaped by more distal background factors, including cultural values, personality, and social experiences, through their influence on individuals' beliefs and evaluations of a behavior (Ajzen, 1991, 2011). This perspective provides a suitable theoretical framework for understanding AI plagiarism because students' decisions to use generative AI are not determined solely by institutional regulations but also by how they evaluate the ethical acceptability of AI use and perceive relevant social expectations.

The moderating role of performance-based goal orientation is theoretically justified because AI plagiarism differs from conventional plagiarism in its ethical ambiguity. Students holding similar cultural values may nevertheless differ in their behavioral intentions depending on the salience of achievement goals. When performance-based goals are highly salient, students may place greater emphasis on academic outcomes than on ethical concerns (Fritz et al., 2023; Guo et al., 2022), increasing the likelihood that culturally shaped evaluations of AI use are translated into intentions to engage in AI plagiarism. Conversely, students with weaker performance-based goals may be less motivated to instrumentalize AI regardless of their cultural orientation. Previous studies have consistently demonstrated positive associations between performance-oriented goals and plagiarism-related behaviors; however, these studies have examined performance goals primarily as independent predictors rather than as boundary conditions explaining when cultural values become behaviorally consequential (Uzun & Kilis, 2020; Zhang, 2024). This represents an important theoretical gap because understanding when cultural orientation influences AI plagiarism is equally important as understanding whether such influence exists in Indonesian college students' context.

Therefore, this study addresses this gap by examining the intention to engage in AI-based plagiarism—as opposed to conventional plagiarism—and investigating the roles of individualism and collectivism within the Indonesian context. It introduces performance-based goal orientation as a theoretically grounded moderator variable and integrates these relationships into the Theory of Planned Behavior (TPB) framework. In doing so, the study contributes to the development of the TPB within the emerging context of generative AI while providing new empirical evidence regarding the cultural and motivational mechanisms

underlying the intention to commit AI-based plagiarism among university students. Therefore, we propose hypotheses as follow:

- H1.** Individualism is significantly associated with AI plagiarism intention.
- H2.** Collectivism is significantly associated with AI plagiarism intention.
- H3.** Performance-based goal orientation moderates the relationship between individualism and AI plagiarism intention.
- H4.** Performance-based goal orientation moderates the relationship between collectivism and AI plagiarism intention.

2. METHODS

2.1 Research Design

This study employed a quantitative, cross-sectional, non-experimental research design to examine the relationships between cultural orientation (individualism and collectivism), performance-based goal orientation, and AI plagiarism intention among Indonesian university students. The proposed research model was developed based on the Theory of Planned Behavior (Ajzen, 1991), in which cultural orientation served as the independent variable, AI plagiarism intention as the dependent variable, and performance-based goal orientation as the moderating variable. A cross-sectional survey design was considered appropriate because the study sought to examine associations among latent psychological constructs measured at a single point in time without manipulating any variables.

2.2 Participants and Procedure

Participants were undergraduate, master's, and doctoral students enrolled at Indonesian universities. A convenience sampling technique was employed to recruit participants who are willing to fill the questionnaire that met following criteria: (a) currently enrolled at an Indonesian university, (b) at least 18 years of age, and (c) having prior experience using generative AI applications (e.g., ChatGPT, Claude, Gemini AI, or similar AI tools) for academic purposes.

The minimum sample size was estimated using G*Power 3.1 following Cohen (1988)'s and (Faul et al., 2007)'s recommendations that suggest a medium effect size ($f^2 = .15$), statistical power of .90, and a significance level of .05. The analysis indicated a minimum sample size of 173 participants. We obtained 214 valid responses, exceeding the minimum recommended sample size.

Data were collected using an online questionnaire administered through Google Forms and distributed via university networks and social media platforms. Before completing the questionnaire, participants were required to read and electronically approve an informed consent form explaining the study objectives, voluntary participation, anonymity, confidentiality, and the right to withdraw at any time without consequences.

2.3 Measures

All instruments were originally developed in English and were translated into Indonesian following the cross-cultural adaptation guidelines proposed by Beaton et al., (2000). The adaptation process consisted of forward translation by two independent bilingual translators that have TOEFL score above 550, synthesis of the translated versions, back-translation into English, expert review, and final reconciliation to ensure semantic and conceptual equivalence.

AI plagiarism intention was measured using an adapted version of the Intention to Plagiarize Scale developed by (Farooq & Sultana, 2021). The original instrument comprises sixteen items across three dimensions: positive attitude, negative attitude, and subjective norm. All items were adapted to specifically assess respondents' intention to use generative AI in ways that violate academic integrity principles. Responses were recorded on a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

Performance-based goal orientation was measured using the Achievement Goal Questionnaire–Revised (AGQ-R) developed by Elliot and Murayama (2008). The study employed the performance-approach and performance-avoidance dimensions, comprising 6 items. Responses were recorded using a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

Cultural orientation was assessed using the Individualism–Collectivism Scale (INDCOL) developed by Triandis and Gelfand (1998). The original scale consists of sixteen items representing four dimensions: horizontal individualism, vertical individualism, horizontal collectivism, and vertical collectivism. Consistent with the objectives of this study, these dimensions were aggregated into two higher-order constructs representing individualism and collectivism. Responses were recorded using a six-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

2.4 Data Analysis

The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented in SmartPLS 4. PLS-SEM was selected because the primary objective of this study was theory extension and prediction involving multiple latent constructs and moderating relationships. Furthermore, PLS-SEM is particularly appropriate for predictive research, complex structural models, and situations in which multivariate normality cannot be assumed (Hair et al., 2022).

Before testing the proposed hypotheses, the potential influence of common method bias (CMB) was assessed using the full collinearity assessment procedure proposed by Kock (2015). Unlike Harman's single-factor test, which has been criticized for its limited ability to detect method bias, the full collinearity approach simultaneously evaluates both vertical and lateral collinearity among latent constructs. Following Kock's recommendation, full collinearity variance inflation factor (VIF) values were examined, with values below 3.3 indicating that common method bias was unlikely to threaten the validity of the findings. Because all latent

constructs exhibited full collinearity VIF values below the recommended threshold, the model was considered free from substantial common method bias.

Following the recommendations of Hair et al. (2022), the analysis proceeded in two stages. First, the measurement model was evaluated by examining indicator reliability through outer loadings, internal consistency reliability using Cronbach's alpha, ρ_A , and composite reliability (CR), convergent validity using Average Variance Extracted (AVE), and discriminant validity using the Heterotrait–Monotrait ratio (HTMT). Before evaluating the structural model, the assumption of linear relationships among the latent constructs was examined by testing potential quadratic effects. Following Sarstedt et al (2021), quadratic terms were created for each predictor and estimated within the PLS-SEM framework to determine whether nonlinear relationships provided a significantly better explanation of AI plagiarism intention than the corresponding linear relationships. A non-significant quadratic effect indicates that the assumption of linearity is tenable and that the linear structural model can be retained.

Second, the structural model was evaluated by examining collinearity diagnostics, path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). The significance of both direct and moderating effects was estimated using the bootstrapping procedure with 5,000 resamples. The moderating effect of performance-based goal orientation was estimated using the product indicator approach because all latent constructs were modeled as reflective constructs (Hair et al., 2022).

3. RESULTS AND DISCUSSIONS

3.1 Demographic Characteristics

The table below portrays demographic characteristics of respondents. A total of 214 university students participated in this study. As shown in Table 1, the sample was predominantly female (70.1%, $n = 150$), while male participants accounted for 29.9% ($n = 64$). The average gender code ($M = 1.70$) indicates that female students constituted the majority of respondents.

Regarding educational level, undergraduate students represented the largest proportion of the sample (52.3%, $n = 112$), followed by master's students (42.5%, $n = 91$) and doctoral students (5.1%, $n = 11$). This distribution suggests that the findings primarily reflect the perspectives of undergraduate and postgraduate students who are actively engaged in higher education and are likely to encounter generative AI in their academic activities.

With respect to academic cohort, most respondents entered university in 2024 (57.9%, $n = 124$), followed by the 2022 cohort (15.4%, $n = 33$), the 2023 cohort (14.0%, $n = 30$), and the 2021 cohort (12.6%, $n = 27$). The predominance of relatively recent cohorts indicates that the sample largely comprised students who began their studies during the widespread adoption of generative AI technologies in higher education.

Table 1. Demographic Characteristics

Demographic	Frequency	Percentage (%)	Mean
Gender			1.70
Male	64	29.91	
Female	150	70.01	
Level of study			1.53
Undergraduate	112	52.33	
Master	91	42.52	
Doctoral	11	5.14	
Academic cohort			1.10
2021	27	12.62	
2022	33	15.42	
2023	30	14.02	
2024	124	57.94	

3.2 Descriptive Statistics

Table 2. Descriptive Statistics

	M	SD	1	2	3	4	5	6	7
Gender	1.70	0.46	1						
Level of study	1.53	0.59	- 0.23 **	1					
Academic cohort	3.17	1.10	-.09	.38**	1				
AI-giarism intention	29.53	7.83	-.09	-.38**	-.09	1			
Collectivism	33.02	4.69	-.02	-.14*	-.04	.33**	1		
Individualism	22.28	3.63	-.11	-.26**	-.11	.18**	.28**	1	
Performance-based approach	28. 67	5.0 7	.1 2	- .34**	- .11	.18**	-.35**	-.41**	1

Table 2 presents the descriptive statistics and bivariate correlations among the study variables. AI plagiarism intention showed a significant positive correlation with individualism ($r = .18, p < .01$) and collectivism ($r = .33, p < .01$). Performance-based goal orientation was also positively correlated with AI plagiarism intention ($r = .18, p < .01$), suggesting that students who were more strongly motivated by academic performance were more likely to report intentions to use AI in ways that violate academic integrity.

Regarding the demographic variables, level of study was negatively correlated with AI plagiarism intention ($r = -.38, p < .01$), indicating that students at higher academic levels tended to report lower intentions to engage in AI-assisted plagiarism.

3.3 Measurement Model Evaluation

Measurement model evaluation initially assessed the outer loading of each item. Item below .04 is recommended to be excluded in the structural model evaluation for not being able to actually represent its construct in the research context (Hair et al., 2019). In the first evaluation, we found some items with outer loading below .04: one item of collectivism (0.38), 2 items of individualism (0.37; 0.31), and 8 items in AI-plagiarism intention (0.25-0.36). After excluding them, reliability surpassed 0.7, all outer loadings are above 0.4 and AVE surpassed 0.5 was achieved which can be seen by table 3.

Table 3. outer loading, reliability and AVE

Variable	Outer Loading	Composite Reliability	Reliability (α)	AVE
AI-giarism intention	0.53-0.76	0.84	0.82	0.52
Collectivism	0.51-0.78	0.76	0.73	0.54
Individualism	0.47-0.83	0.76	0.71	0.57
Performance-based approach	0.68– 0.82	0.89	0.86	0.59

Discriminant validity which was assessed by HTMT also indicated good validity where all variables show HTMT values below 0.9 (0.16-0.46). This suggested that all latent variables distinct from one another.

To assess linearity, quadratic effects were carried out and all associations between variables were insignificant ($p > 0.05$), suggested that all variables have linear relationships.

We assessed the risk of common method bias by employing full collinearity test. First, we input random dependent variable scores by inputting command “RAND()” in our raw data sheet. Next, we built a dummy model which put all variables as the predictor to this new random dependent variable. The VIF scores show no collinearity because it ranges from 1.23-1.96, putting in under 3.3. Therefore, it can be concluded that the data has no common method bias risk.

3.4 Structural Model Evaluation

We test our hypotheses by evaluating the structural model and performing bootstrapping with 5,000 sub samples. The results can be seen by the graphical output produced on SmartPLS 4 and. the path coefficient table.

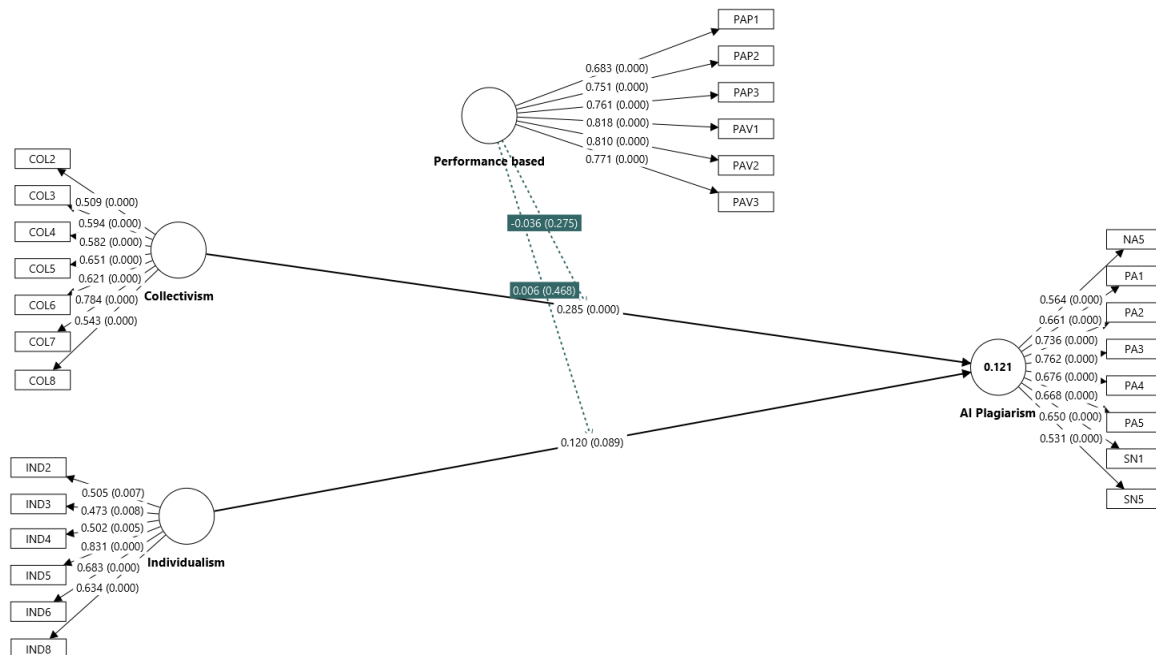


Figure 9. Structural Model Evaluation

Table 4. Path Coefficient

Path	β	T statistics/p value	Confidence interval (95%)		Results
			Lower	Upper	
Individualism→AI plagiarism intention(H1)	0.12	1.41 /0.08	-0.06	0.22	Not supported
Collectivism→AI plagiarism intention(H2)	0.32	4.72/0.00	0.17	0.40	Supported
Performance-based*individualism →AI plagiarism intention(H3)	-0.01	0.01 /0.47	-0.13	0.01	Not supported
Performance-based*collectivism →AI plagiarism intention(H4)	-0.01	0.21/0.41	-.12	0.07	Not supported

Table 4 and figure 1 indicates that among four hypotheses, only hypothesis 2 was supported significantly in this research ($\beta = 0.32$, $t = 4.72$, $p < .001$). The positive coefficient indicates that students with stronger collectivistic orientations were more likely to report higher intentions to engage in AI-assisted plagiarism. In contrast, individualism was not significantly associated with AI plagiarism intention ($\beta = 0.12$, $t = 1.41$, $p = .08$), indicating that Hypothesis 1 was not supported. Likewise, the interaction effect between performance-based goal orientation and individualism on AI plagiarism intention was not statistically significant ($\beta = -0.01$, $t = 0.01$, $p = .47$), leading to inability to support Hypothesis 3. Similarly, the interaction between performance-based goal orientation and collectivism did not significantly predict AI plagiarism intention ($\beta = -0.01$, $t = 0.21$, $p = .41$), indicating that Hypothesis 4 was also not

supported. Overall, the R^2 for the model is 0.12, indicating that 12.1 % of AI plagiarism intention's variance can be explained by the whole model.

Predictive power of our model was justified by running PLS predict to get Q^2 predict relevance and cross-validated predictive ability test (CVPAT) in SmartPLS4. Overall, the model shows good predictive power since the model's Q^2 predict is above 0 ($Q^2 = 0.2$). Additionally, all predictor items in PLS model have less root mean square error (RMSE) and mean absolute error (MAE) compared to the model projected in linear model made in regression.

3.5 Discussion

This study proposed hypotheses based on TPB to investigate the values carried by cultural orientation and individual's performance-oriented motivation are related to student's AI plagiarism intention in higher education institution (HEI). The results are explained below.

This finding suggests that the individualistic cultural orientation may not be sufficient to account for students' intentions to engage in AI-assisted plagiarism. The implication of the result is not that culture is unimportant, but that the psychological meaning of plagiarism itself has changed because of the development of generative AI. Unlike traditional plagiarism, AI-assisted writing falls into an ethically grey area where students often view AI as a legitimate educational tool rather than a way to steal ideas (Chan, 2025). Therefore, the direct effect of individualism on AI plagiarism intention might be distinguished, because students with more individualistic attitudes might not perceive AI-assisted writing as being inconsistent with the notions of originality or personal responsibility. This finding is consistent with the Theory of Planned Behavior (TPB), which conceptualizes cultural values as distal background factors that influence behavioral intention indirectly through attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991, 2011). Therefore, individualistic values are unlikely to predict AI plagiarism intention unless they first shape students' ethical evaluations of AI use or their perceptions of acceptable academic practices. For instance, individualistic students were less susceptible to academic dishonesty when the mindset to prioritize individual's growth holds greater value than just merely gaining good grades (Thomas, 2017).

In many higher education institutions, however, policies governing generative AI remain inconsistent and continue to evolve, allowing students to develop diverse interpretations regarding the legitimacy of AI-assisted writing. Under such conditions, technology-specific beliefs may become more influential than relatively stable cultural values in shaping behavioral intention. The present findings also extend recent discussions on AI-giarism and post-plagiarism. Chan (2025) reported that students increasingly distinguish AI-assisted writing from conventional plagiarism, evaluating AI use according to the extent of human contribution rather than solely on originality or authorship.

The findings revealed a significant positive relationship between collectivism and AI plagiarism intention, supporting Hypothesis 2. This result suggests that students with stronger collectivistic orientations were more likely to report intentions to use generative AI in ways

that violate academic integrity. Although this finding appears counterintuitive given the common assumption that collectivistic values promote cooperation and prosocial behavior, it provides important evidence that the influence of collectivism on AI-assisted plagiarism is primarily shaped by social norms rather than by moral evaluations of the behavior itself.

From the perspective of the Theory of Planned Behavior (Ajzen, 1991, 2011), collectivism represents a cultural background factor that strongly influences subjective norms, namely individuals' perceptions of what important others expect them to do. Individuals with collectivistic orientations generally place greater emphasis on maintaining harmonious interpersonal relationships, fulfilling collective expectations, and conforming to prevailing group practices than on expressing personal preferences (Triandis & Gelfand, 1998). Consequently, when generative AI becomes increasingly normalized within academic communities, students with stronger collectivistic values may become more willing to adopt similar practices because conformity to peer behavior is perceived as socially appropriate. This claim aligns with findings in some collectivist countries like Ethiopia and Nigeria that perceive AI utilization as more of a collaboration, not ethical misconduct (Guadu et al., 2026). In this context, the intention to use AI is likely to be guided less by personal ethical judgments than by perceptions of what classmates, peers, or lecturers implicitly consider acceptable.

The present study found that performance-based goal orientation did not significantly moderate the relationships between individualism and AI plagiarism intention or between collectivism and AI plagiarism intention. Consequently, Hypotheses 3 and 4 were not supported. Although this result differs from previous studies linking performance-oriented goals to academic misconduct, it provides important evidence that performance motivation may not strengthen the influence of cultural orientation on AI plagiarism intention within contemporary higher education.

The proposed moderation of performance-based goal which posits that students with strong performance goals strive to demonstrate competence relative to others and are therefore more likely to adopt strategies that maximize academic success (Elliot & Murayama, 2008). Earlier studies consistently reported that performance-oriented students are more vulnerable to unethical academic behaviors, particularly when academic competition is intense and success is primarily evaluated through grades (Baran & Jonason, 2020; Huang et al., 2024; Krou et al., 2021). Based on this perspective, it was reasonable to expect that performance-based goal orientation would amplify the effects of cultural orientation on AI plagiarism intention.

However, the present findings suggest that this mechanism may not operate in the context of generative AI. One plausible explanation is that AI has become increasingly normalized as an educational technology rather than being viewed solely as a means of academic dishonesty. Recent studies indicate that university students use generative AI for a wide range of purposes, including brainstorming, language editing, summarizing literature, programming assistance, and idea development (Chan, 2025; Dwivedi et al., 2023). Consequently, AI is no longer perceived exclusively as a shortcut for achieving higher grades but also as a legitimate

cognitive support tool that facilitates learning (Hutson, 2024). Under these circumstances, students with both high and low performance-based goals may perceive AI as beneficial, thereby reducing the extent to which achievement motivation differentiates their intentions to engage in AI-assisted plagiarism.

Another explanation concerns the nature of performance-based goals themselves. Achievement Goal Theory explains why students strive for success, but it does not specify how students evaluate the ethical acceptability of the strategies they use to achieve that success (Fritz et al., 2023; Krou et al., 2021). Whether students consider AI-assisted writing to be appropriate depends more directly on their ethical judgments, perceptions of institutional regulations, and subjective norms than on their achievement goals alone. This interpretation is consistent with the Theory of Planned Behavior (Ajzen, 1991), which emphasizes that behavioral intention is primarily determined by attitudes, subjective norms, and perceived behavioral control. Therefore, performance-based goals may influence students' desire to succeed academically, but they may not alter how cultural values are translated into AI plagiarism intention unless they simultaneously shape these proximal cognitive determinants.

4. CONCLUSION

This study examined the relationships between individualism, collectivism, and AI plagiarism intention, as well as the moderating role of performance-based goal orientation among Indonesian university students. The findings revealed that only collectivism was positively associated with AI plagiarism intention, whereas individualism showed no significant relationship. Furthermore, performance-based goal orientation did not moderate the relationships between cultural orientation and AI plagiarism intention. These findings suggest that students' intentions to engage in AI-assisted plagiarism are influenced more by collectivistic values associated with conformity to social expectations than by values emphasizing personal autonomy or achievement motivation.

The present study makes several theoretical contributions to the growing literature on AI plagiarism. First, the findings extend the Theory of Planned Behavior (TPB) by demonstrating that cultural orientation does not uniformly predict AI plagiarism intention. While collectivism appears to remain relevant through its close association with subjective norms, individualism alone was insufficient to explain students' behavioral intentions in AI-mediated learning environments. This finding suggests that the emergence of generative AI has altered the behavioral meaning of plagiarism itself, requiring researchers to reconsider the applicability of theoretical models originally developed for conventional plagiarism. Second, the absence of significant moderating effects indicates that performance-based goal orientation may not function as an important boundary condition in explaining AI plagiarism intention. Instead, the findings imply that AI-specific psychological mechanisms, such as perceived ethical acceptability of AI, AI literacy, institutional AI policies, and subjective norms regarding AI use, may provide stronger explanatory power than traditional achievement motivation

constructs. Consequently, this study contributes to the emerging view that AI plagiarism should be conceptualized as a distinct form of academic misconduct requiring theoretical frameworks that integrate cultural, technological, and contextual influences.

From a practical perspective, the findings highlight that preventing AI plagiarism cannot rely solely on strengthening students' individual responsibility or achievement motivation. Instead, higher education institutions should recognize the importance of social norms in shaping students' AI-related behaviors. Universities should therefore establish clear institutional guidelines regarding acceptable AI use, integrate AI literacy into academic integrity education, and encourage transparent disclosure of AI assistance in academic work. Because students often interpret the ethical acceptability of AI through observations of peers and instructors, consistent communication of institutional expectations and responsible AI practices may be more effective than punitive approaches alone. Developing a shared academic culture surrounding ethical AI use is likely to reduce ambiguity and support responsible adoption of generative AI in higher education.

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference regarding the relationships among the study variables. Longitudinal or experimental studies are needed to examine how students' AI plagiarism intentions evolve as institutional policies and AI technologies continue to develop. Second, data were collected using self-report questionnaires, which may be susceptible to social desirability bias despite procedural and statistical efforts to minimize common method bias. Third, the study focused exclusively on Indonesian university students. Although Indonesia provides an important context because of its predominantly collectivistic culture, caution should be exercised when generalizing the findings to countries with different cultural characteristics or AI governance policies. Finally, although participants were required to have prior experience using generative AI, the study did not directly measure AI literacy or the types of academic assignments for which AI was used. These variables should be considered in future studies.

Future research should move beyond traditional predictors of plagiarism by incorporating AI-specific antecedents that better reflect the evolving educational landscape. Variables such as AI literacy, perceived ethical acceptability of AI-generated content, trust in generative AI, perceived detection risk, institutional AI policy clarity, and descriptive and injunctive norms may provide a more comprehensive explanation of AI plagiarism intention. Comparative cross-cultural studies involving countries with different cultural orientations would further clarify whether collectivism consistently predicts AI plagiarism or whether its influence depends on institutional norms surrounding AI use. Additionally, future studies may investigate more complex mechanisms, including mediation by attitudes or subjective norms within the TPB framework, to better understand how cultural values are translated into AI-related academic behaviors.

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