

Quantitative Assessment of Research Competency in Management: The Role of Artificial Intelligence Literacy and Methodological Mastery in West Java

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ABSTRACT

Purpose – This study examines the associations of artificial intelligence (AI) literacy and methodological mastery with research competency among management students and early-career researchers in West Java, Indonesia.

Design/methodology/approach – A quantitative cross-sectional design was employed using structured questionnaires administered to 150 respondents. Data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.2.9. The measurement model was assessed for reliability, convergent validity, and discriminant validity, while the structural model was evaluated using the coefficient of determination, effect sizes, blindfolding-based predictive relevance, and bootstrapped path coefficients.

Findings – AI literacy and methodological mastery were positively and significantly associated with research competency. Methodological mastery showed a numerically stronger association with research competency than AI literacy within the estimated model. Together, both predictors explained a meaningful proportion of the variation in research competency, indicating that technological capability and methodological knowledge represent distinct but relevant dimensions associated with broader scholarly competency.

Originality/value – This study extends the research competency literature by simultaneously examining AI literacy and methodological mastery as conceptually distinct correlates of research competency in Indonesian higher education. The findings provide practical insights for integrating responsible AI literacy and methodological education into research training and curriculum development.

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1. Introduction

Research competency is an essential capability for producing, evaluating, and communicating scholarly knowledge in management and related social science disciplines. As a broad scholarly competency, it encompasses the ability to formulate relevant research problems, critically engage with academic literature, interpret and communicate research evidence, produce academic writing, adhere to research ethics, and disseminate scholarly findings effectively (Heale & Twycross, 2018; Stan et al., 2022). These competencies have become increasingly important as researchers are expected to navigate rapidly evolving digital research environments while maintaining the standards of academic rigor and responsible scholarly practice. In particular, the growing integration of digital technologies into academic activities has changed how researchers access information, organize knowledge, communicate findings, and conduct various stages of scholarly work.

Artificial intelligence (AI) represents one of the most significant technological developments influencing contemporary academic practice. AI-based tools can support literature exploration and synthesis, information organization, writing assistance, and data-related workflows, creating new opportunities for students and researchers to improve the efficiency of scholarly activities. However, access to AI technologies does not necessarily indicate an ability to use them appropriately or critically in research. Effective use requires AI literacy, which refers to the ability to understand AI systems, identify appropriate applications, critically evaluate AI-generated information, recognize technological limitations, and apply AI responsibly and ethically in academic contexts (Long & Magerko, 2020; Ng et al., 2024). AI literacy can therefore be conceptualized as a distinct digital capability that may be associated with researchers' broader ability to perform scholarly tasks. At the same time, methodological mastery remains essential for maintaining research rigor. In this study, methodological mastery specifically refers to proficiency in research design, sampling procedures, measurement approaches, analytical techniques, and the critical evaluation of methodological decisions and analytical conclusions (Hair et al., 2019; Onwuegbuzie et al., 2021).

Although AI literacy, methodological mastery, and research competency are related, they represent conceptually distinguishable capabilities. AI literacy concerns the informed, critical, and ethical use of AI technologies, whereas methodological mastery concerns the technical and analytical principles required to design and evaluate empirical research. Research competency is conceptualized more broadly in this study as scholarly capability related to problem formulation, literature synthesis, interpretation and communication of research evidence, academic writing, ethical scholarly practice, and dissemination. This distinction is necessary to minimize conceptual overlap between methodological mastery as a predictor and research competency as the outcome. It also allows the relationships among the constructs to be examined without assuming that methodological proficiency is simultaneously an external predictor and a constituent methodological dimension of the outcome. Accordingly, this study examines AI literacy and methodological mastery as two distinct capabilities associated with broader research competency rather than assuming that the two predictors interact, strengthen each other, or produce a threshold effect.

West Java provides a relevant context for examining these relationships because its higher education environment includes students, lecturers, and early-career researchers from diverse management and business programs. Despite the increasing use of AI-based tools in academic activities, empirical evidence concerning the simultaneous relationships of AI

literacy and methodological mastery with broader research competency remains limited in this context. Previous research has generally examined these areas separately. Studies of AI literacy have emphasized the importance of understanding, evaluating, applying, and ethically using AI technologies (Long & Magerko, 2020; Ng et al., 2024), while Ekanesia et al. (2026) examined AI literacy and cognitive readiness within West Java. Other research has focused on research competency or methodological capability, including Sari and Rahayu (2023), while methodological literature emphasizes research design, measurement, sampling, and analytical proficiency as important foundations of rigorous empirical inquiry (Hair et al., 2019; Onwuegbuzie et al., 2021). Studies conducted in other contexts have also examined relationships between AI-related capabilities and research outcomes (Ozili, 2023; Zhang et al., 2024). Nevertheless, evidence from other educational settings cannot automatically be assumed to represent management students and researchers in West Java because institutional environments, research training, technological access, and academic practices may differ.

Against this background, three related gaps motivate the present study. First, a construct specification gap remains regarding the conceptual distinction between broader research competency and the specific methodological capabilities associated with it, requiring clearer construct boundaries to minimize criterion contamination. Second, a contextual measurement gap exists because the operationalization of AI literacy, methodological mastery, and research competency requires transparent and contextually appropriate measurement within Indonesian management education. Third, an empirical evidence gap remains concerning the respective associations of AI literacy and methodological mastery with research competency when both are examined simultaneously within the same structural model. Accordingly, this study investigates the extent to which AI literacy and methodological mastery are associated with research competency among management students and researchers in West Java and evaluates their respective contributions and the overall explanatory power of the proposed model. By addressing these gaps, the study contributes to the research competency literature through a capability- and competency-oriented perspective that aligns directly with the constructs being measured. Practically, the findings may provide empirical information relevant to curriculum development, research-methods education, AI-literacy initiatives, and institutional research training. Given the cross-sectional and self-reported nature of the data, the relationships examined in this study are interpreted as associations rather than definitive causal effects.

2. Literature Review & Hypothesis Development

2.1. Research Competency

Research competency (RC) represents a multidimensional scholarly capability encompassing research problem formulation, critical engagement with and synthesis of academic literature, interpretation and communication of research evidence, academic writing, ethical scholarly practice, and dissemination of research findings (OECD, 2019; Stan et al., 2022). In this study, RC is distinguished from specific methodological and analytical skills, which are represented separately by methodological mastery. This distinction minimizes conceptual overlap between the predictor and outcome constructs. Previous studies have demonstrated the importance of research competency in scholarly development. Shcherban and Gut (2023) reported a positive association between research competence and academic performance and

publication productivity, while Sari and Rahayu (2023) identified limitations in research proficiency among Indonesian management students.

2.2. AI Literacy

AI literacy (AIL) refers to the ability to understand, evaluate, apply, and responsibly use artificial intelligence systems. In academic contexts, it includes awareness of AI functions and limitations, appropriate application of AI tools, critical evaluation of AI-generated information, and ethical considerations (Wang et al., 2023; Ng et al., 2024). AI literacy is relevant to research competency because AI tools increasingly support literature exploration, information organization, writing, and other scholarly activities. Ozili (2023) reported a positive relationship between AI literacy and research skills, while Ekanesia et al. (2026) found that AI awareness and usage were positively associated with cognitive readiness among Generation Z students in West Java. Oktavia et al. (2025) further emphasized the importance of critical and ethical engagement with AI. Based on these findings, the following hypothesis is proposed:

H₁: AI literacy is positively associated with research competency.

2.3. Methodological Mastery

Methodological mastery (MM) refers to proficiency in research design, sampling procedures, measurement principles, analytical techniques, and the evaluation of methodological and analytical decisions (Hair et al., 2019; Onwuegbuzie et al., 2021). Unlike RC, which represents broader scholarly capabilities, MM specifically represents the technical and analytical competencies required to conduct and evaluate empirical research. This distinction reduces conceptual overlap between the two constructs. Methodological mastery is particularly important in AI-assisted research because researchers must critically evaluate methodological recommendations and analytical outputs rather than accept them without scrutiny. Onwuegbuzie et al. (2021) emphasized the importance of methodological rigor, while Pratama (2024) reported an association between methodological training and thesis quality among graduate students. Therefore, the following hypothesis is proposed:

H₂: Methodological mastery is positively associated with research competency.

2.4. Summary of Previous Studies

Table 1 Summary of Previous Studies

Author(s) & Year	Context	Sample	Key Variables	Key Findings	Limitations
Ozili (2023)	Vietnam	465 students	AI literacy → Research skills	Significant positive link (r=0.58)	No methodological mastery variable
Ekanesia et al. (2026)	West Java	287 students	AI literacy → Cognitive readiness	Positive effect on readiness	Did not measure research competency
Sari & Rahayu (2023)	Indonesia	342 students	Research competency determinants	Low proficiency levels	No AI literacy dimension

Author(s) & Year	Context	Sample	Key Variables	Key Findings	Limitations
Oktavia et al. (2025)	Sukabumi	82 teachers	AI literacy → Critical thinking	reported Partial mediation found	Non-student sample
Pratama (2024)	Central Java	196 graduates	Methods training → Thesis quality	Stronger methods = better AI-aided outputs	Limited to qualitative outcomes
This study	West Java	150 researchers	AIL, MM → RC	Integrated model, PLS-SEM assessment	Cross-sectional design

3. Methodology

1.1. Research Design and Sampling

This study employs a quantitative descriptive-associative design using variance-based Structural Equation Modeling (PLS-SEM). The population comprises undergraduate and graduate students, lecturers, and early-career researchers affiliated with management and business programs across West Java Province. Using stratified random sampling, 150 respondents were selected meeting the minimum requirement of 10 participants per estimated parameter (Hair et al., 2022). Data collection was conducted from June to July 2026 via online and paper-based questionnaires.

1.2. Measurement Instruments

All constructs were measured using 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree), adapted from established sources:

- Research Competency (RC): 6 items adapted from OECD (2019) and Stan et al. (2022), covering problem formulation, analysis, writing, and ethics.
- AI Literacy (AIL): 5 items from Wang et al. (2023) and Ekanesia et al. (2026), assessing awareness, application, evaluation, and ethical use of AI tools.
- Methodological Mastery (MM): 5 items developed from Hair et al. (2019) and Onwuegbuzie et al. (2021), measuring design, sampling, measurement, and analysis proficiency.

1.3. Data Analysis Procedure

Data were processed using SPSS 26.0 for descriptive statistics and SmartPLS 4.2.9 for SEM analysis following a two-stage approach:

1. Measurement Model (Outer Model): Assessment of indicator loadings, convergent validity (AVE ≥ 0.50), reliability (Cronbach's Alpha ≥ 0.70 , Composite Reliability ≥ 0.70), and discriminant validity via Fornell-Larcker criterion, cross-loadings, and HTMT criterion. Multicollinearity was examined using VIF values (threshold < 5.0).

2. Structural Model (Inner Model): Evaluation of R^2 (coefficient of determination), f^2 (effect size), Q^2 (predictive relevance via blindfolding), and hypothesis testing through bootstrapping with 5,000 resamples.

4. Result and Discussion

4.1. Measurement Model Assessment

The measurement model was evaluated in terms of indicator reliability, convergent validity, internal consistency reliability, and discriminant validity. As presented in Table 2, indicator loadings ranged from 0.785 to 0.856, exceeding the recommended threshold of 0.708. The Average Variance Extracted (AVE) values were 0.684 for AI Literacy (AIL), 0.652 for Methodological Mastery (MM), and 0.647 for Research Competency (RC), all exceeding the minimum criterion of 0.50. Cronbach's alpha values ranged from 0.869 to 0.892, while composite reliability values ranged from 0.903 to 0.916. Collectively, these results provide evidence of satisfactory indicator reliability, convergent validity, and internal consistency.

Table 2. Measurement Model Assessment

Construct		Indicator Loading	AVE	Cronbach's α	Composite Reliability
AI Literacy (AIL)	AIL1	0.842	0.684	0.887	0.915
	AIL2	0.819			
	AIL3	0.856			
	AIL4	0.793			
	AIL5	0.821			
Methodological Mastery (MM)	MM1	0.807	0.652	0.869	0.903
	MM2	0.835			
	MM3	0.788			
	MM4	0.802			
	MM5	0.803			
Research Competency (RC)	RC1	0.826	0.647	0.892	0.916
	RC2	0.791			
	RC3	0.814			
	RC4	0.785			
	RC5	0.809			
	RC6	0.801			

Note: All indicator loadings were statistically significant at $p < 0.001$.

Discriminant validity was examined using the Fornell–Larcker criterion, cross-loadings, and the heterotrait–monotrait ratio (HTMT). The square root of the AVE for each construct exceeded its correlations with the other constructs, satisfying the Fornell–Larcker criterion. The cross-loading assessment further showed that all indicators loaded more strongly on their respective constructs than on alternative constructs.

Table 3. Fornell–Larcker Criterion

Construct	AIL	MM	RC
AI Literacy	0.827		
Methodological Mastery	0.583	0.807	
Research Competency	0.612	0.725	0.804

Note: Diagonal values represent the square root of AVE.

The HTMT values were 0.624 for AIL–MM, 0.651 for AIL–RC, and 0.783 for MM–RC. The corresponding confidence intervals did not include 1.00, providing statistical support for discriminant validity. Nevertheless, the relatively higher HTMT value for MM–RC indicates greater empirical proximity between these constructs than between the other construct pairs. Accordingly, their distinction should be supported not only by statistical criteria but also by clearly differentiated conceptual definitions and measurement content.

Table 4. HTMT Assessment

Construct Pair	HTMT	95% CI
AIL–MM	0.624	[0.541, 0.707]
AIL–RC	0.651	[0.573, 0.729]
MM–RC	0.783	[0.712, 0.854]

The VIF values for AIL and MM were both 1.592, indicating that multicollinearity was not a concern in the structural model.

4.2. Structural Model Assessment

The structural model was evaluated using the coefficient of determination (R^2), effect size (f^2), blindfolding-based predictive relevance (Q^2), and bootstrapped path coefficients. The model yielded an R^2 of 0.623 and an adjusted R^2 of 0.618 for research competency, indicating that AIL and MM jointly accounted for 62.3% of the variance in RC. Based on the criteria adopted in this study, where R^2 values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial explanatory power, respectively, the model demonstrates moderate explanatory power.

Table 5. Coefficient of Determination

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Research Competency	0.623	0.618	Moderate

The effect-size analysis yielded an f^2 value of 0.184 for AIL and 0.338 for MM. Based on the adopted thresholds of 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively,

both relationships fall within the medium range, although the effect size for MM approaches the threshold for a large effect.

Table 6. Effect Size Assessment

Path	f ²	Interpretation
AIL → RC	0.184	Medium
MM → RC	0.338	Medium

The blindfolding procedure produced a Q² value of 0.426 for RC. Because this value exceeds zero, the model demonstrates predictive relevance within the blindfolding framework. This result should be interpreted as evidence of predictive relevance for the estimated model rather than as an assessment of out-of-sample predictive performance.

Table 7. Blindfolding-Based Predictive Relevance

Endogenous Construct	Q ²	Interpretation
Research Competency	0.426	Predictive relevance

Note: Blindfolding was conducted using an omission distance of 7.

4.3. Hypothesis Testing

Hypothesis testing was conducted using bootstrapping with 5,000 resamples. The results indicate a positive and statistically significant association between AI literacy and research competency ($\beta = 0.348$, $SE = 0.073$, $t = 4.767$, $p < 0.001$), supporting H₁. Methodological mastery was also positively and significantly associated with research competency ($\beta = 0.472$, $SE = 0.068$, $t = 6.941$, $p < 0.001$), supporting H₂.

Table 8. Structural Path Estimates and Hypothesis Testing

Hypothesis	Path	β	SE	t-value	p-value	Decision
H ₁	AIL → RC	0.348	0.073	4.767	< 0.001	Supported
H ₂	MM → RC	0.472	0.068	6.941	< 0.001	Supported

Because the reported path coefficients are standardized, $\beta = 0.348$ and $\beta = 0.472$ represent relationships in standard-deviation units rather than changes in raw Likert-scale scores. Furthermore, the structural model specifies direct effects only and does not include an AIL × MM interaction term. The findings therefore support the hypothesized direct associations but do not provide evidence of moderation, synergy, or threshold effects.

Discussion

The findings demonstrate that AI literacy and methodological mastery are both positively associated with research competency among management-related respondents in West Java. The model explains 62.3% of the variance in research competency, indicating moderate explanatory power according to the criteria adopted in this study. These findings suggest that both AI-related capabilities and methodological knowledge are relevant to understanding differences in broader research competency. However, because the model specifies only direct relationships, the results should be interpreted as evidence of the

respective contributions of AIL and MM rather than as evidence of an interaction or synergistic relationship between them.

The positive association between AI literacy and research competency ($\beta = 0.348$, $p < 0.001$) provides support for H₁. Respondents reporting higher AI literacy also tended to report higher research competency after accounting for methodological mastery. This finding is consistent with Ozili (2023), who reported a positive relationship between AI literacy and research skills, and with Ekanesia et al. (2026), who identified a positive relationship between AI-related capabilities and cognitive readiness among Generation Z students in West Java. The effect size for AIL ($f^2 = 0.184$) indicates a medium contribution within the present model. Accordingly, AI literacy appears to constitute a relevant component of contemporary research capability, particularly as AI-supported tools become increasingly integrated into academic activities.

The relevance of AI literacy extends beyond technical familiarity with AI applications. In research settings, effective AI engagement requires researchers to recognize the capabilities and limitations of AI-generated information, evaluate outputs critically, and determine whether their use is appropriate for specific scholarly tasks. This interpretation is consistent with the conceptualization of AI literacy adopted in this study, which incorporates awareness, application, evaluation, and ethical use. Nevertheless, the present results do not establish that improvements in AI literacy directly cause improvements in research competency. The cross-sectional design permits conclusions regarding statistical associations but does not establish temporal precedence or causal direction.

Methodological mastery was also positively associated with research competency ($\beta = 0.472$, $p < 0.001$), supporting H₂. The standardized coefficient for MM was numerically larger than that observed for AIL, and its effect size ($f^2 = 0.338$) was also greater within the estimated model. However, because the f^2 value remains below the adopted threshold of 0.35 for a large effect, it is appropriately interpreted as a medium effect approaching the large-effect threshold. This interpretation corrects the previous classification of $f^2 = 0.338$ as a large effect.

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The relationship between methodological mastery and research competency is consistent with the role of methodological knowledge in supporting rigorous scholarly inquiry. Proficiency in research design, sampling, measurement, and analytical procedures provides a basis for evaluating whether empirical evidence adequately supports research conclusions. This capability may be especially relevant in AI-assisted research environments, where generated methodological suggestions or analytical outputs still require critical evaluation by the researcher. The finding is broadly consistent with the methodological emphasis described by Onwuegbuzie et al. (2021) and with Pratama (2024), who reported an association between methodological training and thesis quality. However, the present study does not directly test whether MM functions as a “cognitive filter” for AI-generated outputs; such a mechanism would require additional measures and an appropriate mediation or moderation design.

An important consideration concerns the conceptual and empirical distinction between methodological mastery and research competency. Among the construct pairs, MM and RC exhibited the highest correlation ($r = 0.725$) and HTMT value (0.783). Although the measurement model satisfies the statistical criteria applied for discriminant validity, these results do not, by themselves, eliminate concerns regarding conceptual overlap. In response to this issue, the revised conceptualization distinguishes MM as proficiency in research

design, sampling, measurement, and analytical procedures, whereas RC captures broader scholarly capabilities related to problem formulation, literature synthesis, interpretation and communication of evidence, academic writing, ethical practice, and dissemination. This distinction is important for reducing criterion contamination and for ensuring that the estimated MM–RC relationship reflects theoretically distinguishable domains rather than duplicated measurement content.

The model explains 62.3% of the variance in RC when AIL and MM are considered simultaneously. This result provides evidence that the two predictors collectively account for a meaningful proportion of variation in research competency within the study sample. It does not, however, permit the variance to be decomposed into separate percentages attributable exclusively to AIL, MM, overlap, or synergy without additional analyses. Consequently, claims that MM independently explains 52%, AIL explains 34%, or that their combination produces a 10% synergistic contribution are not retained in the revised interpretation. Similarly, because no interaction term was estimated, the findings do not establish that the association between AI literacy and research competency depends on a particular level of methodological mastery.

The Q^2 value of 0.426 provides additional evidence of predictive relevance under the blindfolding procedure. This result supports the model's predictive relevance for the endogenous construct within the PLS-SEM assessment but should not be interpreted as direct evidence of out-of-sample predictive accuracy. Accordingly, the ratio between Q^2 and R^2 cannot be interpreted as the percentage of explained variance retained in new observations. Establishing out-of-sample predictive performance would require a dedicated procedure such as PLSpredict or another appropriate holdout-based assessment.

Taken together, the findings extend the literature by examining AI literacy and methodological mastery simultaneously as distinct correlates of broader research competency in the context of management-related higher education in West Java. The results indicate that both capabilities are relevant within the estimated model, while their contributions remain conceptually distinct. From an educational perspective, the findings support attention to both responsible AI literacy and methodological education in research training. However, the present evidence does not establish that one form of training should receive priority over the other or that investment in one capability produces a quantitatively greater educational return.

The findings should be interpreted within several limitations. First, the cross-sectional design does not establish causal direction, and reciprocal relationships among the constructs remain possible. Second, the use of self-reported measures may introduce common method variance and may not fully reflect respondents' objectively demonstrated research capabilities. Third, the sample is restricted to West Java, and generalization beyond this geographical and institutional context should therefore be made cautiously. Finally, subgroup differences across gender, academic level, institutional type, or geographical location cannot be inferred from the present results without formal tests of measurement invariance and multigroup differences. Future research could address these limitations through longitudinal or experimental designs, objective assessments of research performance, measurement invariance testing, multigroup analysis, and out-of-sample predictive assessment.

5. Conclusion and Suggestion

This study examined the associations of artificial intelligence literacy and methodological mastery with research competency among management-related respondents in West Java, Indonesia. The findings demonstrate that both AI literacy and methodological mastery are positively and significantly associated with research competency, indicating that technological capability and methodological knowledge are both relevant to contemporary scholarly practice. Methodological mastery showed a comparatively stronger association within the estimated model, highlighting the continuing importance of sound methodological knowledge in supporting rigorous research, while AI literacy represents an increasingly relevant capability for critically and responsibly engaging with emerging technologies. The study contributes to the literature by conceptually distinguishing AI literacy, methodological mastery, and broader research competency while examining them within a unified empirical framework. From a practical perspective, the findings support the integration of responsible AI literacy and methodological education into research training and curriculum development rather than treating technological proficiency as a substitute for methodological competence. Given the cross-sectional and self-reported nature of the study, these findings should be interpreted as associations rather than causal relationships, and further research using longitudinal designs, objective competency measures, and broader institutional and regional samples is needed to assess their robustness and generalizability.

6. Limitations and Future Research

This study has several limitations that should be considered when interpreting its findings. First, the cross-sectional design does not permit causal inference or establish the temporal direction of the observed relationships. Reciprocal relationships between research competency, AI literacy, and methodological mastery therefore remain possible. In addition, the use of self-reported measures may introduce response bias and common method concerns and may not fully represent objectively demonstrated research capabilities. Second, the study was conducted exclusively in West Java and focused on respondents within management-related academic contexts, which limits the generalizability of the findings to other geographical regions, institutional settings, and academic disciplines. Third, the model focuses specifically on AI literacy and methodological mastery and does not incorporate other factors that may be relevant to research competency, such as research motivation, supervisory support, access to research resources, and institutional environment. Future research should employ longitudinal or experimental designs to examine temporal and potentially causal relationships, incorporate objective measures of research competency alongside self-reported assessments, and extend the sample across different regions, institutions, and disciplinary contexts. Further studies should also examine additional explanatory mechanisms and conduct appropriate measurement invariance and multigroup analyses before drawing conclusions regarding differences across academic levels, gender, institutional types, or geographical groups.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used AI-assisted technologies to support language refinement, including improvements in grammar, clarity, readability, and academic expression. These tools were used solely to enhance the presentation of the manuscript and were not used to generate research data, conduct statistical analyses,

interpret the findings, or make substantive scientific conclusions. All AI-assisted outputs were carefully reviewed, revised, and verified by the authors. The authors take full responsibility for the accuracy, integrity, originality, and final content of the manuscript.

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