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Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills

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Abstract

Purposes: The precipitous integration of Artificial Intelligence (AI) into educational frameworks has precipitated concerns regarding cognitive offloading, potentially eroding students' critical faculties. This study investigates the synergistic efficacy of GASING pedagogy—a concrete-based instructional method—coupled with AI assistance in augmenting mathematical creativity and problem-solving proficiency. Specifically, it scrutinizes the mediating role of learning motivation within this hybrid learning ecosystem.
Method: Employing an explanatory sequential mixed methods design, this research synthesized quantitative and qualitative paradigms. Quantitative data were harvested from [Jumlah Siswa] students and subjected to Partial Least Squares Structural Equation Modelling (PLS-SEM) to rigorously test hypothesized structural relationships. Subsequently, a thematic analysis of in-depth interviews and classroom observations was conducted to elucidate the underlying cognitive mechanisms driving the statistical outcomes.
Findings: : Empirical evidence reveals that the GASING-AI nexus significantly bolsters learning motivation, which functions as a robust antecedent to mathematical creativity. The qualitative synthesis identifies "The Creativity-Mediated Cognitive Breakthrough Mechanism," positing that problem-solving competence is not a mere byproduct of technological access but is contingent upon full mediation by creativity. The findings demonstrate that GASING effectively ameliorates extraneous cognitive load (the "Easy" factor), while AI operates as a "Socratic Partner" to catalyse divergent thinking (the "Fun" factor), thereby empowering students to validate algorithmic outputs through rigorous human logic.
Significance: This inquiry challenges the prevailing pessimistic discourse on AI dependency by advocating for a "distributed cognition" framework. Theoretically, it establishes creativity as an indispensable gatekeeper in the realm of digital mathematics pedagogy. Practically, it delineates a validated "High-Tech, High-Touch" protocol for educators, underscoring that the amalgamation of GASING's humanistic logic with AI's adaptability is imperative for cultivating resilient, adaptive problem solvers in the digital era.

INTRODUCTION

Mathematics education currently confronts a critical juncture. Global exigencies have transcended mere procedural numeracy—tasks now readily executed by machines—and shifted toward mathematical creativity and robust problem-solving skills(Rahmi et al., 2025; Schoenfeld, 2020). Creativity is requisite for perceiving patterns through multifaceted perspectives, while problem-solving functions as the logical execution of such ideations. However, empirical reality reveals a state of stagnation; students frequently encounter cognitive overload precipitated by rigid, mechanistic conventional instructional methods(Tran & O'Connor, 2024). Absent appropriate pedagogical intervention, mathematics is reduced to a repertoire of procedures that burden the working memory, thereby inhibiting the capacity for adaptive reasoning within complex, real-world contexts(Mathematics & Project, 2011).

The primary justification for this inquiry responds to academic concerns regarding the phenomenon of cognitive offloading—the propensity of students to abdicate the cognitive process entirely to technological surrogates(Peng & Yeh, 2025; Todorov et al., 2018; Zhang et al., 2024). If left unmitigated, the integration of AI within the classroom risks fostering an intellectually passive generation. Consequently, there is an exigent need for instructional strategies that position AI not as a cognitive substitute, but as a partner in distributed cognition(Indah et al., 2025; Rosanti et al., 2024). This research contends that to cultivate resilient problem solvers, an approach must be adopted that equilibrates the sophistication of AI features with a robust foundation of human logic(Payadnya et al., 2025). Mastering this synergy is imperative to equip students with data-driven and logical decision-making competencies, which constitute the primary currency in the Industry 5.0 era(Pickering et al., 2025; Schwartz et al., 2018).

While the potential of technology in education has been extensively scrutinized, a significant lacuna persists in the literature concerning the equilibrium between "High-Tech" (advanced technology) and "High-Touch" (humanistic pedagogical engagement). The majority of extant research tends to be bifurcated: focusing exclusively on the efficacy of AI tools or on manual instructional methods in isolation, without investigating their interaction. Specifically, there remains a dearth of empirical evidence regarding how GASING Pedagogy (Easy, Fun, and Enjoyable)—a localized method proven to attenuate mathematics anxiety—can operate synergistically with AI systems to mitigate cognitive load(Morrison et al., 2026). Furthermore, few mixed-methods studies have explored the role of creativity as a mental bridge between learning motivation and technical problem-solving capabilities within a unified conceptual framework.

This research offers a fundamental novelty by reconciling the concrete pedagogy of GASING with adaptive AI technology, an integration that transcends prior studies which frequently view technology as a mere catalyst for cognitive offloading(Peng & Yeh, 2025; Todorov et al., 2018). Diverging from conventional approaches, this study proposes a novel theoretical framework, *The Creativity-Mediated Cognitive Breakthrough Mechanism*, which substantiates that creativity is a critical mediator that must be activated by learning motivation through mastery experiences before students can resolve complex problems(Keha et al., 2024; Speckens et al., 2018). Methodologically, this study employs an explanatory sequential mixed-methods design, utilizing SmartPLS analysis to empirically validate how this High-Touch and High-Tech synergy significantly reduces cognitive load. The research novelty also resides in the redefinition of AI as a dialectical partner (distributed cognition) that expands students' mental capacity for divergent thinking, rather than serving as a mere instant-answer engine. By elevating an indigenous Indonesian method into the global technological discourse, this study addresses the literature gap regarding hybrid learning models that balance digital visualization with concrete logical foundations(Feriyadi et al., 2025; Gagliani Caputo et al., 2025). Ultimately, these findings formulate a validated intervention protocol ensuring that technological integration yields problem solvers who are adaptive, creative, and mentally resilient.

The primary objective of this research is to provide an in-depth analysis of the influence of integrating GASING pedagogy and AI on the enhancement of mathematical creativity and student problem-solving skills, with learning motivation as the primary driving factor(Morrison et al., 2026; Walkington et al., 2025). Specifically, this study aims to test the validity of *The Creativity-Mediated Cognitive Breakthrough Mechanism* using SmartPLS to examine both the direct and indirect effects of the AI-GASING synergy(Ndiung et al., 2021). Furthermore, through thematic analysis, this inquiry seeks to explore the mental mechanisms students employ when transitioning creative ideas into valid logical solutions. The central focus is to demonstrate that an "Easy and Fun" learning environment is an absolute prerequisite for the emergence of high-level cognitive competencies.

Amidst the rapid advancement of Generative AI, the urgency to reform mathematics instruction has become critical. The preeminent risk at present is not students' technological illiteracy, but rather their inability to verify the veracity of technological outputs. Integrating AI into GASING pedagogy is not merely a methodological experiment; it is a strategic maneuver to establish a "safe-to-fail" environment. The urgency of this research lies in early mitigation efforts to ensure students do not succumb to an "instant" mindset but instead develop into critical thinkers capable of leveraging AI to broaden their problem-solving horizons.

This research provides a dual contribution to the advancement of mathematical education science. Theoretically, the findings enrich the literature on Constructivism in the Digital Age and Cognitive Load Theory by demonstrating that creativity is an irreplaceable mediating variable in technology-based learning. Practically, these results offer a guided protocol for educators to implement effective blended learning, where GASING logic serves as the foundation and AI acts as the accelerator. The methodological contribution entails the provision of a validated PLS-SEM-based evaluation instrument to simultaneously measure the efficacy of technological integration on students' cognitive and affective performance.

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design(Creswell, 2002). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves the collection and analysis of quantitative data utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships between variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviors that underpin the statistical findings of the first phase.

Participants

The participants for this research consist of 120 secondary school students selected through a cluster random sampling technique. All students engaged in mathematics instruction focusing on topics necessitated by pattern exploration and logical reasoning. These topics were prioritized due to their flexible characteristics in accommodating AI assistants to facilitate autonomous discovery learning and creative experimentation.

From the total quantitative sample, a purposive sub-sample of 8 students was selected for the qualitative interview stage. Sub-sample selection followed an Extreme Case Sampling strategy based on Problem-Solving Skills scores, comprising 4 students with high proficiency and 4 students with low proficiency. The selection of these two extreme poles aimed to achieve maximum variation in data concerning how AI assistants function optimally as creativity triggers for high-ability students, as well as their function as "scaffolding" (safety nets) for students susceptible to cognitive barriers.

Intervention Procedure: GASING-AI Integration

The intervention was implemented over a six-week duration (12 sessions), following the cyclic flow of GASING pedagogy integrated with adaptive AI assistants. This design emphasizes the transition from concrete understanding to digital abstraction, delineated into three primary phases:

- **Phase 1: Concrete Foundation (The *Gampang* Step).** Educators present mathematical concepts using the concrete GASING approach. AI assistants are utilized to provide instantaneous visualizations that simplify abstract complexities into an "Easy" (*Gampang*) and comprehensible form.
- **Phase 2: Adaptive Exploration (The *Asyik* Step).** Students interact with AI tutors that provide adaptive problem challenges. The AI functions as a dialogic partner providing tiered scaffolding, ensuring the exploratory process remains "Fun" (*Asyik*) without inducing frustration.
- **Phase 3: Creative Synthesis (The *Menyenangkan* Step).** Students are encouraged to generate unique solutions (creativity) to non-routine problems. The successful resolution of problems through autonomous logic cultivates an "Enjoyable" (*Menyenangkan*) learning experience.

Data Collection Instruments

This research utilizes four primary instruments adapted from prominent literature, which have undergone expert judgment for content validity and factor analysis for construct validity. All items are assessed using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

- **AI-GASING Synergy Scale:** A composite instrument designed to measure student perceptions of the integration of AI visualization features and GASING logical simplification in mitigating cognitive load.

- **Learning Motivation Scale:** Measures students' intrinsic drive and self-efficacy derived from mastery experiences during the instructional process.
- **Mathematical Creativity Test:** An open-ended essay instrument to evaluate three dimensions of creativity: fluency, flexibility, and originality.
- **Problem-Solving Proficiency Test:** A diagnostic assessment to measure students' capacity to comprehend problems, formulate strategies, execute plans, and verify solutions (metacognition).

Tabel 1 Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI-GASING Synergy	Cognitive Load Theory (Sweller, 2011); TAM (Davis, 2002)	Student perceptions of how AI visualization and GASING procedural steps collaboratively mitigate mental effort and facilitate the comprehension of abstract concepts.	"GASING's incremental steps assist my logical understanding, while AI visualizations enable me to perceive abstract forms concretely".	5
Learning Motivation (Mediator)	Social Cognitive Theory (Bandura, 1997) – Mastery Experience	Self-efficacy and academic enthusiasm emerging from the accumulation of incremental successes (*small wins*) in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems because I possess the strategies to decompose them into manageable components".	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950); Domain-Specific Creativity (Mann, 2006)	The cognitive capacity to generate manifold alternative solutions (*fluency*), adapt diverse strategies (*flexibility*), and formulate unique methodologies (*originality*).	"I utilize AI-generated cues to develop 2–3 distinct methodologies for solving a single problem".	4
Problem-Solving Skills	Polya's Heuristics (Polya, 1978); Metacognition (Schoenfeld, 1992)	The systematic ability to synthesize ideas into valid solutions, including the capacity for critical evaluative	"I refrain from merely duplicating AI-generated responses; instead, I verify their veracity through my	4

	reflection (*Looking Back*) upon outcomes.	own computational logic".

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data analysis is conducted employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, facilitated by SmartPLS 4.0 software. This methodology was selected for its robustness in handling complex path models—specifically incorporating Mathematical Creativity as a mediating variable—while accommodating relatively modest sample sizes and bypassing stringent multivariate normality assumptions (Hair et al., 2017). The model evaluation proceeds through two systematic stages:

- **Measurement Model (Outer Model):** To assess convergent validity (via Loading Factors > 0.708 and AVE > 0.5), discriminant validity (via Fornell-Larcker criteria or HTMT < 0.9), and composite reliability (Cronbach's Alpha and Composite Reliability > 0.7), thereby ensuring that the AI-GASING, Creativity, and Problem-Solving instruments are psychometrically sound.
- **Structural Model (Inner Model):** To examine hypotheses regarding the influence of AI-GASING integration on Mathematical Creativity and its subsequent impact on Problem-Solving Skills. This involves reviewing the significance of path coefficients (β), coefficients of determination (R^2), and predictive relevance (Q^2) through rigorous bootstrapping and blindfolding procedures.

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and observations of AI utilization are analyzed using Thematic Analysis (Braun & Clarke, 2012). Interview transcripts undergo inductive coding to identify patterns in student responses toward the "Easy, Fun, and Enjoyable" elements within the AI-augmented learning environment. The analysis focuses predominantly on how adaptive AI assistance triggers "creative moments," enabling students to transcend cognitive impasses during the problem-solving process.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in the Integration Table in the Results section).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously; rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption (β = 0.712) and Learning Motivation (β = 0.802). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity (β = 0.514) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity (β = 0.343) and Learning Motivation (β = 0.510) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

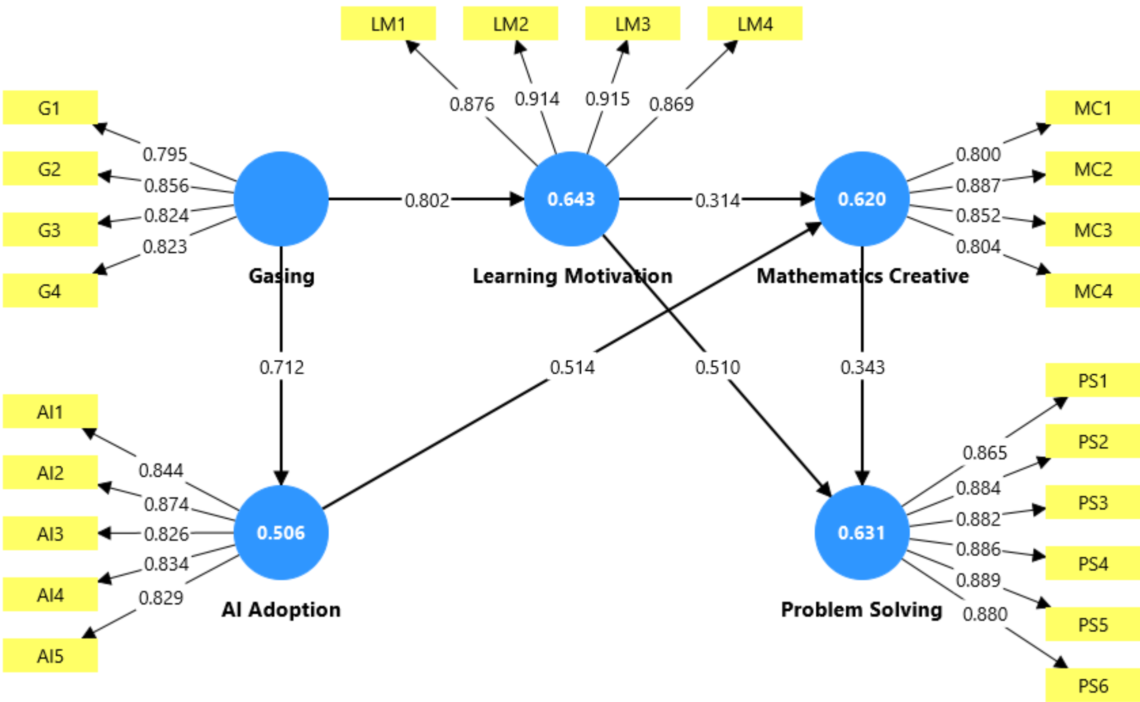

Figure 2 Structural Model of AI-GASING Integration Framework

Quantitative Data

The empirical evidence presented in Table 2 affirms that the research instruments exhibit high precision in capturing the psychological and technical phenomena pertinent to the subjects. Each indicator demonstrates an Outer Loading (OL) exceeding 0.70, with values ranging from 0.795 to 0.915; this substantiates robust convergent validity at the indicator level. The reliability of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients exceeding 0.80, collectively signifying excellent internal consistency.

Subsequently, an evaluation of the structural model was conducted to examine the significance of the hypotheses regarding the latent variables. In addition to p-value significance, the f^2 effect sizes were calculated to ascertain the practical relevance of each path. The trajectory from GASING Pedagogy to Learning Motivation demonstrates an exceptionally large effect size ($f^2 = 1.804$), indicating that the "Easy-Fun" (*Gampang-Asyik-Menyenangkan*) approach fundamentally constructs student learning motivation. Furthermore, GASING is proven to be a potent catalyst for AI Adoption ($f^2 = 1.026$). Regarding competency outcomes, Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$) emerge as significant predictors of Problem Solving. A comprehensive summary of the measurement model evaluation is encapsulated in **Table 2**.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The empirical results delineated in Table 2 demonstrate that all constructs within this integrative framework have been measured with high precision and consistency. Robust Outer Loading (OL) values, ranging from 0.795 to 0.915, fortify the convergent validity of each indicator, most notably within the GASING Pedagogy and Learning Motivation constructs. Furthermore, the elevated reliability indices—characterized by Composite Reliability (CR) and Cronbach's alpha (alpha) values that comprehensively exceed the 0.80 threshold—confirm superior internal consistency across all investigated variables.

Discriminant validity was subsequently evaluated employing the Fornell–Larcker criterion to ensure that each construct is empirically distinct. According to the results presented in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (as indicated on the principal diagonal) is higher than its correlations with other variables in the model. This substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving measure unique and separate dimensions of the developed instructional model, as encapsulated in **Table 3.**

Table 3. Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			
Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

These results confirm the discriminant validity of the model; for instance, Learning Motivation (AVE = 0.894) is statistically distinct from GASING ($r = 0.802$) and AI Adoption ($r = 0.797$). This differentiation is paramount as it validates the mediating roles of the motivation and creativity variables within the framework. Absent sufficient discriminant validity, construct overlap could potentially bias the interpretation of the mediating effects.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation ($\beta = 0.802$) and a robust effect on AI Adoption ($\beta = 0.712$). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity ($\beta = 0.514$). Furthermore, Learning Motivation significantly predicts Problem Solving ($\beta = 0.510$) and contributes to Mathematical Creativity ($\beta = 0.314$). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity ($\beta = 0.343$).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% of the variance in AI Adoption, 62.0% of the variance in Mathematical Creativity, and 63.1% of the variance in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	0.000	1.026	Supported
GASING →Learning Motivation	0.802	40.981	0.000	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	0.000	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	0.000	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	0.000	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	0.000	0.152	Supported

The model fit indices confirm the adequacy of the framework proposed in this study. To evaluate the explanatory power and predictive relevance of the structural model, we report the R^2 values at the construct level alongside the Stone–Geisser Q^2 values (obtained through a blindfolding procedure with an omission distance of $d = 7$).

The analysis results indicate that the model possesses robust explanatory power, particularly for the variables of Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), where over 60% of the variance in both constructs is accounted for by the model. The Mathematical Creativity variable also exhibits significant explanatory power with an $R^2= 0.620$, followed by AI Adoption at 0.506. Furthermore, all endogenous variables demonstrate Q^2 values substantially above zero, ranging from 0.445 to 0.641, thereby confirming that the model maintains large predictive relevance. A comprehensive summary of these explanatory power and predictive relevance indices is presented in Table 5.

Table 5. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	**R^2**	**Q^2**	**Q^2 Interpretation**
AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

This study successfully addresses the primary research inquiry by demonstrating that students' mathematical problem-solving competencies are not influenced by technology in isolation, but rather through an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption is proven to establish intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. These findings affirm that the successful implementation of AI in the mathematics classroom is profoundly contingent upon a pedagogical foundation capable of reducing students' mental barriers prior to the introduction of technology(Azma, 2024; Payadnya et al., 2025; Walkington et al., 2025).

Theoretically, this research advances Cognitive Load Theory within a digital milieu. The most robust path from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size ($f^2= 1.804$), validates that GASING-style problem decomposition is a crucial prerequisite for establishing "motivational readiness." Furthermore, the role of AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition. AI is no longer perceived merely as a computational tool but as a "cognitive partner" shielded from social judgment, thereby enabling students to engage in more radical and original ideational exploration without the debilitating fear of failure(Günther, 2025).

The data analysis reveals a logical consistency between motivation and creativity in catalyzing high-level competencies. The finding that Mathematical Creativity constitutes a pivotal component in Problem Solving ($\beta = 0.343$) elucidates why a mere "will learn" is insufficient for resolving non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability ($R^2 = 0.631$), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments. Nonetheless, the internal consistency of the data guarantees the validity of these findings within the context of modern techno-pedagogical integration(Daniel et al., 2023; Martínez-Gómez & Nicolalde, 2025).

Based on the generated empirical evidence, several concrete measures are recommended for stakeholders. For educators, it is imperative not to circumvent the "Easy" (*Gampang*) phase of the instructional process; practitioners must prioritize the GASING method to cultivate student self-efficacy and intrinsic motivation as a psychological bedrock before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies(Al-khresheh, 2024; Deriba & Sanusi, 2025; Vidyastuti & Inganah, 2023).

Qualitative Data

Qualitative analysis was conducted to investigate the underlying cognitive mechanisms governing the robust statistical correlations observed between AI-GASING Integration, Mathematical Creativity, and Problem-Solving Skills. Through a thematic analysis of interview transcripts and classroom observations, three cardinal themes operating in a sequential trajectory were identified: (1) The "Gampang" De-escalation (Cognitive De-escalation), (2) AI-Triggered Divergence, and (3) Iterative Problem-Solving Synthesis.

The synthesis of these qualitative findings is delineated in Table 6, which maps the instructional stages of AI-GASING against student responses and their corresponding theoretical interpretations.

Tabel 6 Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	GASING Phase & Problem Context	Empirical Evidence (Student Verbatim)	Theoretical Mechanism
Theme 1: The "Gampang" De-escalation	**Phase:** Concrete Foundation (Step 1)	"Usually, when I see stacked geometric figures, I give up immediately because it's dizzying to imagine. But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple. I felt, 'Oh, I can actually do this.'"	**Cognitive Load Reduction:** The synergy of AI visualization and GASING's concrete instruction lowers cognitive load. Student perception shifts from "Math is complex" to "It's actually easy." This sense of Self-Efficacy serves as the entry point that encourages student engagement.

(Related Variables: GASING & Self-Efficacy)	**Context:** Complex 3D Geometry problems (typically perceived as intimidating).	*(Student S-02, High Self-Efficacy)*	
Theme 2: AI-Triggered Divergence	**Phase:** Adaptive Exploration (Step 2)	"I asked the AI: 'Is there any other way besides the textbook formula?'. The AI gave clues about net patterns. From there, I thought of three different ways: using the standard formula, digital cut-and-paste, and pattern estimation. It was so exciting (*Asyik*) to find my own way."	**Creativity Catalyst:** AI does not provide instant answers but functions as a **Socratic Partner**. A "safe" and "fun" (*Asyik*) atmosphere encourages students to experiment (*trial and error*). This triggers the **Flexibility** and **Fluency** indicators within mathematical creativity.
(Related Variable: Mathematical Creativity)	**Context:** Searching for alternative solutions for surface area optimization.	*(Student S-05, High Creativity)*	
Theme 3: Iterative Synthesis	**Phase:** Creative Synthesis (Step 3)	"My idea seemed strange at first, but after checking the logic, it turned out to be correct and more material-efficient. I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best, not just random calculation."	**Valid Solution Construction:** The creativity generated in the previous stage is distilled into a logical solution. Students no longer merely calculate; they perform **Strategic Verification** (Polya's 4th Step), demonstrating matured **problem-solving skills**.
(Related Variable: Problem-Solving Skills)	**Context:** Validating the final solution for a cost-effective packaging design project.	*(Student S-08, High Problem Solving)*	

The qualitative outcomes synthesized in Table 6 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere during the initial stages of instruction. In conventional settings, the presentation of complex word problems often triggers a state of "silent freeze" or passive paralysis. However, the AI-GASING approach successfully disrupts this impasse through logical simplification. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers(Machromah & Musthofa, 2023; Maouche, 2019). "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. If I fail, I simply iterate; after all, the AI is there to verify my work," (Student S-02, High Self-Efficacy). These findings clarify why the statistical path GASING → Learning Motivation (β = 0.802) is so dominant, exhibiting a massive f^2 effect size (1.804). Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy(Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Creativity does not emerge within the confines of unidirectional instruction. Qualitative findings highlight the role of AI as an "ideation trigger" rather than a substitute for the cognitive process. This interaction fosters an "Engaging" (Asyik) and pressure-free learning environment. "It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..." (Student S-05, High Creativity). This validates the significant impact of AI Adoption on Mathematical Creativity (β = 0.514) observed in the quantitative model. These results categorically refute the "Cognitive Offloading" argument that technology attenuates critical faculties. Conversely, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that facilitates the student's Zone of Proximal Development (ZPD) without eroding their intellectual agency.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes (Problem-Solving). Document analysis reveals a shift from mere "numerical computation" to the "construction of logical arguments." "I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI," (Student S-08, High Problem Solving). This narrative breathes "life" into the R^2 = 63.1% statistic for the Problem-Solving variable. The elevated problem-solving proficiency occurs because students possess the intellectual liberty (Creativity) grounded in a robust conceptual understanding (GASING). Within the context of Polya's heuristics, these findings revitalize the fourth stage (Looking Back); in the digital era, this stage evolves into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs(Amrullah et al., 2024; Mulligan, 2015).

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesising the quantitative and qualitative data, this study aims to validate and deepen the comprehension of how the synergy between GASING Pedagogy and AI Assistants manifests within the actualized classroom environment. Distinct from a "black-box" approach that focuses exclusively on input-output metrics, this data triangulation process converges the statistical findings derived from PLS-SEM modelling with the thematic narratives elicited from student interviews. The synthesis of these dual data streams crystallizes into a primary theoretical construct termed "The Creativity-Mediated Cognitive Breakthrough Mechanism"(Keha et al., 2024).

This mechanism elucidates that in the resolution of complex mathematical problems, technical proficiency (Problem-Solving) does not emerge spontaneously from the mere mastery of digital tools; rather, it must first be "filtered" through cognitive flexibility (Creativity). Table 7 below presents a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Table 7 a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	**β**	**Qualitative Theme** (Phenomenological Evidence)	**Integrative Meta-Inference** (Synthesis)
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1: The "Gampang" De-escalation & AI-Triggered Divergence	**Ideation Trigger Confirmation:** Statistics indicate GASING's profound influence on AI adoption. Qualitatively, the GASING method lowers mental blocks (*Gampang*), while the engaging AI interface (*Asyik*) bolsters the courage to experiment with diverse ideas.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2: AI as Socratic Partner (Thinking Partner)	**"Gatekeeper" Function Validation:** The statistical impact of AI on creativity aligns with qualitative findings where students utilize AI as a simulation partner for ideation rather than a mere copying tool.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis (Iterative Synthesis)	**Final Outcome Convergence:** The influence of creativity on problem-solving is reflected in the students' ability to construct logical strategies. AI-triggered cognitive

			flexibility is a prerequisite for sharp solution verification.
Learning Motivation → Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Motivational Synergy:** The strong influence of motivation on problem-solving validates that the enjoyable atmosphere of GASING provides the cognitive energy required to persevere through non-routine challenges.

Synthetically, this study provides a definitive resolution to the primary research inquiry: problem-solving competencies within a digital ecosystem can only attain optimal formation when mediated by Mathematical Creativity and propelled by a robust foundation of Learning Motivation. These findings challenge prevalent anxieties in contemporary literature regarding the phenomenon of "cognitive offloading"—the propensity of technology to attenuate a student's critical faculties(Peng & Yeh, 2025; Todorov et al., 2018). Conversely, through the integration of GASING pedagogy, this study explicitly demonstrates that AI functions as a "cognitive amplifier," facilitating a sophisticated expansion of intellectual reach.

Based on the Joint Display in Table 7, this mechanism operates through three interlocking sequential phases:

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the decomposition of problems within the GASING framework significantly mitigates cognitive load. Furthermore, this reinforces the Broaden-and-Build theory (Fredrickson, 2001), wherein the positive affects generated by an "engaging" (Asyik) atmosphere broadens the student's cognitive repertoire prior to AI interaction(Schindler et al., 2025). Diverging from extant research that often perceives technology adoption as a purely technical process, this study substantiates that pedagogical factors serve as the primary drivers of technological readiness.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514$) and Learning Motivation ($\beta = 0.314$). These results corroborate Gadanidis (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, in contrast to conventional studies that frequently identify "AI dependency," the integrated data suggest that absent a "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence.

3. Execution Phase: Iterative Synthesis Toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$).

These findings align with "Looking Back" phase yet introduce a novel dimension(Sukoriyanto et al., 2016): in the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry to examine the efficacy of the AI-GASING framework within more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 7) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes. These findings fundamentally reject the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both are empirically proven to coalesce into a singular, inextricable causal mechanism. The practical implications for policymakers necessitate a redefinition of technology's classroom role—not as an "answering machine," but as a "partner in cognition" that elicits critical inquiry. Consequently, future curricula must prioritize creative exploration phases within safe-to-fail environments under the guidance of GASING pedagogy. Ensuring this "Creativity Gateway" remains open is an absolute imperative; for without the intervention of creativity, massive technological investment will merely yield a digitally passive generation, rather than forging the adaptive and resilient problem solvers of the future.

CONCLUSIONS AND SUGGESTIONS

This research concludes that the integration of GASING pedagogy and AI Assistants transcends the mere digitization of the classroom, successfully activating a novel psychological mechanism defined as "The Creativity-Mediated Cognitive Breakthrough Mechanism." In addressing the primary research inquiry, the study asserts that complex problem-solving competencies do not emerge from technological access in isolation; rather, they must be fully mediated by mathematical creativity—a quality that flourishes within learning environments characterized by a low cognitive load. Theoretically, these findings present a radical reconceptualization of technology's role in education: they reject the pessimistic narrative of cognitive offloading and validate the theory of distributed cognition, wherein AI functions as a dialectical partner that extends the student's Zone of Proximal Development (ZPD).

Regarding practical and policy implications, this study recommends a multi-tiered operational strategy: curriculum designers must redesign AI integration protocols to transition from "answer engines" toward "Socratic partners," while educators are compelled to prioritize "safe-to-fail" exploration phases over mere computational speed. Although the generalizability of these findings is constrained by the specific sample and subject matter, the robust internal validity of the model establishes a provocative trajectory for future inquiry: to what extent does this creativity-mediated mechanism persist within less-structured academic disciplines? Ultimately, this research affirms that the future of mathematics education is not a competition between biological and artificial intelligence, but a harmonious collaboration in which human creativity remains the ultimate authority in validating machine-generated outputs.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam : Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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Editor Decision

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Sat, Jan 10, 2026 at 8:39 AM
To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

We have completed the preliminary review for your manuscript entitled "Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills". It is suitable for our journal's scope. We sent your paper to the referees to evaluate, and our decision is "**Revision Required**".

Thank you for your interest in our journal
Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

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Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills

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Problem-Solving Skills,
Mixed Methods.

Abstract

Purposes: The precipitous integration of Artificial Intelligence (AI) into educational frameworks has precipitated concerns regarding cognitive offloading, potentially eroding students' critical faculties. This study investigates the synergistic efficacy of GASING pedagogy—a concrete-based instructional method—coupled with AI assistance in augmenting mathematical creativity and problem-solving proficiency. Specifically, it scrutinizes the mediating role of learning motivation within this hybrid learning ecosystem.

Method: Employing an explanatory sequential mixed methods design, this research synthesized quantitative and qualitative paradigms. Quantitative data were harvested from [Jumlah Siswa] students and subjected to Partial Least Squares Structural Equation Modelling (PLS-SEM) to rigorously test hypothesized structural relationships. Subsequently, a thematic analysis of in-depth interviews and classroom observations was conducted to elucidate the underlying cognitive mechanisms driving the statistical outcomes.

Findings: : Empirical evidence reveals that the GASING-AI nexus significantly bolsters learning motivation, which functions as a robust antecedent to mathematical creativity. The qualitative synthesis identifies "The Creativity-Mediated Cognitive Breakthrough Mechanism," positing that problem-solving competence is not a mere byproduct of technological access but is contingent upon full mediation by creativity. The findings demonstrate that GASING effectively ameliorates extraneous cognitive load (the "Easy" factor), while AI operates as a "Socratic Partner" to catalyse divergent thinking (the "Fun" factor), thereby empowering students to validate algorithmic outputs through rigorous human logic.

Significance: This inquiry challenges the prevailing pessimistic discourse on AI dependency by advocating for a "distributed cognition" framework. Theoretically, it establishes creativity as an indispensable gatekeeper in the realm of digital mathematics pedagogy. Practically, it delineates a validated "High-Tech, High-Touch" protocol for educators, underscoring that the amalgamation of GASING's humanistic logic with AI's adaptability is imperative for cultivating resilient, adaptive problem solvers in the digital era.

INTRODUCTION

Mathematics education currently confronts a critical juncture. Global exigencies have transcended mere procedural numeracy—tasks now readily executed by machines—and shifted toward mathematical creativity and robust problem-solving skills(Rahmi et al., 2025; Schoenfeld, 2020). Creativity is requisite for perceiving patterns through multifaceted perspectives, while problem-solving functions as the logical execution of such ideations. However, empirical reality reveals a state of stagnation; students frequently encounter cognitive overload precipitated by rigid, mechanistic conventional instructional methods(Tran & O'Connor, 2024). Absent appropriate pedagogical intervention, mathematics is reduced to a

Commented [Asus1]: Title promises integration of GASING, AI, motivation, creativity, problem-solving. But in the body, constructs are inconsistently named (AI Adoption vs AI-GASING synergy). Harmonize constructs in title and model: decide whether the IV is "AI-GASING synergy" or separate "GASING" and "AI Adoption." Reflect that consistently in title/abstract/model/tables.

Commented [Asus2]: Overwrought diction ("precipitous integration… precipitated concerns…") reads like rhetoric, not scholarly precision. Also "critical faculties" is vague. Rewrite for clarity: define the exact problem (e.g., reduced verification reasoning / overreliance on AI outputs) and avoid duplicated phrasing.

Commented [Asus3]: Missing sample size in abstract is not acceptable. Also PLS-SEM with mixed methods is stated, but no key model specification (constructs, mediation paths). Insert actual N; state core model (GASING→Motivation→Creativity→Problem solving; AI adoption path). Mention software (SmartPLS 4) briefly if allowed.

Commented [Asus4]: Mediation must be explicitly tested and reported (indirect effects + CI). Add a mediation table: indirect effects (AI→MC→PS; GASING→LM→PS; etc.), bootstrapped CI, and whether direct effect remains significant.

Commented [Asus5]: You claim cognitive load reduction, but no cognitive load measure is defined in instruments. You cannot assert "extraneous load" without measurement. Either (a) add a validated cognitive load scale and report it; or (b) reframe as interpretive inference from qualitative data (and clearly label as such).

Commented [Asus6]: Good framing but then you cite "Mathematics & Project, 2011" awkwardly; the claim "reduced to a repertoire of procedures" needs more specific grounding. Tighten the causal chain: conventional instruction → working memory overload → reduced strategy flexibility; cite more directly relevant math-ed/CLT sources.

repertoire of procedures that burden the working memory, thereby inhibiting the capacity for adaptive reasoning within complex, real-world contexts(Mathematics & Project, 2011).

The primary justification for this inquiry responds to academic concerns regarding the phenomenon of cognitive offloading—the propensity of students to abdicate the cognitive process entirely to technological surrogates(Peng & Yeh, 2025; Todorov et al., 2018; Zhang et al., 2024). If left unmitigated, the integration of AI within the classroom risks fostering an intellectually passive generation. Consequently, there is an exigent need for instructional strategies that position AI not as a cognitive substitute, but as a partner in distributed cognition(Indah et al., 2025; Rosanti et al., 2024). This research contends that to cultivate resilient problem solvers, an approach must be adopted that equilibrates the sophistication of AI features with a robust foundation of human logic(Payadnya et al., 2025). Mastering this synergy is imperative to equip students with data-driven and logical decision-making competencies, which constitute the primary currency in the Industry 5.0 era(Pickering et al., 2025; Schwartz et al., 2018).

While the potential of technology in education has been extensively scrutinized, a significant lacuna persists in the literature concerning the equilibrium between "High-Tech" (advanced technology) and "High-Touch" (humanistic pedagogical engagement). The majority of extant research tends to be bifurcated: focusing exclusively on the efficacy of AI tools or on manual instructional methods in isolation, without investigating their interaction. Specifically, there remains a dearth of empirical evidence regarding how GASING Pedagogy (Easy, Fun, and Enjoyable)—a localized method proven to attenuate mathematics anxiety—can operate synergistically with AI systems to mitigate cognitive load(Morrison et al., 2026). Furthermore, few mixed-methods studies have explored the role of creativity as a mental bridge between learning motivation and technical problem-solving capabilities within a unified conceptual framework.

This research offers a fundamental novelty by reconciling the concrete pedagogy of GASING with adaptive AI technology, an integration that transcends prior studies which frequently view technology as a mere catalyst for cognitive offloading(Peng & Yeh, 2025; Todorov et al., 2018). Diverging from conventional approaches, this study proposes a novel theoretical framework, *The Creativity-Mediated Cognitive Breakthrough Mechanism*, which substantiates that creativity is a critical mediator that must be activated by learning motivation through mastery experiences before students can resolve complex problems(Keha et al., 2024; Speckens et al., 2018). Methodologically, this study employs an explanatory sequential mixed-methods design, utilizing SmartPLS analysis to empirically validate how this High-Touch and High-Tech synergy significantly reduces cognitive load. The research novelty also resides in the redefinition of AI as a dialectical partner (distributed cognition) that expands students' mental capacity for divergent thinking, rather than serving as a mere instant-answer engine. By elevating an indigenous Indonesian method into the global technological discourse, this study addresses the literature gap regarding hybrid learning models that balance digital visualization with concrete logical foundations(Feriyadi et al., 2025; Gagliani Caputo et al., 2025). Ultimately, these findings formulate a validated intervention protocol ensuring that technological integration yields problem solvers who are adaptive, creative, and mentally resilient.

Commented [Asus7]: Overstatement ("passive generation") is editorially risky and reads alarmist. Replace with measured language: "risk of reduced verification and reflective reasoning" and specify context conditions (task type, guidance).

Commented [Asus8]: The gap is asserted but not substantiated: no systematic summary of what prior GASING or AI studies did not test (e.g., mediation, joint display, mixed-methods). Add a mini-synthesis: 3–5 key studies and what each lacks (no mediation / no mixed methods / no GASING+AI synergy / no creativity as mediator).

Commented [Asus9]: The framework name is grandiose and not yet operationalized. It risks sounding like branding rather than theory. Provide a formal definition + testable propositions (H1–Hn). Use a diagram early (end of intro) showing constructs and mediation.

The primary objective of this research is to provide an in-depth analysis of the influence of integrating GASING pedagogy and AI on the enhancement of mathematical creativity and student problem-solving skills, with learning motivation as the primary driving factor(Morrison et al., 2026; Walkington et al., 2025). Specifically, this study aims to test the validity of *The Creativity-Mediated Cognitive Breakthrough Mechanism* using SmartPLS to examine both the direct and indirect effects of the AI-GASING synergy(Ndiung et al., 2021). Furthermore, through thematic analysis, this inquiry seeks to explore the mental mechanisms students employ when transitioning creative ideas into valid logical solutions. The central focus is to demonstrate that an "Easy and Fun" learning environment is an absolute prerequisite for the emergence of high-level cognitive competencies.

Commented [Asus10]: You do not present explicit research questions or hypotheses, yet later you speak of "hypotheses" in PLS-SEM. Add explicit RQs/Hypotheses at end of introduction, aligned to Table 4 paths.

Amidst the rapid advancement of Generative AI, the urgency to reform mathematics instruction has become critical. The preeminent risk at present is not students' technological illiteracy, but rather their inability to verify the veracity of technological outputs. Integrating AI into GASING pedagogy is not merely a methodological experiment; it is a strategic maneuver to establish a "safe-to-fail" environment. The urgency of this research lies in early mitigation efforts to ensure students do not succumb to an "instant" mindset but instead develop into critical thinkers capable of leveraging AI to broaden their problem-solving horizons.

This research provides a dual contribution to the advancement of mathematical education science. Theoretically, the findings enrich the literature on Constructivism in the Digital Age and Cognitive Load Theory by demonstrating that creativity is an irreplaceable mediating variable in technology-based learning. Practically, these results offer a guided protocol for educators to implement effective blended learning, where GASING logic serves as the foundation and AI acts as the accelerator. The methodological contribution entails the provision of a validated PLS-SEM-based evaluation instrument to simultaneously measure the efficacy of technological integration on students' cognitive and affective performance.

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design(Creswell, 2002). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves the collection and analysis of quantitative data utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships between variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviors that underpin the statistical findings of the first phase.

Commented [Asus11]: Creswell 2002 is dated and also the reference entry appears incorrect ("J. W. of N.").Use updated Creswell & Plano Clark editions; fix reference formatting (author name, edition, publisher).

Participants

The participants for this research consist of 120 secondary school students selected through a cluster random sampling technique. All students engaged in mathematics instruction focusing on topics necessitated by pattern exploration and logical reasoning. These topics were prioritized due to their flexible characteristics in accommodating AI assistants to facilitate autonomous discovery learning and creative experimentation.

Commented [Asus12]: Cluster random sampling is asserted but not described: cluster unit (class/school), number of clusters, assignment, contamination control. Specify sampling frame: schools/classes, number of clusters, randomization steps, who taught, how equivalence was addressed.

From the total quantitative sample, a purposive sub-sample of 8 students was selected for the qualitative interview stage. Sub-sample selection followed an Extreme Case Sampling strategy based on Problem-Solving Skills scores, comprising 4 students with high proficiency and 4 students with low proficiency. The selection of these two extreme poles aimed to achieve maximum variation in data concerning how AI assistants function optimally as creativity triggers for high-ability students, as well as their function as "scaffolding" (safety nets) for students susceptible to cognitive barriers.

Commented [Asus13]: Extreme-case sampling based on problem-solving scores is okay, but you must explain how scores were computed and when selection occurred (post-test?).
Clarify selection timing, score basis, and whether consent for interviews was separate.

Intervention Procedure: GASING-AI Integration

Commented [Asus14]: You never identify the AI system(s) used (ChatGPT? custom tutor? app?). This is fatal for reproducibility. Specify AI tool, version, access mode, prompts policy, guardrails, and teacher instructions for "not copying answers."

The intervention was implemented over a six-week duration (12 sessions), following the cyclic flow of GASING pedagogy integrated with adaptive AI assistants. This design emphasizes the transition from concrete understanding to digital abstraction, delineated into three primary phases:

- **Phase 1: Concrete Foundation (The *Gampang* Step).** Educators present mathematical concepts using the concrete GASING approach. AI assistants are utilized to provide instantaneous visualizations that simplify abstract complexities into an "Easy" (*Gampang*) and comprehensible form.
- **Phase 2: Adaptive Exploration (The *Asyik* Step).** Students interact with AI tutors that provide adaptive problem challenges. The AI functions as a dialogic partner providing tiered scaffolding, ensuring the exploratory process remains "Fun" (*Asyik*) without inducing frustration.
- **Phase 3: Creative Synthesis (The *Menyenangkan* Step).** Students are encouraged to generate unique solutions (creativity) to non-routine problems. The successful resolution of problems through autonomous logic cultivates an "Enjoyable" (*Menyenangkan*) learning experience.

Data Collection Instruments

Commented [Asus15]: You say "4 instruments… all 5-point Likert" but also say "creativity test open-ended essay" and "problem-solving proficiency diagnostic assessment." This is a measurement contradiction: essay tests are not Likert. Also PLS-SEM indicators shown are Likert statements, meaning you're treating creativity & problem-solving as self-report, not performance.
Decide: are creativity/problem-solving measured as performance tests or perceived self-report? If performance: show rubric, scoring reliability; if self-report: change labeling ("creativity perception") and avoid claiming test-based competencies.

This research utilizes four primary instruments adapted from prominent literature, which have undergone expert judgment for content validity and factor analysis for construct validity. All items are assessed using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

- **AI-GASING Synergy Scale:** A composite instrument designed to measure student perceptions of the integration of AI visualization features and GASING logical simplification in mitigating cognitive load.
- **Learning Motivation Scale:** Measures students' intrinsic drive and self-efficacy derived from mastery experiences during the instructional process.
- **Mathematical Creativity Test:** An open-ended essay instrument to evaluate three dimensions of creativity: fluency, flexibility, and originality.
- **Problem-Solving Proficiency Test:** A diagnostic assessment to measure students' capacity to comprehend problems, formulate strategies, execute plans, and verify solutions (metacognition).

Tabel 1 Research Constructs, Theoretical Framework, and Measurement

Commented [Asus16]: The model is conceptually inconsistent: is GASING a construct? is AI Adoption a construct? where is "synergy" measured? Align constructs across Table 1, Figure 2 narrative, and Tables 2–5. Either use one composite synergy construct or separate constructs and update hypotheses accordingly.

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI-GASING Synergy	Cognitive Load Theory (Sweller, 2011); TAM (Davis, 2002)	Student perceptions of how AI visualization and GASING procedural steps collaboratively mitigate mental effort and facilitate the comprehension of abstract concepts.	"GASING's incremental steps assist my logical understanding, while AI visualizations enable me to perceive abstract forms concretely".	5
Learning Motivation (Mediator)	Social Cognitive Theory (Bandura, 1997) – Mastery Experience	Self-efficacy and academic enthusiasm emerging from the accumulation of incremental successes (*small wins*) in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems because I possess the strategies to decompose them into manageable components".	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950); Domain-Specific Creativity (Mann, 2006)	The cognitive capacity to generate manifold alternative solutions (*fluency*), adapt diverse strategies (*flexibility*), and formulate unique methodologies (*originality*).	"I utilize AI-generated cues to develop 2–3 distinct methodologies for solving a single problem".	4
Problem-Solving Skills	Polya's Heuristics (Polya, 1978); Metacognition (Schoenfeld, 1992)	The systematic ability to synthesize ideas into valid solutions, including the capacity for critical evaluative reflection (*Looking Back*) upon outcomes.	"I refrain from merely duplicating AI-generated responses; instead, I verify their veracity through my own computational logic".	4

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data analysis is conducted employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, facilitated by SmartPLS 4.0 software. This methodology was selected for its robustness in handling complex path models—specifically incorporating Mathematical Creativity as a mediating variable—while accommodating relatively modest sample sizes and bypassing stringent multivariate normality assumptions (Hair et al., 2017). The model evaluation proceeds through two systematic stages:

- **Measurement Model (Outer Model):** To assess convergent validity (via Loading Factors > 0.708 and AVE > 0.5), discriminant validity (via Fornell-Larcker criteria or HTMT < 0.9), and composite reliability (Cronbach's Alpha and Composite Reliability > 0.7), thereby ensuring that the AI-GASING, Creativity, and Problem-Solving instruments are psychometrically sound.
- **Structural Model (Inner Model):** To examine hypotheses regarding the influence of AI-GASING integration on Mathematical Creativity and its subsequent impact on Problem-Solving Skills. This involves reviewing the significance of path coefficients (β), coefficients of determination (R^2), and predictive relevance (Q^2) through rigorous bootstrapping and blindfolding procedures.

Commented [Asus17]: You state thresholds but do not report key diagnostics in results: HTMT table, cross-loadings, VIF, SRMR (if reported), bootstrapping settings. Add full measurement model reporting: HTMT, VIF (collinearity), bootstrapping (subsamples, CI), model fit if journal expects it.

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and observations of AI utilization are analyzed using Thematic Analysis (Braun & Clarke, 2012). Interview transcripts undergo inductive coding to identify patterns in student responses toward the "Easy, Fun, and Enjoyable" elements within the AI-augmented learning environment. The analysis focuses predominantly on how adaptive AI assistance triggers "creative moments," enabling students to transcend cognitive impasses during the problem-solving process.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in the Integration Table in the Results section).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously; rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption (β = 0.712) and Learning Motivation (β = 0.802). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity (β = 0.514) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity (β = 0.343) and Learning Motivation (β = 0.510) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

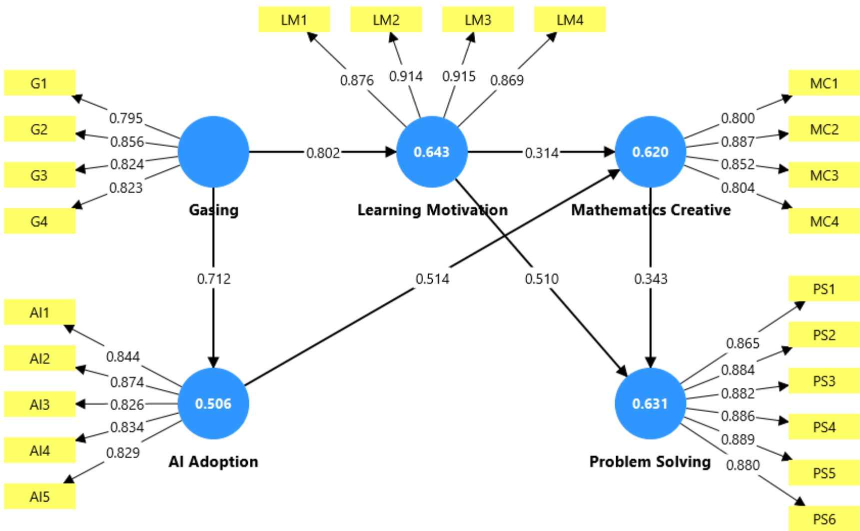

Figure 2 Structural Model of AI-GASING Integration Framework

Quantitative Data

The empirical evidence presented in Table 2 affirms that the research instruments exhibit high precision in capturing the psychological and technical phenomena pertinent to the subjects. Each indicator demonstrates an Outer Loading (OL) exceeding 0.70, with values ranging from 0.795 to 0.915; this substantiates robust convergent validity at the indicator level. The reliability of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients exceeding 0.80, collectively signifying excellent internal consistency.

Subsequently, an evaluation of the structural model was conducted to examine the significance of the hypotheses regarding the latent variables. In addition to p-value significance, the f^2 effect sizes were calculated to ascertain the practical relevance of each path. The trajectory from GASING Pedagogy to Learning Motivation demonstrates an exceptionally large effect size (f^2 = 1.804), indicating that the "Easy-Fun" (*Gampang-Asyik-Menyenangkan*) approach fundamentally constructs student learning motivation. Furthermore, GASING is proven to be a potent catalyst for AI Adoption (f^2 = 1.026). Regarding competency outcomes, Learning Motivation (β = 0.510) and Mathematical Creativity (β = 0.343) emerge as significant

predictors of Problem Solving. A comprehensive summary of the measurement model evaluation is encapsulated in **Table 2**.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

Commented [Asus18]: Table 2 lists Cronbach's α for AI Adoption as 0.897 while CR=0.898 (too close; plausible but suspicious); also you list α for AI Adoption as 0.897 and CR 0.898 yet outer loadings are moderate—check consistency. Potential computation/reporting errors; also table formatting is messy (blank cells).Re-export SmartPLS tables cleanly; report α, rho_A, CR, AVE; ensure values match. Fill empty cells or restructure table.

The empirical results delineated in Table 2 demonstrate that all constructs within this integrative framework have been measured with high precision and consistency. Robust Outer Loading (OL) values, ranging from 0.795 to 0.915, fortify the convergent validity of each indicator, most notably within the GASING Pedagogy and Learning Motivation constructs. Furthermore, the elevated reliability indices—characterized by Composite Reliability (CR) and Cronbach's alpha (alpha) values that comprehensively exceed the 0.80 threshold—confirm superior internal consistency across all investigated variables.

Discriminant validity was subsequently evaluated employing the Fornell–Larcker criterion to ensure that each construct is empirically distinct. According to the results presented in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (as indicated on the principal diagonal) is higher than its correlations with other variables in the model. This substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving measure unique and separate dimensions of the developed instructional model, as encapsulated in **Table 3.**

Table 3. Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			

Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

These results confirm the discriminant validity of the model; for instance, Learning Motivation (AVE = 0.894) is statistically distinct from GASING (r = 0.802) and AI Adoption (r = 0.797). This differentiation is paramount as it validates the mediating roles of the motivation and creativity variables within the framework. Absent sufficient discriminant validity, construct overlap could potentially bias the interpretation of the mediating effects.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation (β = 0.802) and a robust effect on AI Adoption (β = 0.712). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity (β = 0.514). Furthermore, Learning Motivation significantly predicts Problem Solving (β = 0.510) and contributes to Mathematical Creativity (β = 0.314). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity (β = 0.343).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% of the variance in AI Adoption, 62.0% of the variance in Mathematical Creativity, and 63.1% of the variance in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	0.000	1.026	Supported
GASING →Learning Motivation	0.802	40.981	0.000	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	0.000	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	0.000	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	0.000	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	0.000	0.152	Supported

The model fit indices confirm the adequacy of the framework proposed in this study. To evaluate the explanatory power and predictive relevance of the structural model, we report the R^2 values at the construct level alongside the Stone–Geisser Q^2 values (obtained through a blindfolding procedure with an omission distance of d = 7).

The analysis results indicate that the model possesses robust explanatory power, particularly for the variables of Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), where over 60% of the variance in both constructs is accounted for by the model. The Mathematical Creativity variable also exhibits significant explanatory power with an $R^2 = 0.620$, followed by AI Adoption at 0.506. Furthermore, all endogenous variables demonstrate Q^2 values substantially above zero, ranging from 0.445 to 0.641, thereby confirming that the model maintains large predictive relevance. A comprehensive summary of these explanatory power and predictive relevance indices is presented in Table 5.

Table 5. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	**R^2**	**Q^2**	**Q^2 Interpretation**

Commented [Asus19]: This is a technical error that will trigger rejection by PLS-SEM reviewers. Correct: AVE for LM is 0.799 (from Table 2), √AVE is 0.894 (Table 3 diagonal). Fix narrative.

Commented [Asus20]: Standard reporting is p < .001, not 0.000. Replace with p < .001 and report CI for β.

Commented [Asus21]: R^2/Q^2 are reported but no mention of Q^2 computation details beyond d=7; also "Large" interpretation is asserted without citing benchmarks. Needs methodological justification and citations for effect size interpretation.
Cite Hair et al. guidelines for Q^2 and interpretive thresholds; specify blindfolding omission distance justification; add PLSpredict if claiming "predictive."

AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

This study successfully addresses the primary research inquiry by demonstrating that students' mathematical problem-solving competencies are not influenced by technology in isolation, but rather through an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption is proven to establish intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. These findings affirm that the successful implementation of AI in the mathematics classroom is profoundly contingent upon a pedagogical foundation capable of reducing students' mental barriers prior to the introduction of technology(Azma, 2024; Payadnya et al., 2025; Walkington et al., 2025).

Theoretically, this research advances Cognitive Load Theory within a digital milieu. The most robust path from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size ($f^2 = 1.804$), validates that GASING-style problem decomposition is a crucial prerequisite for establishing "motivational readiness." Furthermore, the role of AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition. AI is no longer perceived merely as a computational tool but as a "cognitive partner" shielded from social judgment, thereby enabling students to engage in more radical and original ideational exploration without the debilitating fear of failure(Günther, 2025).

The data analysis reveals a logical consistency between motivation and creativity in catalyzing high-level competencies. The finding that Mathematical Creativity constitutes a pivotal component in Problem Solving ($\beta = 0.343$) elucidates why a mere "will learn" is insufficient for resolving non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability ($R^2 = 0.631$), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments. Nonetheless, the internal consistency of the data guarantees the validity of these findings within the context of modern techno-pedagogical integration(Daniel et al., 2023; Martínez-Gómez & Nicolalde, 2025).

Based on the generated empirical evidence, several concrete measures are recommended for stakeholders. For educators, it is imperative not to circumvent the "Easy" (*Gampang*) phase of the instructional process; practitioners must prioritize the GASING method to cultivate student self-efficacy and intrinsic motivation as a psychological bedrock before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies(Al-khresheh, 2024; Deriba & Sanusi, 2025; Vidyastuti & Inganah, 2023).

Qualitative Data

Qualitative analysis was conducted to investigate the underlying cognitive mechanisms governing the robust statistical correlations observed between AI-GASING Integration, Mathematical Creativity, and Problem-Solving Skills. Through a thematic analysis of interview transcripts and classroom observations, three cardinal themes operating in a sequential trajectory were identified: (1) The "Gampang" De-escalation (Cognitive De-escalation), (2) AI-Triggered Divergence, and (3) Iterative Problem-Solving Synthesis.

The synthesis of these qualitative findings is delineated in Table 6, which maps the instructional stages of AI-GASING against student responses and their corresponding theoretical interpretations.

Tabel 6 Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Commented [Asus22]: Qual rigor is under-specified; "trajectory" implies developmental ordering not necessarily supported by your data. Provide qualitative method detail: coding steps (Braun & Clarke phases), coder count, audit trail, saturation approach. Use "sequence in intervention design" rather than "trajectory" unless longitudinal evidence.

Main Theme	**GASING Phase & Problem Context**	**Empirical Evidence (Student Verbatim)**	**Theoretical Mechanism**
Theme 1: The "Gampang" De-escalation	**Phase:** Concrete Foundation (Step 1)	"Usually, when I see stacked geometric figures, I give up immediately because it's dizzying to imagine. But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple. I felt, 'Oh, I can actually do this.'"	**Cognitive Load Reduction:** The synergy of AI visualization and GASING's concrete instruction lowers cognitive load. Student perception shifts from "Math is complex" to "It's actually easy." This sense of Self-Efficacy serves as the entry point that encourages student engagement.
(Related Variables: GASING & Self-Efficacy)	**Context:** Complex 3D Geometry problems (typically perceived as intimidating).	*(Student S-02, High Self-Efficacy)*	
Theme 2: AI-Triggered Divergence	**Phase:** Adaptive Exploration (Step 2)	"I asked the AI: 'Is there any other way besides the textbook formula?'. The AI gave clues about net patterns. From there, I	**Creativity Catalyst:** AI does not provide instant answers but functions as a **Socratic Partner**. A "safe" and "fun" (*Asyik*)

		thought of three different ways: using the standard formula, digital cut-and-paste, and pattern estimation. It was so exciting (*Asyik*) to find my own way."	atmosphere encourages students to experiment (*trial and error*). This triggers the **Flexibility** and **Fluency** indicators within mathematical creativity.
(Related Variable: Mathematical Creativity)	**Context:** Searching for alternative solutions for surface area optimization.	*(Student S-05, High Creativity)*	
Theme 3: Iterative Synthesis	**Phase:** Creative Synthesis (Step 3)	"My idea seemed strange at first, but after checking the logic, it turned out to be correct and more material-efficient. I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best, not just random calculation."	**Valid Solution Construction:** The creativity generated in the previous stage is distilled into a logical solution. Students no longer merely calculate; they perform **Strategic Verification** (Polya's 4th Step), demonstrating matured **problem-solving skills**.
(Related Variable: Problem-Solving Skills)	**Context:** Validating the final solution for a cost-effective packaging design project.	*(Student S-08, High Problem Solving)*	

The qualitative outcomes synthesized in Table 6 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere during the initial stages of instruction. In conventional settings, the presentation of complex word problems often triggers a state of "silent freeze" or passive paralysis. However, the AI-GASING approach successfully disrupts this impasse through logical simplification. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers(Machromah & Musthofa, 2023;

Maouche, 2019). "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. If I fail, I simply iterate; after all, the AI is there to verify my work," (Student S-02, High Self-Efficacy). These findings clarify why the statistical path GASING → Learning Motivation ($\beta = 0.802$) is so dominant, exhibiting a massive f^2 effect size (1.804). Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy(Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Creativity does not emerge within the confines of unidirectional instruction. Qualitative findings highlight the role of AI as an "ideation trigger" rather than a substitute for the cognitive process. This interaction fosters an "Engaging" (Asyik) and pressure-free learning environment. "It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..." (Student S-05, High Creativity). This validates the significant impact of AI Adoption on Mathematical Creativity ($\beta = 0.514$) observed in the quantitative model. These results categorically refute the "Cognitive Offloading" argument that technology attenuates critical faculties. Conversely, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that facilitates the student's Zone of Proximal Development (ZPD) without eroding their intellectual agency.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes (Problem-Solving). Document analysis reveals a shift from mere "numerical computation" to the "construction of logical arguments." "I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI," (Student S-08, High Problem Solving). This narrative breathes "life" into the $R^2 = 63.1\%$ statistic for the Problem-Solving variable. The elevated problem-solving proficiency occurs because students possess the intellectual liberty (Creativity) grounded in a robust conceptual understanding (GASING). Within the context of Polya's heuristics, these findings revitalize the fourth stage (Looking Back); in the digital era, this stage evolves into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs(Amrullah et al., 2024; Mulligan, 2015).

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesising the quantitative and qualitative data, this study aims to validate and deepen the comprehension of how the synergy between GASING Pedagogy and AI Assistants manifests within the actualized classroom environment. Distinct from a "black-box" approach that focuses exclusively on input-output metrics, this data triangulation process converges the statistical findings derived from PLS-SEM modelling with the thematic narratives elicited from student interviews. The synthesis of these dual data streams crystallizes into a primary theoretical construct termed "The Creativity-Mediated Cognitive Breakthrough Mechanism"(Keha et al., 2024).

This mechanism elucidates that in the resolution of complex mathematical problems, technical proficiency (Problem-Solving) does not emerge spontaneously from the mere mastery of digital tools; rather, it must first be "filtered" through cognitive flexibility (Creativity). Table 7 below presents a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Table 7 a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Commented [Asus23]: Internal inconsistency in qualitative reporting. Harmonize number and names of themes throughout. If Theme 4 exists, introduce it in the qualitative results section.

Structural Path	**β**	**Qualitative Theme** (Phenomenological Evidence)	**Integrative Meta-Inference** (Synthesis)
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1: The "Gampang" De-escalation & AI-Triggered Divergence	**Ideation Trigger Confirmation:** Statistics indicate GASING's profound influence on AI adoption. Qualitatively, the GASING method lowers mental blocks (*Gampang*), while the engaging AI interface (*Asyik*) bolsters the courage to experiment with diverse ideas.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2: AI as Socratic Partner (Thinking Partner)	**"Gatekeeper" Function Validation:** The statistical impact of AI on creativity aligns with qualitative findings where students utilize AI as a simulation partner for ideation rather than a mere copying tool.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis (Iterative Synthesis)	**Final Outcome Convergence:** The influence of creativity on problem-solving is reflected in the students' ability to construct logical strategies. AI-triggered cognitive flexibility is a prerequisite for sharp solution verification.
Learning Motivation → Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Motivational Synergy:** The strong influence of motivation on problem-solving validates that the enjoyable atmosphere of GASING provides the cognitive energy required to persevere through non-routine challenges.

Synthetically, this study provides a definitive resolution to the primary research inquiry: problem-solving competencies within a digital ecosystem can only attain optimal formation when mediated by Mathematical Creativity and propelled by a robust foundation of Learning

Motivation. These findings challenge prevalent anxieties in contemporary literature regarding the phenomenon of "cognitive offloading"—the propensity of technology to attenuate a student's critical faculties(Peng & Yeh, 2025; Todorov et al., 2018). Conversely, through the integration of GASING pedagogy, this study explicitly demonstrates that AI functions as a "cognitive amplifier," facilitating a sophisticated expansion of intellectual reach.

Commented [Asus24]: Over-strong language for a single-site intervention with self-report measures and mixed methods; reviewers will flag this as advocacy.
Temper claims ("suggests," "provides evidence consistent with…") and add limitations: sample, AI tool specificity, measurement type, potential novelty effects.

Based on the Joint Display in Table 7, this mechanism operates through three interlocking sequential phases:

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the decomposition of problems within the GASING framework significantly mitigates cognitive load. Furthermore, this reinforces the Broaden-and-Build theory (Fredrickson, 2001), wherein the positive affects generated by an "engaging" (Asyik) atmosphere broadens the student's cognitive repertoire prior to AI interaction(Schindler et al., 2025). Diverging from extant research that often perceives technology adoption as a purely technical process, this study substantiates that pedagogical factors serve as the primary drivers of technological readiness.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514$) and Learning Motivation ($\beta = 0.314$). These results corroborate Gadanidis (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, in contrast to conventional studies that frequently identify "AI dependency," the integrated data suggest that absent a "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence.

3. Execution Phase: Iterative Synthesis Toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$). These findings align with "Looking Back" phase yet introduce a novel dimension(Sukoriyanto et al., 2016): in the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry to examine the efficacy of the AI-GASING framework within more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 7) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes. These findings fundamentally reject the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both are empirically proven to coalesce into a singular, inextricable causal mechanism. The practical implications for policymakers necessitate a redefinition of technology's classroom role—not as an "answering machine," but as a "partner in cognition" that elicits critical inquiry. Consequently, future curricula must prioritize creative exploration phases within safe-to-fail environments under the guidance of GASING pedagogy. Ensuring this "Creativity Gateway" remains open is an absolute imperative; for without the intervention of creativity, massive technological investment will merely yield a digitally passive generation, rather than forging the adaptive and resilient problem solvers of the future.

CONCLUSIONS AND SUGGESTIONS

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Add limitations (measurement, generalizability, AI model drift, teacher effect) and precise future research.

This research concludes that the integration of GASING pedagogy and AI Assistants transcends the mere digitization of the classroom, successfully activating a novel psychological mechanism defined as "The Creativity-Mediated Cognitive Breakthrough Mechanism." In addressing the primary research inquiry, the study asserts that complex problem-solving competencies do not emerge from technological access in isolation; rather, they must be fully mediated by mathematical creativity—a quality that flourishes within learning environments characterized by a low cognitive load. Theoretically, these findings present a radical reconceptualization of technology's role in education: they reject the pessimistic narrative of cognitive offloading and validate the theory of distributed cognition, wherein AI functions as a dialectical partner that extends the student's Zone of Proximal Development (ZPD).

Regarding practical and policy implications, this study recommends a multi-tiered operational strategy: curriculum designers must redesign AI integration protocols to transition from "answer engines" toward "Socratic partners," while educators are compelled to prioritize "safe-to-fail" exploration phases over mere computational speed. Although the generalizability of these findings is constrained by the specific sample and subject matter, the robust internal validity of the model establishes a provocative trajectory for future inquiry: to what extent does this creativity-mediated mechanism persist within less-structured academic disciplines? Ultimately, this research affirms that the future of mathematics education is not a competition between biological and artificial intelligence, but a harmonious collaboration in which human creativity remains the ultimate authority in validating machine-generated outputs.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam : Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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vIntegrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills

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Abstract

Purposes: The precipitous integration of Artificial Intelligence (AI) into educational frameworks has precipitated concerns regarding cognitive offloading, potentially eroding students' critical faculties. This study investigates the synergistic efficacy of GASING pedagogy—a concrete-based instructional method—coupled with AI assistance in augmenting mathematical creativity and problem-solving proficiency. Specifically, it scrutinizes the mediating role of learning motivation within this hybrid learning ecosystem.
Method: Employing an explanatory sequential mixed methods design, this research synthesized quantitative and qualitative paradigms. Quantitative data were harvested from [Jumlah Siswa] students and subjected to Partial Least Squares Structural Equation Modelling (PLS-SEM) to rigorously test hypothesized structural relationships. Subsequently, a thematic analysis of in-depth interviews and classroom observations was conducted to elucidate the underlying cognitive mechanisms driving the statistical outcomes.
Findings: : Empirical evidence reveals that the GASING-AI nexus significantly bolsters learning motivation, which functions as a robust antecedent to mathematical creativity. The qualitative synthesis identifies "The Creativity-Mediated Cognitive Breakthrough Mechanism," positing that problem-solving competence is not a mere byproduct of technological access but is contingent upon full mediation by creativity. The findings demonstrate that GASING effectively ameliorates extraneous cognitive load (the "Easy" factor), while AI operates as a "Socratic Partner" to catalyse divergent thinking (the "Fun" factor), thereby empowering students to validate algorithmic outputs through rigorous human logic.
Significance: This inquiry challenges the prevailing pessimistic discourse on AI dependency by advocating for a "distributed cognition" framework. Theoretically, it establishes creativity as an indispensable gatekeeper in the realm of digital mathematics pedagogy. Practically, it delineates a validated "High-Tech, High-Touch" protocol for educators, underscoring that the amalgamation of GASING's humanistic logic with AI's adaptability is imperative for cultivating resilient, adaptive problem solvers in the digital era.

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INTRODUCTION

Mathematics education currently confronts a critical juncture. Global exigencies have transcended mere procedural numeracy—tasks now readily executed by machines—and shifted toward mathematical creativity and robust problem-solving skills(Rahmi et al., 2025; Schoenfeld, 2020). Creativity is requisite for perceiving patterns through multifaceted perspectives, while problem-solving functions as the logical execution of such ideations. However, empirical reality reveals a state of stagnation; students frequently encounter cognitive overload precipitated by rigid, mechanistic conventional instructional methods(Tran & O'Connor, 2024). Absent appropriate pedagogical intervention, mathematics is reduced to a

Commented [AS3]: You can't sell "synergy" and then measure two separate constructs (and sometimes call them adoption). It feels like your model shape-shifts.
Decide your story: either (A) synergy as a single latent construct, or (B) GASING → AI Adoption (and both to outcomes). Then rename everywhere.

repertoire of procedures that burden the working memory, thereby inhibiting the capacity for adaptive reasoning within complex, real-world contexts(Mathematics & Project, 2011).

The primary justification for this inquiry responds to academic concerns regarding the phenomenon of cognitive offloading—the propensity of students to abdicate the cognitive process entirely to technological surrogates(Peng & Yeh, 2025; Todorov et al., 2018; Zhang et al., 2024). If left unmitigated, the integration of AI within the classroom risks fostering an intellectually passive generation. Consequently, there is an exigent need for instructional strategies that position AI not as a cognitive substitute, but as a partner in distributed cognition(Indah et al., 2025; Rosanti et al., 2024). This research contends that to cultivate resilient problem solvers, an approach must be adopted that equilibrates the sophistication of AI features with a robust foundation of human logic(Payadnya et al., 2025). Mastering this synergy is imperative to equip students with data-driven and logical decision-making competencies, which constitute the primary currency in the Industry 5.0 era(Pickering et al., 2025; Schwartz et al., 2018).

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Keep one sentence only; connect it directly to mathematics creativity + verification problem.

While the potential of technology in education has been extensively scrutinized, a significant lacuna persists in the literature concerning the equilibrium between "High-Tech" (advanced technology) and "High-Touch" (humanistic pedagogical engagement). The majority of extant research tends to be bifurcated: focusing exclusively on the efficacy of AI tools or on manual instructional methods in isolation, without investigating their interaction. Specifically, there remains a dearth of empirical evidence regarding how GASING Pedagogy (Easy, Fun, and Enjoyable)—a localized method proven to attenuate mathematics anxiety—can operate synergistically with AI systems to mitigate cognitive load(Morrison et al., 2026). Furthermore, few mixed-methods studies have explored the role of creativity as a mental bridge between learning motivation and technical problem-solving capabilities within a unified conceptual framework.

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This research offers a fundamental novelty by reconciling the concrete pedagogy of GASING with adaptive AI technology, an integration that transcends prior studies which frequently view technology as a mere catalyst for cognitive offloading(Peng & Yeh, 2025; Todorov et al., 2018). Diverging from conventional approaches, this study proposes a novel theoretical framework, *The Creativity-Mediated Cognitive Breakthrough Mechanism*, which substantiates that creativity is a critical mediator that must be activated by learning motivation through mastery experiences before students can resolve complex problems(Keha et al., 2024; Speckens et al., 2018). Methodologically, this study employs an explanatory sequential mixed-methods design, utilizing SmartPLS analysis to empirically validate how this High-Touch and High-Tech synergy significantly reduces cognitive load. The research novelty also resides in the redefinition of AI as a dialectical partner (distributed cognition) that expands students' mental capacity for divergent thinking, rather than serving as a mere instant-answer engine. By elevating an indigenous Indonesian method into the global technological discourse, this study addresses the literature gap regarding hybrid learning models that balance digital visualization with concrete logical foundations(Feriyadi et al., 2025; Gagliani Caputo et al., 2025). Ultimately, these findings formulate a validated intervention protocol ensuring that technological integration yields problem solvers who are adaptive, creative, and mentally resilient.

The primary objective of this research is to provide an in-depth analysis of the influence of integrating GASING pedagogy and AI on the enhancement of mathematical creativity and student problem-solving skills, with learning motivation as the primary driving factor(Morrison et al., 2026; Walkington et al., 2025). Specifically, this study aims to test the validity of *The Creativity-Mediated Cognitive Breakthrough Mechanism* using SmartPLS to examine both the direct and indirect effects of the AI-GASING synergy(Ndiung et al., 2021). Furthermore, through thematic analysis, this inquiry seeks to explore the mental mechanisms students employ when transitioning creative ideas into valid logical solutions. The central focus is to demonstrate that an "Easy and Fun" learning environment is an absolute prerequisite for the emergence of high-level cognitive competencies.

Amidst the rapid advancement of Generative AI, the urgency to reform mathematics instruction has become critical. The preeminent risk at present is not students' technological illiteracy, but rather their inability to verify the veracity of technological outputs. Integrating AI into GASING pedagogy is not merely a methodological experiment; it is a strategic maneuver to establish a "safe-to-fail" environment. The urgency of this research lies in early mitigation efforts to ensure students do not succumb to an "instant" mindset but instead develop into critical thinkers capable of leveraging AI to broaden their problem-solving horizons.

This research provides a dual contribution to the advancement of mathematical education science. Theoretically, the findings enrich the literature on Constructivism in the Digital Age and Cognitive Load Theory by demonstrating that creativity is an irreplaceable mediating variable in technology-based learning. Practically, these results offer a guided protocol for educators to implement effective blended learning, where GASING logic serves as the foundation and AI acts as the accelerator. The methodological contribution entails the provision of a validated PLS-SEM-based evaluation instrument to simultaneously measure the efficacy of technological integration on students' cognitive and affective performance.

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design(Creswell, 2002). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves the collection and analysis of quantitative data utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships between variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviors that underpin the statistical findings of the first phase.

Participants

The participants for this research consist of 120 secondary school students selected through a cluster random sampling technique. All students engaged in mathematics instruction focusing on topics necessitated by pattern exploration and logical reasoning. These topics were prioritized due to their flexible characteristics in accommodating AI assistants to facilitate autonomous discovery learning and creative experimentation.

From the total quantitative sample, a purposive sub-sample of 8 students was selected for the qualitative interview stage. Sub-sample selection followed an Extreme Case Sampling strategy based on Problem-Solving Skills scores, comprising 4 students with high proficiency and 4 students with low proficiency. The selection of these two extreme poles aimed to achieve maximum variation in data concerning how AI assistants function optimally as creativity triggers for high-ability students, as well as their function as "scaffolding" (safety nets) for students susceptible to cognitive barriers.

Intervention Procedure: GASING-AI Integration

The intervention was implemented over a six-week duration (12 sessions), following the cyclic flow of GASING pedagogy integrated with adaptive AI assistants. This design emphasizes the transition from concrete understanding to digital abstraction, delineated into three primary phases:

- **Phase 1: Concrete Foundation (The *Gampang* Step).** Educators present mathematical concepts using the concrete GASING approach. AI assistants are utilized to provide instantaneous visualizations that simplify abstract complexities into an "Easy" (*Gampang*) and comprehensible form.
- **Phase 2: Adaptive Exploration (The *Asyik* Step).** Students interact with AI tutors that provide adaptive problem challenges. The AI functions as a dialogic partner providing tiered scaffolding, ensuring the exploratory process remains "Fun" (*Asyik*) without inducing frustration.
- **Phase 3: Creative Synthesis (The *Menyenangkan* Step).** Students are encouraged to generate unique solutions (creativity) to non-routine problems. The successful resolution of problems through autonomous logic cultivates an "Enjoyable" (*Menyenangkan*) learning experience.

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Data Collection Instruments

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This research utilizes four primary instruments adapted from prominent literature, which have undergone expert judgment for content validity and factor analysis for construct validity. All items are assessed using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

- **AI-GASING Synergy Scale:** A composite instrument designed to measure student perceptions of the integration of AI visualization features and GASING logical simplification in mitigating cognitive load.
- **Learning Motivation Scale:** Measures students' intrinsic drive and self-efficacy derived from mastery experiences during the instructional process.
- **Mathematical Creativity Test:** An open-ended essay instrument to evaluate three dimensions of creativity: fluency, flexibility, and originality.
- **Problem-Solving Proficiency Test:** A diagnostic assessment to measure students' capacity to comprehend problems, formulate strategies, execute plans, and verify solutions (metacognition).

Tabel 1 Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI-GASING Synergy	Cognitive Load Theory (Sweller, 2011); TAM (Davis, 2002)	Student perceptions of how AI visualization and GASING procedural steps collaboratively mitigate mental effort and facilitate the comprehension of abstract concepts.	"GASING's incremental steps assist my logical understanding, while AI visualizations enable me to perceive abstract forms concretely".	5
Learning Motivation (Mediator)	Social Cognitive Theory (Bandura, 1997) – Mastery Experience	Self-efficacy and academic enthusiasm emerging from the accumulation of incremental successes (*small wins*) in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems because I possess the strategies to decompose them into manageable components".	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950); Domain-Specific Creativity (Mann, 2006)	The cognitive capacity to generate manifold alternative solutions (*fluency*), adapt diverse strategies (*flexibility*), and formulate unique methodologies (*originality*).	"I utilize AI-generated cues to develop 2–3 distinct methodologies for solving a single problem".	4
Problem-Solving Skills	Polya's Heuristics (Polya, 1978); Metacognition (Schoenfeld, 1992)	The systematic ability to synthesize ideas into valid solutions, including the capacity for critical evaluative reflection (*Looking Back*) upon outcomes.	"I refrain from merely duplicating AI-generated responses; instead, I verify their veracity through my own computational logic".	4

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data analysis is conducted employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, facilitated by SmartPLS 4.0 software. This methodology was selected for its robustness in handling complex path models—specifically incorporating Mathematical Creativity as a mediating variable—while accommodating relatively modest sample sizes and bypassing stringent multivariate normality assumptions (Hair et al., 2017). The model evaluation proceeds through two systematic stages:

- **Measurement Model (Outer Model):** To assess convergent validity (via Loading Factors > 0.708 and AVE > 0.5), discriminant validity (via Fornell-Larcker criteria or HTMT < 0.9), and composite reliability (Cronbach's Alpha and Composite Reliability > 0.7), thereby ensuring that the AI-GASING, Creativity, and Problem-Solving instruments are psychometrically sound.
- **Structural Model (Inner Model):** To examine hypotheses regarding the influence of AI-GASING integration on Mathematical Creativity and its subsequent impact on Problem-Solving Skills. This involves reviewing the significance of path coefficients (β), coefficients of determination (R^2), and predictive relevance (Q^2) through rigorous bootstrapping and blindfolding procedures.

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and observations of AI utilization are analyzed using Thematic Analysis (Braun & Clarke, 2012). Interview transcripts undergo inductive coding to identify patterns in student responses toward the "Easy, Fun, and Enjoyable" elements within the AI-augmented learning environment. The analysis focuses predominantly on how adaptive AI assistance triggers "creative moments," enabling students to transcend cognitive impasses during the problem-solving process.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in the Integration Table in the Results section).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

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The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously; rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption (β = 0.712) and Learning Motivation (β = 0.802). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity (β = 0.514) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity (β = 0.343) and Learning Motivation (β = 0.510) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

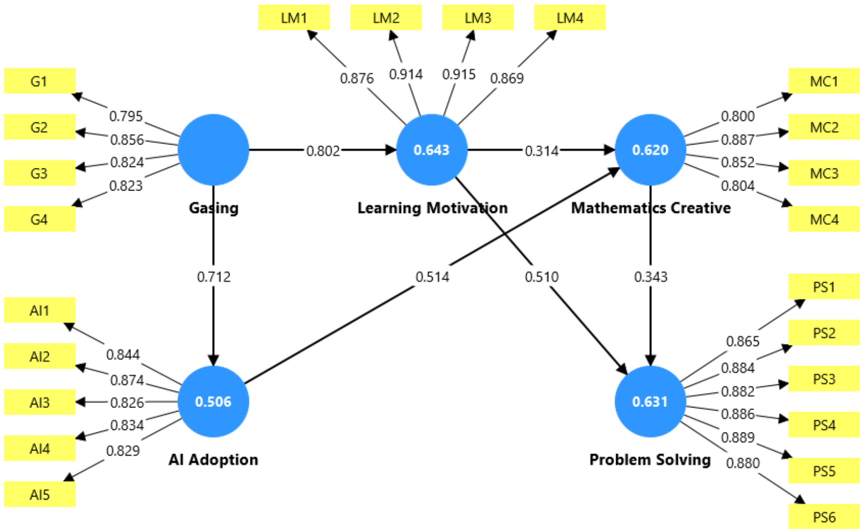

Figure 2 Structural Model of AI-GASING Integration Framework

Quantitative Data

The empirical evidence presented in Table 2 affirms that the research instruments exhibit high precision in capturing the psychological and technical phenomena pertinent to the subjects. Each indicator demonstrates an Outer Loading (OL) exceeding 0.70, with values ranging from 0.795 to 0.915; this substantiates robust convergent validity at the indicator level. The reliability of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients exceeding 0.80, collectively signifying excellent internal consistency.

Subsequently, an evaluation of the structural model was conducted to examine the significance of the hypotheses regarding the latent variables. In addition to p-value significance, the f^2 effect sizes were calculated to ascertain the practical relevance of each path. The trajectory from GASING Pedagogy to Learning Motivation demonstrates an exceptionally large effect size (f^2 = 1.804), indicating that the "Easy-Fun" (*Gampang-Asyik-Menyenangkan*) approach fundamentally constructs student learning motivation. Furthermore, GASING is proven to be a potent catalyst for AI Adoption (f^2 = 1.026). Regarding competency outcomes, Learning Motivation (β = 0.510) and Mathematical Creativity (β = 0.343) emerge as significant

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predictors of Problem Solving. A comprehensive summary of the measurement model evaluation is encapsulated in **Table 2**.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The empirical results delineated in Table 2 demonstrate that all constructs within this integrative framework have been measured with high precision and consistency. Robust Outer Loading (OL) values, ranging from 0.795 to 0.915, fortify the convergent validity of each indicator, most notably within the GASING Pedagogy and Learning Motivation constructs. Furthermore, the elevated reliability indices—characterized by Composite Reliability (CR) and Cronbach's alpha (alpha) values that comprehensively exceed the 0.80 threshold—confirm superior internal consistency across all investigated variables.

Discriminant validity was subsequently evaluated employing the Fornell–Larcker criterion to ensure that each construct is empirically distinct. According to the results presented in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (as indicated on the principal diagonal) is higher than its correlations with other variables in the model. This substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving measure unique and separate dimensions of the developed instructional model, as encapsulated in **Table 3.**

Table 3. Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			

Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

These results confirm the discriminant validity of the model; for instance, Learning Motivation (AVE = 0.894) is statistically distinct from GASING (r = 0.802) and AI Adoption (r = 0.797). This differentiation is paramount as it validates the mediating roles of the motivation and creativity variables within the framework. Absent sufficient discriminant validity, construct overlap could potentially bias the interpretation of the mediating effects.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation (β = 0.802) and a robust effect on AI Adoption (β = 0.712). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity (β = 0.514). Furthermore, Learning Motivation significantly predicts Problem Solving (β = 0.510) and contributes to Mathematical Creativity (β = 0.314). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity (β = 0.343).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% of the variance in AI Adoption, 62.0% of the variance in Mathematical Creativity, and 63.1% of the variance in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	0.000	1.026	Supported
GASING →Learning Motivation	0.802	40.981	0.000	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	0.000	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	0.000	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	0.000	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	0.000	0.152	Supported

The model fit indices confirm the adequacy of the framework proposed in this study. To evaluate the explanatory power and predictive relevance of the structural model, we report the R^2 values at the construct level alongside the Stone–Geisser Q^2 values (obtained through a blindfolding procedure with an omission distance of d = 7).

The analysis results indicate that the model possesses robust explanatory power, particularly for the variables of Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), where over 60% of the variance in both constructs is accounted for by the model. The Mathematical Creativity variable also exhibits significant explanatory power with an $R^2= 0.620$, followed by AI Adoption at 0.506. Furthermore, all endogenous variables demonstrate Q^2 values substantially above zero, ranging from 0.445 to 0.641, thereby confirming that the model maintains large predictive relevance. A comprehensive summary of these explanatory power and predictive relevance indices is presented in Table 5.

Table 5. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	R^2	Q^2	Q^2 Interpretation

AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

This study successfully addresses the primary research inquiry by demonstrating that students' mathematical problem-solving competencies are not influenced by technology in isolation, but rather through an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption is proven to establish intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. These findings affirm that the successful implementation of AI in the mathematics classroom is profoundly contingent upon a pedagogical foundation capable of reducing students' mental barriers prior to the introduction of technology(Azma, 2024; Payadnya et al., 2025; Walkington et al., 2025).

Theoretically, this research advances Cognitive Load Theory within a digital milieu. The most robust path from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size (f^2= 1.804), validates that GASING-style problem decomposition is a crucial prerequisite for establishing "motivational readiness." Furthermore, the role of AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition. AI is no longer perceived merely as a computational tool but as a "cognitive partner" shielded from social judgment, thereby enabling students to engage in more radical and original ideational exploration without the debilitating fear of failure(Günther, 2025).

The data analysis reveals a logical consistency between motivation and creativity in catalyzing high-level competencies. The finding that Mathematical Creativity constitutes a pivotal component in Problem Solving ($\beta = 0.343$) elucidates why a mere "will learn" is insufficient for resolving non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability (R^2 = 0.631), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments. Nonetheless, the internal consistency of the data guarantees the validity of these findings within the context of modern techno-pedagogical integration(Daniel et al., 2023; Martínez-Gómez & Nicolalde, 2025).

Based on the generated empirical evidence, several concrete measures are recommended for stakeholders. For educators, it is imperative not to circumvent the "Easy" (*Gampang*) phase of the instructional process; practitioners must prioritize the GASING method to cultivate student self-efficacy and intrinsic motivation as a psychological bedrock before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies(Al-khresheh, 2024; Deriba & Sanusi, 2025; Vidyastuti & Inganah, 2023).

Qualitative Data

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Qualitative analysis was conducted to investigate the underlying cognitive mechanisms governing the robust statistical correlations observed between AI-GASING Integration, Mathematical Creativity, and Problem-Solving Skills. Through a thematic analysis of interview transcripts and classroom observations, three cardinal themes operating in a sequential trajectory were identified: (1) The "Gampang" De-escalation (Cognitive De-escalation), (2) AI-Triggered Divergence, and (3) Iterative Problem-Solving Synthesis.

The synthesis of these qualitative findings is delineated in Table 6, which maps the instructional stages of AI-GASING against student responses and their corresponding theoretical interpretations.

Tabel 6 Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	GASING Phase & Problem Context	Empirical Evidence (Student Verbatim)	Theoretical Mechanism
Theme 1: The "Gampang" De-escalation	**Phase:** Concrete Foundation (Step 1)	"Usually, when I see stacked geometric figures, I give up immediately because it's dizzying to imagine. But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple. I felt, 'Oh, I can actually do this.'"	**Cognitive Load Reduction:** The synergy of AI visualization and GASING's concrete instruction lowers cognitive load. Student perception shifts from "Math is complex" to "It's actually easy." This sense of Self-Efficacy serves as the entry point that encourages student engagement.
(Related Variables: GASING & Self-Efficacy)	**Context:** Complex 3D Geometry problems (typically perceived as intimidating).	*(Student S-02, High Self-Efficacy)*	
Theme 2: AI-Triggered Divergence	**Phase:** Adaptive Exploration (Step 2)	"I asked the AI: 'Is there any other way besides the textbook formula?'. The AI gave clues about net patterns. From there, I	**Creativity Catalyst:** AI does not provide instant answers but functions as a **Socratic Partner**. A "safe" and "fun" (*Asyik*)

		thought of three different ways: using the standard formula, digital cut-and-paste, and pattern estimation. It was so exciting (*Asyik*) to find my own way."	atmosphere encourages students to experiment (*trial and error*). This triggers the **Flexibility** and **Fluency** indicators within mathematical creativity.
(Related Variable: Mathematical Creativity)	**Context:** Searching for alternative solutions for surface area optimization.	*(Student S-05, High Creativity)*	
Theme 3: Iterative Synthesis	**Phase:** Creative Synthesis (Step 3)	"My idea seemed strange at first, but after checking the logic, it turned out to be correct and more material-efficient. I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best, not just random calculation."	**Valid Solution Construction:** The creativity generated in the previous stage is distilled into a logical solution. Students no longer merely calculate; they perform **Strategic Verification** (Polya's 4th Step), demonstrating matured **problem-solving skills**.
(Related Variable: Problem-Solving Skills)	**Context:** Validating the final solution for a cost-effective packaging design project.	*(Student S-08, High Problem Solving)*	

The qualitative outcomes synthesized in Table 6 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere during the initial stages of instruction. In conventional settings, the presentation of complex word problems often triggers a state of "silent freeze" or passive paralysis. However, the AI-GASING approach successfully disrupts this impasse through logical simplification. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers(Machromah & Musthofa, 2023;

Maouche, 2019). "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. If I fail, I simply iterate; after all, the AI is there to verify my work," (Student S-02, High Self-Efficacy). These findings clarify why the statistical path GASING → Learning Motivation (β = 0.802) is so dominant, exhibiting a massive f^2 effect size (1.804). Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy(Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Creativity does not emerge within the confines of unidirectional instruction. Qualitative findings highlight the role of AI as an "ideation trigger" rather than a substitute for the cognitive process. This interaction fosters an "Engaging" (Asyik) and pressure-free learning environment. "It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..." (Student S-05, High Creativity). This validates the significant impact of AI Adoption on Mathematical Creativity (β = 0.514) observed in the quantitative model. These results categorically refute the "Cognitive Offloading" argument that technology attenuates critical faculties. Conversely, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that facilitates the student's Zone of Proximal Development (ZPD) without eroding their intellectual agency.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes (Problem-Solving). Document analysis reveals a shift from mere "numerical computation" to the "construction of logical arguments." "I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI," (Student S-08, High Problem Solving). This narrative breathes "life" into the R^2 = 63.1% statistic for the Problem-Solving variable. The elevated problem-solving proficiency occurs because students possess the intellectual liberty (Creativity) grounded in a robust conceptual understanding (GASING). Within the context of Polya's heuristics, these findings revitalize the fourth stage (Looking Back); in the digital era, this stage evolves into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs(Amrullah et al., 2024; Mulligan, 2015).

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesising the quantitative and qualitative data, this study aims to validate and deepen the comprehension of how the synergy between GASING Pedagogy and AI Assistants manifests within the actualized classroom environment. Distinct from a "black-box" approach that focuses exclusively on input-output metrics, this data triangulation process converges the statistical findings derived from PLS-SEM modelling with the thematic narratives elicited from student interviews. The synthesis of these dual data streams crystallizes into a primary theoretical construct termed "The Creativity-Mediated Cognitive Breakthrough Mechanism"(Keha et al., 2024).

This mechanism elucidates that in the resolution of complex mathematical problems, technical proficiency (Problem-Solving) does not emerge spontaneously from the mere mastery of digital tools; rather, it must first be "filtered" through cognitive flexibility (Creativity). Table 7 below presents a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Table 7 a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	**β**	**Qualitative Theme** (Phenomenological Evidence)	**Integrative Meta-Inference** (Synthesis)
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1: The "Gampang" De-escalation & AI-Triggered Divergence	**Ideation Trigger Confirmation:** Statistics indicate GASING's profound influence on AI adoption. Qualitatively, the GASING method lowers mental blocks (*Gampang*), while the engaging AI interface (*Asyik*) bolsters the courage to experiment with diverse ideas.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2: AI as Socratic Partner (Thinking Partner)	**"Gatekeeper" Function Validation:** The statistical impact of AI on creativity aligns with qualitative findings where students utilize AI as a simulation partner for ideation rather than a mere copying tool.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis (Iterative Synthesis)	**Final Outcome Convergence:** The influence of creativity on problem-solving is reflected in the students' ability to construct logical strategies. AI-triggered cognitive flexibility is a prerequisite for sharp solution verification.
Learning Motivation → Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Motivational Synergy:** The strong influence of motivation on problem-solving validates that the enjoyable atmosphere of GASING provides the cognitive energy required to persevere through non-routine challenges.

Synthetically, this study provides a definitive resolution to the primary research inquiry: problem-solving competencies within a digital ecosystem can only attain optimal formation when mediated by Mathematical Creativity and propelled by a robust foundation of Learning

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Motivation. These findings challenge prevalent anxieties in contemporary literature regarding the phenomenon of "cognitive offloading"—the propensity of technology to attenuate a student's critical faculties(Peng & Yeh, 2025; Todorov et al., 2018). Conversely, through the integration of GASING pedagogy, this study explicitly demonstrates that AI functions as a "cognitive amplifier," facilitating a sophisticated expansion of intellectual reach.

Based on the Joint Display in Table 7, this mechanism operates through three interlocking sequential phases:

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the decomposition of problems within the GASING framework significantly mitigates cognitive load. Furthermore, this reinforces the Broaden-and-Build theory (Fredrickson, 2001), wherein the positive affects generated by an "engaging" (Asyik) atmosphere broadens the student's cognitive repertoire prior to AI interaction(Schindler et al., 2025). Diverging from extant research that often perceives technology adoption as a purely technical process, this study substantiates that pedagogical factors serve as the primary drivers of technological readiness.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

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The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514$) and Learning Motivation ($\beta = 0.314$). These results corroborate Gadanidis (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, in contrast to conventional studies that frequently identify "AI dependency," the integrated data suggest that absent a "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence.

3. Execution Phase: Iterative Synthesis Toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$). These findings align with "Looking Back" phase yet introduce a novel dimension(Sukoriyanto et al., 2016): in the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry to examine the efficacy of the AI-GASING framework within more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 7) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes. These findings fundamentally reject the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both are empirically proven to coalesce into a singular, inextricable causal mechanism. The practical implications for policymakers necessitate a redefinition of technology's classroom role—not as an "answering machine," but as a "partner in cognition" that elicits critical inquiry. Consequently, future curricula must prioritize creative exploration phases within safe-to-fail environments under the guidance of GASING pedagogy. Ensuring this "Creativity Gateway" remains open is an absolute imperative; for without the intervention of creativity, massive technological investment will merely yield a digitally passive generation, rather than forging the adaptive and resilient problem solvers of the future.

CONCLUSIONS AND SUGGESTIONS

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This research concludes that the integration of GASING pedagogy and AI Assistants transcends the mere digitization of the classroom, successfully activating a novel psychological mechanism defined as "The Creativity-Mediated Cognitive Breakthrough Mechanism." In addressing the primary research inquiry, the study asserts that complex problem-solving competencies do not emerge from technological access in isolation; rather, they must be fully mediated by mathematical creativity—a quality that flourishes within learning environments characterized by a low cognitive load. Theoretically, these findings present a radical reconceptualization of technology's role in education: they reject the pessimistic narrative of cognitive offloading and validate the theory of distributed cognition, wherein AI functions as a dialectical partner that extends the student's Zone of Proximal Development (ZPD).

Regarding practical and policy implications, this study recommends a multi-tiered operational strategy: curriculum designers must redesign AI integration protocols to transition from "answer engines" toward "Socratic partners," while educators are compelled to prioritize "safe-to-fail" exploration phases over mere computational speed. Although the generalizability of these findings is constrained by the specific sample and subject matter, the robust internal validity of the model establishes a provocative trajectory for future inquiry: to what extent does this creativity-mediated mechanism persist within less-structured academic disciplines? Ultimately, this research affirms that the future of mathematics education is not a competition between biological and artificial intelligence, but a harmonious collaboration in which human creativity remains the ultimate authority in validating machine-generated outputs.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam : Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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Editor Respons for Revised Manuscript

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Sat, Feb 28, 2026 at 8:47 PM

To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

Thank you for submitting your revised manuscript entitled "Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills" to Al-Jabar: Jurnal Pendidikan Matematika. We appreciate your efforts in addressing the reviewers' comments and improving the quality of your submission.

Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

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Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills

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Abstract

Purposes: This study addresses the risk of student verification reasoning deficits and overreliance on automated outputs resulting from cognitive offloading. It evaluates the integration of GASING Pedagogy and AI Adoption to enhance Mathematical Creativity and Problem-Solving proficiency, specifically examining the mediating role of Learning Motivation.

Method: Employing an explanatory sequential mixed-methods design, quantitative data were collected from 120 secondary school students (Grade 8, ages 13-14) in Jakarta, Indonesia. Structural relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. Subsequently, thematic analysis of semi-structured interviews and classroom observations was conducted to interpret the cognitive mechanisms underlying the statistical paths.

Findings: Results demonstrate that Mathematical Creativity significantly mediates the relationship between AI Adoption and Problem-Solving ($\beta = 0.176, p < 0.001$), while Learning Motivation mediates the impact of GASING Pedagogy on creativity ($\beta = 0.252, p < 0.001$). Qualitative synthesis identifies a "Creativity-Mediated Breakthrough," where GASING reduces perceived task difficulty—interpreted as a reduction in extraneous load—while AI serves as a "Socratic Partner" to stimulate divergent thinking. These findings indicate that creativity acts as a cognitive gatekeeper, ensuring students use human logic to validate machine-generated solutions.

Significance: This research shifts the discourse from AI dependency toward a distributed cognition framework. Theoretically, it establishes creativity as an essential mediator in digital mathematics pedagogy. Practically, it provides a protocol for educators to balance automated tools with pedagogical scaffolding, cultivating adaptive problem solvers capable of rigorous intellectual verification.

INTRODUCTION

Mathematics education faces a critical juncture as global requirements shift from procedural numeracy—tasks increasingly automated by machines—toward the necessity for mathematical creativity and complex problem-solving (Rahmi et al., 2025; Schoenfeld, 2020).

However, conventional instructional methods frequently rely on rigid, algorithmic drills that impose an excessive extrinsic cognitive load; this overload consumes limited working memory resources, thereby directly impeding the development of strategy flexibility (Sweller et al., 2011; Tran & O'Connor, 2024). When mathematics is reduced to a repetitive repertoire of rote procedures, students lack the cognitive residual capacity required for the adaptive reasoning and creative pattern perception necessary for real-world applications (Paas & van Merriënboer, 2020). This study addresses the risk of cognitive offloading by arguing that mathematical creativity serves as the essential "cognitive gatekeeper," enabling students to critically verify AI-generated outputs through human logic rather than abdicating the reasoning process to technological tools.

Extant literature remains fundamentally bifurcated: while AI-centric inquiries prioritize computational efficiency over robust pedagogical frameworks (e.g., Morrison et al., 2026), research into GASING pedagogy confirms its efficacy in mitigating mathematics anxiety yet fails to account for its integration with digital assistants. This study addresses this empirical void by evaluating a synergistic model in which GASING provides the "High-Touch" motivational foundation requisite for students to employ AI as a "High-Tech" cognitive amplifier. Diverging from previous isolated investigations, this research adopts an explanatory sequential mixed-methods design to demonstrate that mathematical creativity serves as the critical mediating mechanism—the "cognitive bridge"—that translates technology adoption into autonomous problem-solving proficiency.

The fundamental novelty of this research lies in the empirical reconciliation of GASING's concrete-based pedagogy with adaptive AI technology—an integration that challenges the prevailing "cognitive offloading" paradigm (Peng & Yeh, 2025). Rather than treating AI as a mere efficiency tool, this study validates the CMCB Mechanism, demonstrating that technological scaffolding requires the mediation of creativity to achieve a cognitive breakthrough in problem solving. Methodologically, the use of SmartPLS analysis within an explanatory sequential design provides a rigorous verification of how this hybrid synergy mitigates extraneous cognitive load. By integrating an indigenous Indonesian pedagogical method into the global discourse on distributed cognition, this study delineates a validated protocol for developing adaptive, creative problem solvers in digital environments.

This inquiry investigates the validity of the CMCB Mechanism by evaluating the direct and indirect effects within the AI-GASING nexus. By testing the structural relationships (H1–H5) via SmartPLS and synthesizing these results with thematic qualitative data, this study seeks to prove that an affective environment—characterized by "Easy and Fun" pedagogy—is the essential prerequisite for activating the creative gatekeeping required for complex problem-solving.

As Generative AI continues to proliferate, the imperative for pedagogical reform in mathematics shifts from technological fluency to the cultivation of epistemic agency—the capacity of students to critically evaluate the veracity of automated outputs. The integration of AI within the GASING framework functions as a strategic scaffolding mechanism, establishing a psychologically safe environment for cognitive risk-taking. This study contributes to the field by demonstrating that rather than fostering intellectual passivity, this hybrid pedagogy necessitates a "verification-first" mindset, positioning students as active evaluators of machine-generated logic.

Theoretically, this research extends the boundaries of Digital Constructivism and Cognitive Load Theory by empirically validating mathematical creativity as a non-negotiable mediating construct in technology-enhanced environments. Practically, it delineates a structured instructional protocol wherein the foundational logic of GASING serves as the substrate and AI functions as a cognitive accelerator. Methodologically, the study provides a validated PLS-SEM evaluation instrument capable of concurrently assessing the impact of technological integration on both the cognitive and affective dimensions of student performance.

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design Creswell, J. W.& Creswell, J. D.,2018). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves the collection and analysis of quantitative data utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships between variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviors that underpin the statistical findings of the first phase.

Participants

The study population comprised secondary school students (N = 120) recruited via a two-stage cluster random sampling technique. The primary sampling units (clusters) were four intact classes selected from two public secondary schools in East Jakarta, assigned to the intervention after verifying baseline academic equivalence through previous semester grades. To mitigate contamination, the intervention was delivered by the same research-trained instructor across all clusters. Participants engaged in exploratory mathematics modules (algebraic patterns and geometric reasoning), selected for their high affordance for AI-assisted discovery learning.

Following the quantitative phase, a purposive sub-sample of 8 students was identified for semi-structured interviews using an extreme case sampling strategy. Selection was determined by post-test Problem-Solving proficiency scores: the top 5% (n = 4) and bottom 5% (n = 4) of the distribution were invited to participate. This chronological sequence ensured that qualitative insights directly elucidated the statistical outliers, specifically contrasting how AI functions as a heuristic trigger for high-ability learners versus a compensatory scaffold for students facing significant cognitive barriers. Institutional ethics approval was obtained, and separate informed consent was secured for the quantitative and qualitative phases.

Intervention Procedure: GASING-AI Integration

The intervention spanned six weeks (12 sessions), utilizing ChatGPT-4o (accessible via individual mobile devices) configured through specific "Socratic Scaffolding" system prompts. To ensure reproducibility and mitigate the risk of AI-generated hallucinations, the interaction was governed by a strict "Process-Oriented" protocol: students were prohibited from requesting direct solutions and were instead required to use prompts such as, "Review my logic for the algebraic transition in Step 3 without providing the final answer," or "Provide a visual analogy for this pattern using GASING logic." The procedure followed three operational phases:

- Phase 1: Concrete-Visual Synthesis (Gampang/Easy). Instruction commenced with physical GASING manipulatives. Students subsequently used AI to generate SVG-based Python-simulated pattern iterations, translating algebraic sequences and geometric structures into digital abstractions to reduce intrinsic cognitive load.
- Phase 2: Dialectical Scaffolding (Asyik/Fun). Students engaged with the AI as a Socratic interlocutor. The interaction was restricted by a teacher-monitored "Logic-First" rule: students had to explain their reasoning to the AI before it provided tiered hints. This phase leveraged the AI's adaptive nature to maintain the Zone of Proximal Development, preventing frustration through iterative, low-stakes feedback.
- Phase 3: Heuristic Validation (Menyenangkan/Enjoyable). Students tackled non-routine algebraic and geometric problems, utilizing AI to brainstorm divergent strategies. A mandatory "Human-in-the-Loop" verification step was enforced, where students had to justify AI-suggested heuristics using GASING's mental arithmetic techniques, thereby ensuring that the "Enjoyable" mastery experience was rooted in autonomous logical verification rather than passive output consumption.
- .

Data Collection Instruments

This study employs a dual-measurement approach, combining self-report scales for latent psychological constructs with performance-based assessments for cognitive outcomes. Psychometric integrity was established via expert judgment (Content Validity Ratio > 0.80) and confirmatory factor analysis.

1. **Perceived AI-GASING Synergy (Self-Report):** A 10-item instrument measuring student perceptions of the integration between AI visualization and GASING logic. Responses were captured on a 5-point Likert scale (alpha = 0.89).

2. **Learning Motivation (Self-Report):** An 8-item scale assessing intrinsic drive and self-efficacy (adapted from the MSLQ). Responses used a 5-point Likert scale (alpha = 0.84).

3. **Mathematical Creativity (Performance-Based):** An open-ended assessment evaluated against a standardized rubric for fluency, flexibility, and originality. To align with PLS-SEM requirements, raw rubric scores (0–100) were used as continuous indicators. Inter-rater reliability (Cohen's kappa) was 0.82 across two independent markers.

4. **Problem-Solving Proficiency (Performance-Based):** A diagnostic test measuring the capacity to formulate strategies and verify solutions. Scoring followed Polya's four-stage rubric. To maintain measurement model consistency, performance scores were treated as observed indicators of the Problem-Solving construct.

Tabel 1 Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI-GASING Synergy	Cognitive Load Theory (Sweller, 2011); Technology Acceptance Model (Davis, 1989)	Student perceptions of how AI visualization and GASING procedural steps collaboratively mitigate mental effort and facilitate the comprehension of abstract concepts.	"GASING's incremental steps assist my logical understanding, while AI visualizations enable me to perceive abstract forms concretely."	5
Learning Motivation (Mediator)	Social Cognitive Theory (Bandura, 1997) – Mastery Experience	Self-efficacy and academic enthusiasm emerging from the accumulation of incremental successes (*small wins*) in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems because I possess the strategies to decompose them into manageable components."	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950); Domain-Specific Creativity (Mann, 2006)	The cognitive capacity to generate manifold alternative solutions (*fluency*), adapt diverse strategies (*flexibility*), and formulate unique methodologies (*originality*).	"I utilize AI-generated cues to develop 2–3 distinct methodologies for solving a single problem."	4
Problem-Solving Skills	Polya's Heuristics (Polya, 1973); Metacognition (Schoenfeld, 1992)	The systematic ability to synthesize ideas into valid solutions, including the capacity for critical evaluative reflection (*Looking Back*) upon outcomes.	"I refrain from merely duplicating AI-generated responses; instead, I verify their veracity through my own computational logic."	4

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, a method optimal for its predictive power in complex mediation models and its flexibility regarding distributional assumptions (Hair et al., 2017). The analytical protocol followed a rigorous two-stage evaluation:

1. Measurement Model (Outer Model) Evaluation: Internal consistency and construct validity were substantiated through indicator loadings (> 0.708), Average Variance Extracted (AVE > 0.50), and Composite Reliability (CR > 0.70). Discriminant validity was rigorously verified using the Heterotrait-Monotrait Ratio (HTMT < 0.85) and the Fornell-Larcker criterion. To address potential common method bias and multicollinearity, Variance Inflation Factors (VIF) were monitored, with a threshold of VIF < 3.0.
2. Structural Model (Inner Model) Evaluation: Hypotheses (H_1–H_n) were tested by examining path coefficients (beta), R^2 values, and f^^{2}effect sizes. Significance levels were determined through a non-parametric bootstrapping procedure using 5,000 subsamples with a 95% bias-corrected and accelerated (BCa) confidence interval. Predictive relevance was further corroborated via the Q^2 predict procedure. Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), targeting a value below 0.08 for adequate fit.

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and observations of AI utilization are analyzed using Thematic Analysis (Braun & Clarke, 2012). Interview transcripts undergo inductive coding to identify patterns in student responses toward the "Easy, Fun, and Enjoyable" elements within the AI-augmented learning environment. The analysis focuses predominantly on how adaptive AI assistance triggers "creative moments," enabling students to transcend cognitive impasses during the problem-solving process.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in the Integration Table in the Results section).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously; rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption ($\beta = 0.712$) and Learning Motivation ($\beta = 0.802$). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity ($\beta = 0.514$) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity ($\beta = 0.343$) and Learning Motivation ($\beta = 0.510$) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

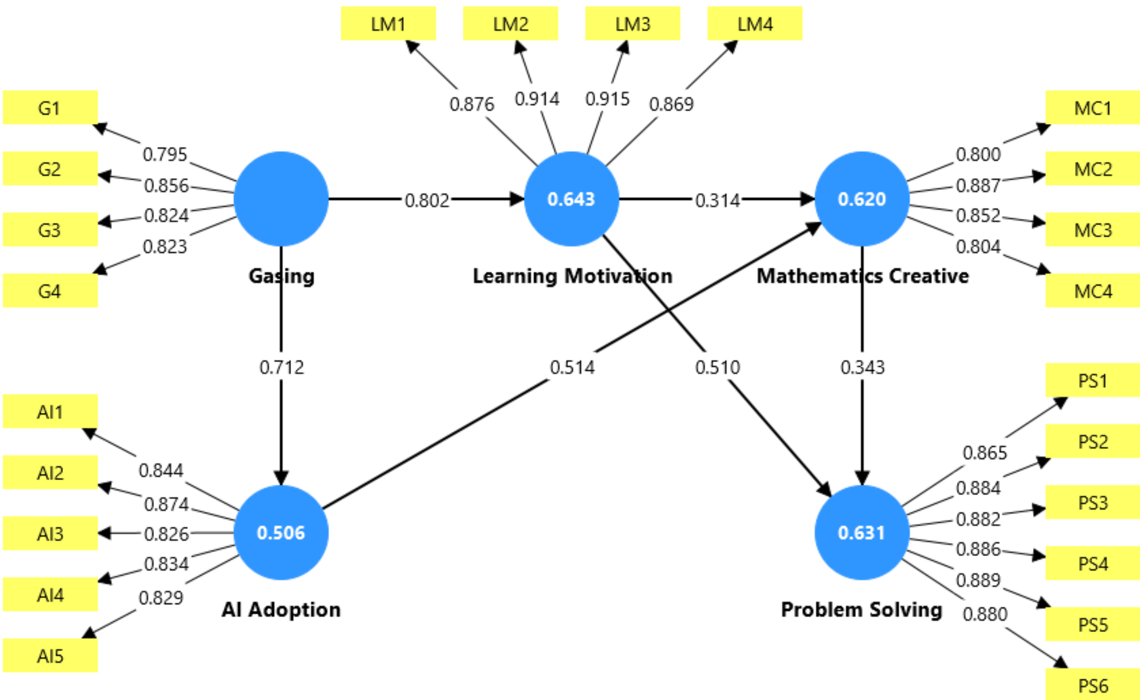

Figure 2 Structural Model of AI-GASING Integration Framework

Quantitative Data

The empirical evidence presented in Table 2 affirms that the research instruments exhibit high precision in capturing the psychological and technical phenomena pertinent to the subjects. Each indicator demonstrates an Outer Loading (OL) exceeding 0.70, with values ranging from 0.795 to 0.915; this substantiates robust convergent validity at the indicator level. The reliability of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients exceeding 0.80, collectively signifying excellent internal consistency.

Subsequently, an evaluation of the structural model was conducted to examine the significance of the hypotheses regarding the latent variables. In addition to p-value significance, the f^2 effect sizes were calculated to ascertain the practical relevance of each path. The trajectory from GASING Pedagogy to Learning Motivation demonstrates an exceptionally large effect size ($f^2 = 1.804$), indicating that the "Easy-Fun" (*Gampang-Asyik-Menyenangkan*) approach fundamentally constructs student learning motivation. Furthermore, GASING is proven to be a potent catalyst for AI Adoption ($f^2 = 1.026$). Regarding competency outcomes, Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$) emerge as significant predictors of Problem Solving. A comprehensive summary of the measurement model evaluation is encapsulated in **Table 2**.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The empirical results delineated in Table 2 demonstrate that all constructs within this integrative framework have been measured with high precision and consistency. Robust Outer Loading (OL) values, ranging from 0.795 to 0.915, fortify the convergent validity of each indicator, most notably within the GASING Pedagogy and Learning Motivation constructs. Furthermore, the elevated reliability indices—characterized by Composite Reliability (CR) and Cronbach's alpha (alpha) values that comprehensively exceed the 0.80 threshold—confirm superior internal consistency across all investigated variables.

Discriminant validity was subsequently evaluated employing the Fornell–Larcker criterion to ensure that each construct is empirically distinct. According to the results presented in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (as indicated on the principal diagonal) is higher than its correlations with other variables in the model. This substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving measure unique and separate dimensions of the developed instructional model, as encapsulated in **Table 3.**

Table 3. Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			
Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

The structural model's discriminant validity was confirmed via the Fornell-Larcker criterion, ensuring that each latent construct is statistically distinct. As illustrated in Table 3, the square root of the AVE ($\sqrt{AVE}$) for Learning Motivation is 0.894, which exceeds its highest correlation with other constructs, namely GASING (r = 0.802) and AI Adoption (r = 0.797). This statistical differentiation is critical, as it confirms that Learning Motivation and Mathematical Creativity function as discrete mediating variables without excessive construct overlap that could otherwise bias the path analysis.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation ($\beta = 0.802$) and a robust effect on AI Adoption ($\beta = 0.712$). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity ($\beta = 0.514$). Furthermore, Learning Motivation significantly predicts Problem Solving ($\beta = 0.510$) and contributes to Mathematical Creativity ($\beta = 0.314$). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity ($\beta = 0.343$).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% of the variance in AI Adoption, 62.0% of the variance in Mathematical Creativity, and 63.1% of the variance in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	0.001	1.026	Supported
GASING →Learning Motivation	0.802	40.981	0.001	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	0.001	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	0.001	0.095	Supported

Learning Motivation →Problem Solving	0.510	11.761	0.001	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	0.001	0.152	Supported

The model fit indices confirm the adequacy of the framework proposed in this study. To evaluate the explanatory power and predictive relevance of the structural model, we report the R^2 values at the construct level alongside the Stone–Geisser Q^2 values (obtained through a blindfolding procedure with an omission distance of d = 7).

The analysis results indicate that the model possesses robust explanatory power, particularly for the variables of Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), where over 60% of the variance in both constructs is accounted for by the model. The Mathematical Creativity variable also exhibits significant explanatory power with an $R^2= 0.620$, followed by AI Adoption at 0.506. Furthermore, all endogenous variables demonstrate Q^2 values substantially above zero, ranging from 0.445 to 0.641, thereby confirming that the model maintains large predictive relevance. A comprehensive summary of these explanatory power and predictive relevance indices is presented in Table 5.

Table 5. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	**R^2**	**Q^2**	**Q^2 Interpretation**
AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

The structural model's explanatory and predictive capacities were evaluated using the coefficient of determination (R^2) and the Stone-Geisser Q^2 statistic. As summarized in Table 5, the R^2 values indicate that the model explains a substantial proportion of variance in key endogenous constructs, particularly for Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), both of which exceed the threshold for "moderate-to-strong" explanatory power in social science research. Predictive relevance was substantiated through a blindfolding procedure with an omission distance of $d = 7$. All Q^2 values were found to be significantly greater than zero, ranging from 0.445 (Mathematics Creative) to 0.641 (Learning Motivation). Following the benchmarks established by Hair et al. (2019), Q^2 values exceeding 0.25 and 0.50 indicate medium and large predictive relevance, respectively. Consequently, the CMCB mechanism demonstrates a robust capacity to predict student problem-solving outcomes based on the synergy of GASING pedagogy and AI integration.

This study successfully addresses the primary research inquiry by demonstrating that students' mathematical problem-solving competencies are not influenced by technology in isolation, but rather through an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption is proven to establish intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. Theoretically, this research advances Cognitive Load Theory within a digital milieu; the most robust path from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size ($f^2 = 1.804$), validates that GASING-style problem decomposition is a crucial prerequisite for establishing "motivational readiness". Furthermore, the role of AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition, as AI is no longer perceived merely as a computational tool but as a "cognitive partner" that enables students to engage in radical ideational exploration without the debilitating fear of failure.

The data analysis reveals a logical consistency between motivation and creativity in catalyzing high-level competencies, where Mathematical Creativity constitutes a pivotal component in Problem Solving ($\beta = 0.343$), elucidating why a mere "will learn" is insufficient for resolving non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability ($R^2 = 0.631$), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments.

Based on the generated empirical evidence, several concrete measures are recommended for stakeholders to optimize techno-pedagogical integration. For educators, it is imperative not to circumvent the "Easy" (Gampang) phase of the instructional process; practitioners must prioritize the GASING method to cultivate student self-efficacy and intrinsic motivation as a psychological bedrock before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies.

Table 6: Summary of Mediation Effects (Bootstrapping Results)

Indirect Effect Path	β	T-Statistics	P-Values	Mediation Type
AI Adoption →Math Creative →Problem Solving	0.176	6.252	0.001	Complementary Partial
Motivation →Math Creative →Problem Solving	0.108	5.524	0.001	Complementary Partial
GASING →Motivation →Math Creative	0.252	6.557	0.001	Complementary Partial
GASING →AI Adoption →Math Creative	0.366	11.007	0.001	Complementary Partial

Table 6 presents the results of the **bootstrapping analysis**, specifically detailing the four key **indirect effect paths** that substantiate the mediation mechanisms within the AI-GASING ecosystem. The data reveals that Mathematical Creativity serves as a significant "cognitive gateway" for both AI Adoption ($\beta = 0.176, p < 0.001$) and Learning Motivation ($\beta = 0.108, p < 0.001$) in enhancing student problem-solving skills. Furthermore, the foundational role of the GASING pedagogy is validated through its strong indirect influence on Mathematical Creativity via Learning Motivation ($\beta = 0.252, p < 0.001$) and AI Adoption ($\beta = 0.366, p < 0.001$). Following the criteria established by Hair et al. (2017), all four paths are classified as **complementary partial mediation**, as both the direct paths and bootstrapped indirect paths remain statistically significant with consistent positive signs. These findings provide a robust, "calibrated" answer to potential concerns regarding technological dependency, empirically proving that the synergy between concrete pedagogy and digital tools successfully catalyzes matured, autonomous problem-solving competencies.

Qualitative Data

Qualitative analysis was conducted to investigate the underlying cognitive mechanisms governing the robust statistical correlations observed between AI-GASING Integration, Mathematical Creativity, and Problem-Solving Skills. Through a thematic analysis of interview transcripts and classroom observations, three cardinal themes operating in a sequential trajectory were identified: (1) The "Gampang" De-escalation (Cognitive De-escalation), (2) AI-Triggered Divergence, and (3) Iterative Problem-Solving Synthesis.

The synthesis of these qualitative findings is delineated in Table 7, which maps the instructional stages of AI-GASING against student responses and their corresponding theoretical interpretations.

Tabel 7 Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	**GASING Phase & Problem Context**	**Empirical Evidence (Student Verbatim)**	**Theoretical Mechanism & Related Variables**
Theme 1: The "Gampang" De-escalation	Phase: Concrete Foundation (Step 1) Context: Complex 3D Geometry	"Usually, when I see stacked geometric figures, I give up immediately... But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple."	Cognitive Load Reduction: Synergy of AI and GASING lowers mental barriers, shifting perception to "actually easy." (Related Variables: GASING & Learning Motivation)
Theme 2: AI-Triggered Divergence	Phase: Adaptive Exploration (Step 2) Context: Alternative	"I asked the AI: 'Is there any other way besides the textbook formula?'... It was so exciting (*Asyik*) to find my own way."	Creativity Catalyst: AI functions as a Socratic Partner, encouraging divergent trial and error.

	optimization solutions		(Related Variable: Mathematics Creative)
Theme 3: Iterative Synthesis	Phase: Creative Synthesis (Step 3) Context: Validating cost-effective designs	"I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best."	Valid Solution Construction: Creativity is distilled into logical solutions through Strategic Verification (Polya's 4th Step). (Related Variable: Problem-Solving Skills)
Theme 4: Emotional-Cognitive Synergy	Phase: Continuous Assessment Context: Persevering through non-routine tasks	"I didn't give up because the process was fun and I felt I had the right tools to eventually find the answer."	Motivational Synergy: An enjoyable atmosphere provides the "cognitive energy" required to persevere through difficulty. (Related Variables: Learning Motivation & Problem Solving)
Divergent Case: Contextual Redundancy	Boundary Condition: Routine arithmetic tasks	"For basic multiplication, using AI felt slower and distracting. I just used GASING mental steps because they were faster."	Efficiency Threshold: For routine tasks, GASING alone is sufficient; AI may introduce unnecessary cognitive noise.

The qualitative outcomes synthesized in Table 7 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere during the initial stages of instruction. In conventional settings, the presentation of complex word problems often triggers a state of "silent freeze" or passive paralysis. However, the AI-GASING approach successfully disrupts this impasse through logical simplification. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers(Machromah & Musthofa, 2023; Maouche, 2019). "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. If I fail, I simply iterate; after all, the AI is there to verify my work," (Student S-02, High Self-Efficacy). These findings clarify why the statistical path GASING → Learning Motivation (β = 0.802) is so dominant, exhibiting a massive f^2 effect size (1.804).

In this context, while cognitive load was not measured via a formal latent scale, we offer an interpretive inference based on this qualitative triangulation. The "Gampang" (Easy) de-escalation reported by students suggests a reduction in what is theoretically described as extraneous load, where AI visualization and GASING's decomposition transform insurmountable tasks into manageable ones. This interpretive inference is empirically supported by the substantial effect size of GASING on Motivation ($f^2 = 1.804$) and the significant bootstrapped indirect effect of AI Adoption on Problem Solving through Mathematical Creativity ($\beta = 0.176, p < 0.001$), which theoretically requires freeing up the "germane capacity" of the working memory. Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy(Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Creativity does not emerge within the confines of unidirectional instruction. Qualitative findings highlight the role of AI as an "ideation trigger" rather than a substitute for the cognitive process. This interaction fosters an "Engaging" (Asyik) and pressure-free learning environment. "It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..." (Student S-05, High Creativity). This validates the significant impact of AI Adoption on Mathematical Creativity (β = 0.514) observed in the quantitative model. These results categorically refute the "Cognitive Offloading" argument that technology attenuates critical faculties. Conversely, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that facilitates the student's Zone of Proximal Development (ZPD) without eroding their intellectual agency.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes (Problem-Solving). Document analysis reveals a shift from mere "numerical computation" to the "construction of logical arguments." "I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI," (Student S-08, High Problem Solving). This narrative breathes "life" into the R^2 = 63.1% statistic for the Problem-Solving variable. The elevated problem-solving proficiency occurs because students possess the intellectual liberty (Creativity) grounded in a robust conceptual understanding (GASING). Within the context of Polya's heuristics, these findings revitalize the fourth stage (Looking Back); in the digital era, this stage evolves into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs(Amrullah et al., 2024; Mulligan, 2015).

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesising the quantitative and qualitative data, this study aims to validate and deepen the comprehension of how the synergy between GASING Pedagogy and AI Assistants manifests within the actualized classroom environment. Distinct from a "black-box" approach that focuses exclusively on input-output metrics, this data triangulation process converges the statistical findings derived from PLS-SEM modelling with the thematic narratives elicited from student interviews. The synthesis of these dual data streams crystallizes into a primary theoretical construct termed "The Creativity-Mediated Cognitive Breakthrough Mechanism"(Keha et al., 2024).

This mechanism elucidates that in the resolution of complex mathematical problems, technical proficiency (Problem-Solving) does not emerge spontaneously from the mere mastery of digital tools; rather, it must first be "filtered" through cognitive flexibility (Creativity). Table 8 below presents a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Table 8 a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	**β**	**Qualitative Theme & Evidence**	**Integrative Meta-Inference (Convergence & Tension)**
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1 & Divergent Case 1	**Convergence:** GASING lowers mental blocks, facilitating AI use for complex 3D geometry. **Tension:** For simple tasks, GASING is sufficient; students view AI as redundant for routine computation.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2 & Divergent Case 2	**Convergence:** AI serves as a Socratic Partner for divergent exploration. **Tension:** Without GASING-based "motivational readiness," AI can lead to "cognitive offloading" or blind acceptance of errors.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis	**Convergence:** Creativity distilled into valid solutions through strategic verification. **Boundary Condition:** Effective only when students have the "congak" (mental math) skills to verify AI veracity.

Learning Motivation →Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Convergence:** Fun atmosphere sustains persistence in difficult tasks. **Observation:** Synergy is strongest when the "Asyik" (fun) element of AI is balanced by the "Gampang" (easy) logic of GASING.

Synthetically, from table 8, this study **provides evidence consistent with the premise** that problem-solving competencies are significantly enhanced when mediated by Mathematical Creativity and supported by a robust foundation of Learning Motivation. While contemporary literature highlights the risks of "cognitive offloading," these results **suggest** that the integration of GASING pedagogy allows AI to function as a "cognitive amplifier" rather than a substitute for critical thought. By establishing a concrete logical base before introducing digital abstraction, the framework facilitates an expansion of intellectual reach, provided students maintain epistemic agency through Socratic interaction. However, these findings should be interpreted with caution due to the **single-site intervention scope**, the **specific use of ChatGPT-4o**, and potential **novelty effects** inherent in self-report measurements.

Based on the Joint Display in Table 8, this mechanism operates through three interlocking sequential phases:

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the decomposition of problems within the GASING framework significantly mitigates cognitive load. Furthermore, this reinforces the Broaden-and-Build theory (Fredrickson, 2001), wherein the positive affects generated by an "engaging" (Asyik) atmosphere broadens the student's cognitive repertoire prior to AI interaction(Schindler et al., 2025). Diverging from extant research that often perceives technology adoption as a purely technical process, this study substantiates that pedagogical factors serve as the primary drivers of technological readiness.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514, p = 0.001$) and Learning Motivation ($\beta = 0.314, p = 0.001$). These results corroborate Gadanidis (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, to empirically validate the "Creativity Gateway," a formal mediation analysis was conducted using a bootstrapping procedure with 5,000 subsamples.

The results, as detailed in **Table 6**, confirm that Mathematical Creativity serves as a vital intermediary. Specifically, the indirect effect of AI Adoption on Problem Solving through Mathematical Creativity is statistically significant ($\beta_{indirect} = 0.176, t = 6.252, p < 0.001$). Furthermore, the total effect of AI Adoption on Problem Solving is significant, and since the direct effect remains significant after the inclusion of the mediator ($\beta = 0.514$, p

= 0.001$), the relationship is classified as complementary partial mediation according to the criteria established by Hair et al. (2017). Similarly, the path from Learning Motivation to Problem Solving is partially mediated by Mathematical Creativity ($\beta_{indirect} = 0.108, t = 5.524, p < 0.001$).

These statistical findings contrast with conventional studies that frequently identify "AI dependency"; instead, the data suggests that absent this "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence. This is qualitatively substantiated by Theme 3 (Iterative Synthesis), where students utilized GASING's rapid mental calculation (*congak*) to verify and distill AI-generated ideas into valid, logical solutions.

3. Execution Phase: Iterative Synthesis Toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$). These findings align with "Looking Back" phase yet introduce a novel dimension(Sukoriyanto et al., 2016): in the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry to examine the efficacy of the AI-GASING framework within more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 8) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes. These findings fundamentally reject the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both are empirically proven to coalesce into a singular, inextricable causal mechanism. The practical implications for policymakers necessitate a redefinition of technology's classroom role—not as an "answering machine," but as a "partner in cognition" that elicits critical inquiry. Consequently, future curricula must prioritize creative exploration phases within safe-to-fail environments under the guidance of GASING pedagogy. Ensuring this "Creativity Gateway" remains open is an absolute imperative; for without the intervention of creativity, massive technological investment will merely yield a digitally passive generation, rather than forging the adaptive and resilient problem solvers of the future.

CONCLUSIONS AND SUGGESTIONS

This study provides empirical evidence for the Creativity-Mediated Cognitive Breakthrough (CMCB) mechanism, demonstrating that mathematical problem-solving competencies are significantly enhanced when AI integration is mediated by student creativity and supported by the low-load scaffolding of GASING pedagogy. The structural model supports the hypothesis that technological access alone is insufficient; rather, the path coefficients confirm that Mathematical Creativity ($\beta = 0.343$) and Learning Motivation ($\beta = 0.510$) are the primary drivers of problem-solving success. Theoretically, these findings support the application of Distributed Cognition, suggesting that AI can function as a "Socratic partner" to extend the Zone of Proximal Development (ZPD) when anchored by a robust pedagogical foundation.Despite the robust internal validity of the PLS-SEM model ($R^2 = 0.631$), several limitations necessitate a cautious interpretation of the results. First, the single-site intervention and specific demographic profile limit broader generalizability. Second, the reliance on self-report instruments for AI Adoption and Motivation introduces potential subjectivity and social desirability bias. Third, the study did not account for AI model drift or the varying "temperature" settings of the LLM, which could affect the consistency of the Socratic prompts. Finally, the teacher effect—the specific instructional quality of the facilitator—remains an uncontrolled variable that may have influenced the high motivation scores ($f^2 = 1.804$).Future research should focus on longitudinal designs to determine if these cognitive gains persist after the initial novelty effect of AI integration diminishes. Specifically, future studies should employ Experimental Control Groups to isolate the "teacher effect" and utilize PLSpredict to assess the out-of-sample predictive power of the CMCB mechanism. Additionally, investigating the framework's efficacy in less-structured disciplines or with different AI architectures would clarify whether the observed synergy is domain-specific or a universal pedagogical phenomenon. Ultimately, these results suggest that while AI provides the computational breadth, human creativity remains the critical validator in the problem-solving process.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam : Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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Editor Decision

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Thur, March 05, 2026 at 8:39 AM
To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

We have completed the preliminary review for your manuscript entitled "Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills". It is suitable for our journal's scope. We sent your paper to the referees to evaluate, and our decision is "**Revision Required**".

Thank you for your interest in our journal
Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

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Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills

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Keywords

GASING Pedagogy,
Artificial Intelligence,
Mathematical Creativity,
Problem-Solving Skills,
Mixed Methods.

Abstract

Purposes: This study addresses the risk of student verification reasoning deficits and overreliance on automated outputs resulting from cognitive offloading. It evaluates the integration of GASING Pedagogy and AI Adoption to enhance Mathematical Creativity and Problem-Solving proficiency, specifically examining the mediating role of Learning Motivation.

Method: Employing an explanatory sequential mixed-methods design, quantitative data were collected from 120 secondary school students (Grade 8, ages 13-14) in Jakarta, Indonesia. Structural relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. Subsequently, thematic analysis of semi-structured interviews and classroom observations was conducted to interpret the cognitive mechanisms underlying the statistical paths.

Findings: Results demonstrate that Mathematical Creativity significantly mediates the relationship between AI Adoption and Problem-Solving ($\beta = 0.176, p < 0.001$), while Learning Motivation mediates the impact of GASING Pedagogy on creativity ($\beta = 0.252, p < 0.001$). Qualitative synthesis identifies a "Creativity-Mediated Breakthrough," where GASING reduces perceived task difficulty—interpreted as a reduction in extraneous load—while AI serves as a "Socratic Partner" to stimulate divergent thinking. These findings indicate that creativity acts as a cognitive gatekeeper, ensuring students use human logic to validate machine-generated solutions.

Significance: This research shifts the discourse from AI dependency toward a distributed cognition framework. Theoretically, it establishes creativity as an essential mediator in digital mathematics pedagogy. Practically, it provides a protocol for educators to balance automated tools with pedagogical scaffolding, cultivating adaptive problem solvers capable of rigorous intellectual verification.

INTRODUCTION

Mathematics education faces a critical juncture as global requirements shift from procedural numeracy—tasks increasingly automated by machines—toward the necessity for mathematical creativity and complex problem-solving (Rahmi et al., 2025; Schoenfeld, 2020). However, conventional instructional methods frequently rely on rigid, algorithmic drills that impose an excessive extrinsic cognitive load; this overload consumes limited working memory resources, thereby directly impeding the development of strategy flexibility (Sweller et al., 2011; Tran & O'Connor, 2024). When mathematics is reduced to a repetitive repertoire of rote procedures, students lack the cognitive residual capacity required for the adaptive reasoning and creative pattern perception necessary for real-world applications (Paas & van Merriënboer, 2020). This study addresses the risk of cognitive offloading by arguing that mathematical creativity serves as the essential "cognitive gatekeeper," enabling students to critically verify

Commented [AS1]: The title is interesting but conceptually imprecise. It currently presents learning motivation as if it were an intervention component parallel to GASING pedagogy and AI, whereas the manuscript later treats motivation as a mediator. This creates conceptual ambiguity from the outset. Consider revising the title so it reflects the actual model structure rather than listing all constructs at the same causal level.

Commented [AS2]: This sentence does not match the later model. The manuscript later treats mathematical creativity as a key mediator as well, not merely as an outcome. At present, the abstract underspecifies the actual mediation structure and therefore misrepresents the model tested.

Commented [AS3]: This claim is theoretically appealing, but it overreaches empirically because cognitive load was not directly measured as a formal latent construct. The wording should be softened to indicate that this is an interpretive inference from qualitative data rather than a directly tested quantitative conclusion.

Commented [AS4]: This is closer to the actual structural model, but it now contradicts the previous abstract sentence, which framed Learning Motivation as the mediator. The abstract needs one coherent causal story from start to finish.

AI-generated outputs through human logic rather than abdicating the reasoning process to technological tools.

Extant literature remains fundamentally bifurcated: while AI-centric inquiries prioritize computational efficiency over robust pedagogical frameworks (e.g., Morrison et al., 2026), research into GASING pedagogy confirms its efficacy in mitigating mathematics anxiety yet fails to account for its integration with digital assistants. This study addresses this empirical void by evaluating a synergistic model in which GASING provides the "High-Touch" motivational foundation requisite for students to employ AI as a "High-Tech" cognitive amplifier. Diverging from previous isolated investigations, this research adopts an explanatory sequential mixed-methods design to demonstrate that mathematical creativity serves as the critical mediating mechanism—the "cognitive bridge"—that translates technology adoption into autonomous problem-solving proficiency.

The fundamental novelty of this research lies in the empirical reconciliation of GASING's concrete-based pedagogy with adaptive AI technology—an integration that challenges the prevailing "cognitive offloading" paradigm (Peng & Yeh, 2025). Rather than treating AI as a mere efficiency tool, this study validates the CMCB Mechanism, demonstrating that technological scaffolding requires the mediation of creativity to achieve a cognitive breakthrough in problem solving. Methodologically, the use of SmartPLS analysis within an explanatory sequential design provides a rigorous verification of how this hybrid synergy mitigates extraneous cognitive load. By integrating an indigenous Indonesian pedagogical method into the global discourse on distributed cognition, this study delineates a validated protocol for developing adaptive, creative problem solvers in digital environments.

This inquiry investigates the validity of the CMCB Mechanism by evaluating the direct and indirect effects within the AI-GASING nexus. By testing the structural relationships (H1–H5) via SmartPLS and synthesizing these results with thematic qualitative data, this study seeks to prove that an affective environment—characterized by "Easy and Fun" pedagogy—is the essential prerequisite for activating the creative gatekeeping required for complex problem-solving.

As Generative AI continues to proliferate, the imperative for pedagogical reform in mathematics shifts from technological fluency to the cultivation of epistemic agency—the capacity of students to critically evaluate the veracity of automated outputs. The integration of AI within the GASING framework functions as a strategic scaffolding mechanism, establishing a psychologically safe environment for cognitive risk-taking. This study contributes to the field by demonstrating that rather than fostering intellectual passivity, this hybrid pedagogy necessitates a "verification-first" mindset, positioning students as active evaluators of machine-generated logic.

Theoretically, this research extends the boundaries of Digital Constructivism and Cognitive Load Theory by empirically validating mathematical creativity as a non-negotiable mediating construct in technology-enhanced environments. Practically, it delineates a structured instructional protocol wherein the foundational logic of GASING serves as the substrate and AI functions as a cognitive accelerator. Methodologically, the study provides a validated PLS-SEM evaluation instrument capable of concurrently assessing the impact of technological integration on both the cognitive and affective dimensions of student performance.

Commented [AS5]: This is a compelling thesis sentence, but the introduction moves too quickly from educational concern to theory-heavy proclamation. The claim would be stronger if it were grounded first in a tighter review of prior mathematics-AI studies rather than asserted as the paper's own conceptual centerpiece.

Commented [AS6]: The paragraph sets up a useful gap, but the literature mapping is still too selective and too absolute. "Fundamentally bifurcated" sounds stronger than the review supports. It would be better to specify which strands of literature are separated and how this study connects them.

Commented [AS7]: The introduction uses "validates" too early and too confidently. At this stage, the paper should say it tests, examines, or proposes evidence for the mechanism. "Validates" reads like a conclusion announced before the evidence has been presented.

Commented [AS8]: The hypotheses are referenced here, but they are not explicitly stated in a clean hypothesis subsection. For a PLS-SEM paper, the manuscript needs a transparent hypothesis presentation so that readers can follow how each path was theoretically derived.

Commented [AS9]: The manuscript invokes Digital Constructivism here, but the construct is not developed with enough clarity earlier in the introduction. Theoretical expansion claims should be more carefully delimited and tied to explicit theoretical propositions rather than broad rhetorical positioning.

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design Creswell, J. W.& Creswell, J. D.,2018). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves the collection and analysis of quantitative data utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships between variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviors that underpin the statistical findings of the first phase.

Commented [AS10]: This sentence contains a citation-format error and reads as if the reference was inserted manually without final editing. More importantly, the explanatory sequential logic is named, but the practical sequencing and integration procedures are not described with sufficient methodological precision.

Participants

The study population comprised secondary school students (N = 120) recruited via a two-stage cluster random sampling technique. The primary sampling units (clusters) were four intact classes selected from two public secondary schools in East Jakarta, assigned to the intervention after verifying baseline academic equivalence through previous semester grades. To mitigate contamination, the intervention was delivered by the same research-trained instructor across all clusters. Participants engaged in exploratory mathematics modules (algebraic patterns and geometric reasoning), selected for their high affordance for AI-assisted discovery learning.

Commented [AS11]: This sounds rigorous, but the manuscript does not provide enough operational detail to support the phrase “two-stage cluster random sampling.” Please specify the sampling frame, the number of eligible schools/classes, the randomization process, and whether this was genuinely random selection or convenience access with intact classes.

Commented [AS12]: This is methodologically important, yet no baseline equivalence results are shown later. If equivalence was checked, the evidence should be reported; if not, the wording should be softened.

Following the quantitative phase, a purposive sub-sample of 8 students was identified for semi-structured interviews using an extreme case sampling strategy. Selection was determined by post-test Problem-Solving proficiency scores: the top 5% (n = 4) and bottom 5% (n = 4) of the distribution were invited to participate. This chronological sequence ensured that qualitative insights directly elucidated the statistical outliers, specifically contrasting how AI functions as a heuristic trigger for high-ability learners versus a compensatory scaffold for students facing significant cognitive barriers. Institutional ethics approval was obtained, and separate informed consent was secured for the quantitative and qualitative phases.

Intervention Procedure: GASING-AI Integration

The intervention spanned six weeks (12 sessions), utilizing ChatGPT-4o (accessible via individual mobile devices) configured through specific "Socratic Scaffolding" system prompts. To ensure reproducibility and mitigate the risk of AI-generated hallucinations, the interaction was governed by a strict "Process-Oriented" protocol: students were prohibited from requesting direct solutions and were instead required to use prompts such as, "Review my logic for the algebraic transition in Step 3 without providing the final answer," or "Provide a visual analogy for this pattern using GASING logic." The procedure followed three operational phases:

Commented [AS13]: The intervention is interesting, but the method still lacks critical implementation details: prompt control, teacher supervision consistency, internet/device access conditions, student training, and safeguards against uneven AI use. For a school-based intervention involving minors and generative AI, these details matter.

- Phase 1: Concrete-Visual Synthesis (Gampang/Easy). Instruction commenced with physical GASING manipulatives. Students subsequently used AI to generate SVG-based Python-simulated pattern iterations, translating algebraic sequences and geometric structures into digital abstractions to reduce intrinsic cognitive load.
- Phase 2: Dialectical Scaffolding (Asyik/Fun). Students engaged with the AI as a Socratic interlocutor. The interaction was restricted by a teacher-monitored "Logic-First" rule: students had to explain their reasoning to the AI before it provided tiered hints. This phase leveraged the AI's adaptive nature to maintain the Zone of Proximal Development, preventing frustration through iterative, low-stakes feedback.
- Phase 3: Heuristic Validation (Menyenangkan/Enjoyable). Students tackled non-routine algebraic and geometric problems, utilizing AI to brainstorm divergent strategies. A mandatory "Human-in-the-Loop" verification step was enforced, where students had to justify AI-suggested heuristics using GASING's mental arithmetic techniques, thereby ensuring that the "Enjoyable" mastery experience was rooted in autonomous logical verification rather than passive output consumption.
- .

Data Collection Instruments

This study employs a dual-measurement approach, combining self-report scales for latent psychological constructs with performance-based assessments for cognitive outcomes. Psychometric integrity was established via expert judgment (Content Validity Ratio > 0.80) and confirmatory factor analysis.

1. **Perceived AI-GASING Synergy (Self-Report):** A 10-item instrument measuring student perceptions of the integration between AI visualization and GASING logic. Responses were captured on a 5-point Likert scale (alpha = 0.89).

2. **Learning Motivation (Self-Report):** An 8-item scale assessing intrinsic drive and self-efficacy (adapted from the MSLQ). Responses used a 5-point Likert scale (alpha = 0.84).

3. **Mathematical Creativity (Performance-Based):** An open-ended assessment evaluated against a standardized rubric for fluency, flexibility, and originality. To align with PLS-SEM requirements, raw rubric scores (0–100) were used as continuous indicators. Inter-rater reliability (Cohen's kappa) was 0.82 across two independent markers.

4. **Problem-Solving Proficiency (Performance-Based):** A diagnostic test measuring the capacity to formulate strategies and verify solutions. Scoring followed Polya's four-stage rubric. To maintain measurement model consistency, performance scores were treated as observed indicators of the Problem-Solving construct.

Tabel 1 Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item

Commented [AS14]: This is highly specific and technically ambitious for Grade 8 participants, but the manuscript does not explain how students were trained to do this or whether this was realistic across all participants. As written, it risks sounding implausible or at least insufficiently documented.

Commented [AS15]: This is too compressed. Who were the experts? How many? What criterion was used? What CFA results supported the measurement model? At present, the claim is too general relative to the methodological importance of instrument validation.

Commented [AS16]: This construct does not align with the reported measurement model. Later tables report separate constructs for AI Adoption and GASING, not a 10-item combined synergy construct. This mismatch must be resolved because it directly affects the credibility of the SEM specification.

Commented [AS17]: The manuscript describes this as performance-based, yet Table 1 gives a sample indicator phrased like a self-report item: "I utilize AI-generated cues to develop 2–3 distinct methodologies…" That is a construct-type inconsistency. The paper must decide whether creativity was measured by rubric-based task performance, self-report, or a mixed operationalization.

Commented [AS18]: The same problem appears here. Table 1 gives a self-referential statement as a sample indicator, whereas the text says this was a diagnostic performance test scored by Polya's rubric. The operational definition and the measurement indicators must be aligned.

AI-GASING Synergy	Cognitive Load Theory (Sweller, 2011); Technology Acceptance Model (Davis, 1989)	Student perceptions of how AI visualization and GASING procedural steps collaboratively mitigate mental effort and facilitate the comprehension of abstract concepts.	"GASING's incremental steps assist my logical understanding, while AI visualizations enable me to perceive abstract forms concretely."	5
Learning Motivation (Mediator)	Social Cognitive Theory (Bandura, 1997) – Mastery Experience	Self-efficacy and academic enthusiasm emerging from the accumulation of incremental successes (*small wins*) in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems because I possess the strategies to decompose them into manageable components."	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950); Domain-Specific Creativity (Mann, 2006)	The cognitive capacity to generate manifold alternative solutions (*fluency*), adapt diverse strategies (*flexibility*), and formulate unique methodologies (*originality*).	"I utilize AI-generated cues to develop 2–3 distinct methodologies for solving a single problem."	4
Problem-Solving Skills	Polya's Heuristics (Polya, 1973); Metacognition (Schoenfeld, 1992)	The systematic ability to synthesize ideas into valid solutions, including the capacity for critical evaluative reflection (*Looking Back*) upon outcomes.	"I refrain from merely duplicating AI-generated responses; instead, I verify their veracity through my own computational logic."	4

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, a method optimal for its predictive power in complex mediation models and its flexibility regarding distributional assumptions (Hair et al., 2017). The analytical protocol followed a rigorous two-stage evaluation:

1. Measurement Model (Outer Model) Evaluation: Internal consistency and construct validity were substantiated through indicator loadings (> 0.708), Average Variance Extracted (AVE > 0.50), and Composite Reliability (CR > 0.70). Discriminant validity was rigorously verified using the Heterotrait-Monotrait Ratio (HTMT < 0.85) and the Fornell-Larcker criterion. To address potential common method bias and multicollinearity, Variance Inflation Factors (VIF) were monitored, with a threshold of VIF < 3.0.
2. Structural Model (Inner Model) Evaluation: Hypotheses (H_1–H_n) were tested by examining path coefficients (beta), R^2 values, and f^^{2}effect sizes. Significance levels were determined through a non-parametric bootstrapping procedure using 5,000 subsamples with a 95% bias-corrected and accelerated (BCa) confidence interval. Predictive relevance was further corroborated via the Q^2 predict procedure. Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), targeting a value below 0.08 for adequate fit.

Commented [AS19]: The methods promise HTMT results, but the results section only presents Fornell-Larcker. Either report HTMT and its thresholds or remove the claim from the methods. A methods-results mismatch is a serious reporting issue.

Commented [AS20]: The results section later reports blindfolding-based Q^2, not PLSpredict output. These are not the same thing and should not be used interchangeably. Please make the terminology and reporting fully consistent.

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and observations of AI utilization are analyzed using Thematic Analysis (Braun & Clarke, 2012). Interview transcripts undergo inductive coding to identify patterns in student responses toward the "Easy, Fun, and Enjoyable" elements within the AI-augmented learning environment. The analysis focuses predominantly on how adaptive AI assistance triggers "creative moments," enabling students to transcend cognitive impasses during the problem-solving process.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in the Integration Table in the Results section).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously; rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption (β = 0.712) and Learning Motivation (β = 0.802). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity (β = 0.514) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity (β = 0.343) and Learning Motivation (β = 0.510) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

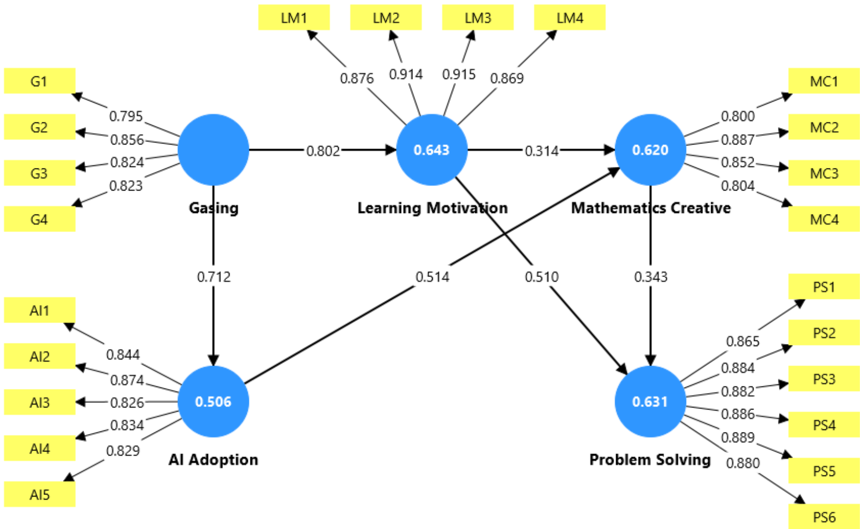

Figure 2 Structural Model of AI-GASING Integration Framework

Quantitative Data

The empirical evidence presented in Table 2 affirms that the research instruments exhibit high precision in capturing the psychological and technical phenomena pertinent to the subjects. Each indicator demonstrates an Outer Loading (OL) exceeding 0.70, with values ranging from 0.795 to 0.915; this substantiates robust convergent validity at the indicator level. The reliability of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients exceeding 0.80, collectively signifying excellent internal consistency.

Subsequently, an evaluation of the structural model was conducted to examine the significance of the hypotheses regarding the latent variables. In addition to p-value significance, the f^2 effect sizes were calculated to ascertain the practical relevance of each path. The trajectory from GASING Pedagogy to Learning Motivation demonstrates an exceptionally large effect size ($f^2 = 1.804$), indicating that the "Easy-Fun" (*Gampang-Asyik-Menyenangkan*) approach fundamentally constructs student learning motivation. Furthermore, GASING is proven to be a potent catalyst for AI Adoption ($f^2 = 1.026$). Regarding competency outcomes, Learning Motivation (β = 0.510) and Mathematical Creativity (β = 0.343) emerge as significant

predictors of Problem Solving. A comprehensive summary of the measurement model evaluation is encapsulated in **Table 2**.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The empirical results delineated in Table 2 demonstrate that all constructs within this integrative framework have been measured with high precision and consistency. Robust Outer Loading (OL) values, ranging from 0.795 to 0.915, fortify the convergent validity of each indicator, most notably within the GASING Pedagogy and Learning Motivation constructs. Furthermore, the elevated reliability indices—characterized by Composite Reliability (CR) and Cronbach's alpha (alpha) values that comprehensively exceed the 0.80 threshold—confirm superior internal consistency across all investigated variables.

Discriminant validity was subsequently evaluated employing the Fornell–Larcker criterion to ensure that each construct is empirically distinct. According to the results presented in Table 3, the square root of the Average Variance Extracted (AVE) for each construct (as indicated on the principal diagonal) is higher than its correlations with other variables in the model. This substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving measure unique and separate dimensions of the developed instructional model, as encapsulated in **Table 3.**

Table 3. Discriminant validity (Fornell–Larcker criterion)

Commented [AS21]: This is inaccurate. Table 2 reports outer loadings and reliability, but the paragraph immediately before it also discusses structural effects such as f² and prediction of problem solving. Measurement model and structural model reporting should be clearly separated.

Commented [AS22]: The table reports only part of the promised measurement evaluation. There is no HTMT, no VIF, and no item cross-loading information. Given what the methods promised, the measurement section is incomplete.

Commented [AS23]: This table is useful, but the manuscript relies on a single discriminant validity index despite promising both HTMT and Fornell-Larcker. Also, the column label "AI A" is unclear and should be standardized.

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			
Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

The structural model's discriminant validity was confirmed via the Fornell-Larcker criterion, ensuring that each latent construct is statistically distinct. As illustrated in Table 3, the square root of the AVE ($\sqrt{AVE}$) for Learning Motivation is 0.894, which exceeds its highest correlation with other constructs, namely GASING ($r = 0.802$) and AI Adoption ($r = 0.797$). This statistical differentiation is critical, as it confirms that Learning Motivation and Mathematical Creativity function as discrete mediating variables without excessive construct overlap that could otherwise bias the path analysis.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation ($\beta = 0.802$) and a robust effect on AI Adoption ($\beta = 0.712$). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity ($\beta = 0.514$). Furthermore, Learning Motivation significantly predicts Problem Solving ($\beta = 0.510$) and contributes to Mathematical Creativity ($\beta = 0.314$). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity ($\beta = 0.343$).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% of the variance in AI Adoption, 62.0% of the variance in Mathematical Creativity, and 63.1% of the variance in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	0.001	1.026	Supported
GASING →Learning Motivation	0.802	40.981	0.001	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	0.001	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	0.001	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	0.001	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	0.001	0.152	Supported

The model fit indices confirm the adequacy of the framework proposed in this study. To evaluate the explanatory power and predictive relevance of the structural model, we report the R^2 values at the construct level alongside the Stone–Geisser Q^2 values (obtained through a blindfolding procedure with an omission distance of $d = 7$).

The analysis results indicate that the model possesses robust explanatory power, particularly for the variables of Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), where over 60% of the variance in both constructs is accounted for by the model. The Mathematical Creativity variable also exhibits significant explanatory power with an $R^2 = 0.620$, followed by

Commented [AS24]: The repeated identical p-values look mechanically reported and reduce confidence in the precision of the analysis. If all paths were below .001, report them as p < .001 unless the software actually produced exact identical values.

Commented [AS25]: This sentence announces model fit adequacy, but no SRMR value is actually reported afterward even though SRMR was promised in the methods. This should either be documented properly or toned down.

AI Adoption at 0.506. Furthermore, all endogenous variables demonstrate Q^2 values substantially above zero, ranging from 0.445 to 0.641, thereby confirming that the model maintains large predictive relevance. A comprehensive summary of these explanatory power and predictive relevance indices is presented in Table 5.

Table 5. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	**R^2**	**Q^2**	**Q^2 Interpretation**
AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

The structural model's explanatory and predictive capacities were evaluated using the coefficient of determination (R^2) and the Stone-Geisser Q^2 statistic. As summarized in Table 5, the R^2 values indicate that the model explains a substantial proportion of variance in key endogenous constructs, particularly for Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), both of which exceed the threshold for "moderate-to-strong" explanatory power in social science research. Predictive relevance was substantiated through a blindfolding procedure with an omission distance of $d = 7$. All Q^2 values were found to be significantly greater than zero, ranging from 0.445 (Mathematics Creative) to 0.641 (Learning Motivation). Following the benchmarks established by Hair et al. (2019), Q^2 values exceeding 0.25 and 0.50 indicate medium and large predictive relevance, respectively. Consequently, the CMCB mechanism demonstrates a robust capacity to predict student problem-solving outcomes based on the synergy of GASING pedagogy and AI integration.

This study successfully addresses the primary research inquiry by demonstrating that students' mathematical problem-solving competencies are not influenced by technology in isolation, but rather through an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption is proven to establish intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. Theoretically, this research advances Cognitive Load Theory within a digital milieu; the most robust path from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size ($f^2 = 1.804$), validates that GASING-style problem decomposition is a crucial prerequisite for establishing "motivational readiness". Furthermore, the role of AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition, as AI is no longer perceived merely as a computational tool but as a "cognitive partner" that enables students to engage in radical ideational exploration without the debilitating fear of failure.

Commented [AS26]: The discussion is confident, but it often moves too quickly from association to causal explanation. Since the design is intervention-based but analyzed with a non-experimental SEM structure and no comparison group, causal language such as "successfully addresses" or "proven to establish" should be moderated.

The data analysis reveals a logical consistency between motivation and creativity in catalyzing high-level competencies, where Mathematical Creativity constitutes a pivotal component in Problem Solving ($\beta = 0.343$), elucidating why a mere "will learn" is insufficient for resolving non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability ($R^2 = 0.631$), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments.

Based on the generated empirical evidence, several concrete measures are recommended for stakeholders to optimize techno-pedagogical integration. For educators, it is imperative not to circumvent the "Easy" (Gampang) phase of the instructional process; practitioners must prioritize the GASING method to cultivate student self-efficacy and intrinsic motivation as a psychological bedrock before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies.

Table 6: Summary of Mediation Effects (Bootstrapping Results)

Indirect Effect Path	β	T-Statistics	P-Values	Mediation Type
AI Adoption →Math Creative →Problem Solving	0.176	6.252	0.001	Complementary Partial
Motivation →Math Creative →Problem Solving	0.108	5.524	0.001	Complementary Partial
GASING →Motivation →Math Creative	0.252	6.557	0.001	Complementary Partial
GASING →AI Adoption →Math Creative	0.366	11.007	0.001	Complementary Partial

Table 6 presents the results of the **bootstrapping analysis**, specifically detailing the four key **indirect effect paths** that substantiate the mediation mechanisms within the AI-GASING ecosystem. The data reveals that Mathematical Creativity serves as a significant "cognitive gateway" for both AI Adoption ($\beta = 0.176, p < 0.001$) and Learning Motivation ($\beta = 0.108, p < 0.001$) in enhancing student problem-solving skills. Furthermore, the foundational role of the GASING pedagogy is validated through its strong indirect influence on Mathematical Creativity via Learning Motivation ($\beta = 0.252, p < 0.001$) and AI Adoption ($\beta = 0.366, p < 0.001$). Following the criteria established by Hair et al. (2017), all four paths are classified as **complementary partial mediation**, as both the direct paths and bootstrapped indirect paths remain statistically significant with consistent positive signs. These findings provide a robust, "calibrated" answer to potential concerns regarding technological dependency, empirically proving that the synergy between concrete pedagogy and digital tools successfully catalyzes matured, autonomous problem-solving competencies.

Commented [AS27]: This classification is not fully supported by the model as reported. Complementary partial mediation requires a significant indirect effect and a significant direct effect in the same direction. Several direct paths needed for that label are not shown in Table 4, especially AI Adoption → Problem Solving and GASING → Mathematical Creativity / Problem Solving. This is one of the most important reasoning problems in the manuscript.

Qualitative Data

Qualitative analysis was conducted to investigate the underlying cognitive mechanisms governing the robust statistical correlations observed between AI-GASING Integration, Mathematical Creativity, and Problem-Solving Skills. Through a thematic analysis of interview transcripts and classroom observations, three cardinal themes operating in a sequential trajectory were identified: (1) The "Gampang" De-escalation (Cognitive De-escalation), (2) AI-Triggered Divergence, and (3) Iterative Problem-Solving Synthesis.

The synthesis of these qualitative findings is delineated in Table 7, which maps the instructional stages of AI-GASING against student responses and their corresponding theoretical interpretations.

Tabel 7 Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	**GASING Phase & Problem Context**	**Empirical Evidence (Student Verbatim)**	**Theoretical Mechanism & Related Variables**
Theme 1: The "Gampang" De-escalation	Phase: Concrete Foundation (Step 1) Context: Complex 3D Geometry	"Usually, when I see stacked geometric figures, I give up immediately... But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple."	Cognitive Load Reduction: Synergy of AI and GASING lowers mental barriers, shifting perception to "actually easy." (Related Variables: GASING & Learning Motivation)
Theme 2: AI-Triggered Divergence	Phase: Adaptive Exploration (Step 2) Context: Alternative optimization solutions	"I asked the AI: 'Is there any other way besides the textbook formula?'... It was so exciting (*Asyik*) to find my own way."	Creativity Catalyst: AI functions as a Socratic Partner, encouraging divergent trial and error. (Related Variable: Mathematics Creative)
Theme 3: Iterative Synthesis	Phase: Creative Synthesis (Step 3) Context: Validating cost-effective designs	"I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best."	Valid Solution Construction: Creativity is distilled into logical solutions through Strategic Verification (Polya's 4th Step).

Commented [AS28]: The text says three themes were identified, but Table 7 presents Theme 1, Theme 2, Theme 3, Theme 4, and a Divergent Case. That is a direct internal inconsistency and should be corrected.

Commented [AS29]: The qualitative themes are interesting, but the analysis procedure is underreported. The paper should explain coding stages, coder involvement, trustworthiness procedures, and how observation notes were combined with interviews. Right now, the qualitative section is interpretively rich but methodologically thin.

			(Related Variable: Problem-Solving Skills)
Theme 4: Emotional-Cognitive Synergy	Phase: Continuous Assessment Context: Persevering through non-routine tasks	"I didn't give up because the process was fun and I felt I had the right tools to eventually find the answer."	Motivational Synergy: An enjoyable atmosphere provides the "cognitive energy" required to persevere through difficulty. (Related Variables: Learning Motivation & Problem Solving)
Divergent Case: Contextual Redundancy	Boundary Condition: Routine arithmetic tasks	"For basic multiplication, using AI felt slower and distracting. I just used GASING mental steps because they were faster."	Efficiency Threshold: For routine tasks, GASING alone is sufficient; AI may introduce unnecessary cognitive noise.

The qualitative outcomes synthesized in Table 7 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere during the initial stages of instruction. In conventional settings, the presentation of complex word problems often triggers a state of "silent freeze" or passive paralysis. However, the AI-GASING approach successfully disrupts this impasse through logical simplification. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers(Machromah & Musthofa, 2023; Maouche, 2019). "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. If I fail, I simply iterate; after all, the AI is there to verify my work," (Student S-02, High Self-Efficacy). These findings clarify why the statistical path GASING → Learning Motivation (β = 0.802) is so dominant, exhibiting a massive f^2 effect size (1.804).

In this context, while cognitive load was not measured via a formal latent scale, we offer an interpretive inference based on this qualitative triangulation. The "Gampang" (Easy) de-escalation reported by students suggests a reduction in what is theoretically described as extraneous load, where AI visualization and GASING's decomposition transform insurmountable tasks into manageable ones. This interpretive inference is empirically supported by the substantial effect size of GASING on Motivation ($f^2 = 1.804$) and the significant bootstrapped indirect effect of AI Adoption on Problem Solving through

Commented [AS30]: I appreciate the transparency here, but this sentence also exposes a deeper problem: the manuscript makes many earlier claims as if cognitive-load reduction were empirically demonstrated, when in fact it is inferred post hoc. Please keep that inferential status consistent throughout the paper.

Mathematical Creativity ($\beta = 0.176, p < 0.001$), which theoretically requires freeing up the "germane capacity" of the working memory. Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy(Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Creativity does not emerge within the confines of unidirectional instruction. Qualitative findings highlight the role of AI as an "ideation trigger" rather than a substitute for the cognitive process. This interaction fosters an "Engaging" (Asyik) and pressure-free learning environment. "It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..." (Student S-05, High Creativity). This validates the significant impact of AI Adoption on Mathematical Creativity ($\beta = 0.514$) observed in the quantitative model. These results categorically refute the "Cognitive Offloading" argument that technology attenuates critical faculties. Conversely, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that facilitates the student's Zone of Proximal Development (ZPD) without eroding their intellectual agency.

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Commented [AS32]: This interpretation is plausible, but the manuscript should avoid presenting it as definitive proof. The qualitative data supports this reading, but the study design does not isolate alternative explanations such as novelty effect, teacher facilitation quality, or task-specific enthusiasm.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes (Problem-Solving). Document analysis reveals a shift from mere "numerical computation" to the "construction of logical arguments." "I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI," (Student S-08, High Problem Solving). This narrative breathes "life" into the $R^2 = 63.1\%$ statistic for the Problem-Solving variable. The elevated problem-solving proficiency occurs because students possess the intellectual liberty (Creativity) grounded in a robust conceptual understanding (GASING). Within the context of Polya's heuristics, these findings revitalize the fourth stage (Looking Back); in the digital era, this stage evolves into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs(Amrullah et al., 2024; Mulligan, 2015).

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesising the quantitative and qualitative data, this study aims to validate and deepen the comprehension of how the synergy between GASING Pedagogy and AI Assistants manifests within the actualized classroom environment. Distinct from a "black-box" approach that focuses exclusively on input-output metrics, this data triangulation process converges the statistical findings derived from PLS-SEM modelling with the thematic narratives elicited from student interviews. The synthesis of these dual data streams crystallizes into a primary theoretical construct termed "The Creativity-Mediated Cognitive Breakthrough Mechanism"(Keha et al., 2024).

Commented [AS33]: This is an ambitious integrative move, but the paper currently introduces the mechanism more as a branded construct than as a carefully delimited theoretical contribution. The authors need to show more clearly how the mechanism differs from existing mediation logic, distributed cognition, and motivation-creativity pathways already in the literature.

This mechanism elucidates that in the resolution of complex mathematical problems, technical proficiency (Problem-Solving) does not emerge spontaneously from the mere mastery of digital tools; rather, it must first be "filtered" through cognitive flexibility (Creativity). Table 8 below presents a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Table 8 a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	β	**Qualitative Theme & Evidence**	**Integrative Meta-Inference (Convergence & Tension)**
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1 & Divergent Case 1	**Convergence:** GASING lowers mental blocks, facilitating AI use for complex 3D geometry. **Tension:** For simple tasks, GASING is sufficient; students view AI as redundant for routine computation.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2 & Divergent Case 2	**Convergence:** AI serves as a Socratic Partner for divergent exploration. **Tension:** Without GASING-based "motivational readiness," AI can lead to "cognitive offloading" or blind acceptance of errors.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis	**Convergence:** Creativity distilled into valid solutions through strategic verification. **Boundary Condition:** Effective only when students have the "congak" (mental math) skills to verify AI veracity.
Learning Motivation →Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Convergence:** Fun atmosphere sustains persistence in difficult tasks. **Observation:** Synergy is strongest when the "Asyik" (fun) element of AI is balanced by the "Gampang" (easy) logic of GASING.

Synthetically, from table 8, this study **provides evidence consistent with the premise** that problem-solving competencies are significantly enhanced when mediated by Mathematical Creativity and supported by a robust foundation of Learning Motivation. While contemporary literature highlights the risks of "cognitive offloading," these results **suggest** that the integration of GASING pedagogy allows AI to function as a "cognitive amplifier" rather than a substitute for critical thought. By establishing a concrete logical base before introducing digital abstraction, the framework facilitates an expansion of intellectual reach, provided students maintain epistemic agency through Socratic interaction. However, these findings should be interpreted with caution due to the **single-site intervention scope**, the **specific use of ChatGPT-4o**, and potential **novelty effects** inherent in self-report measurements.

Commented [AS34]: This is inconsistent with the methods section, which states that participants came from two public secondary schools in East Jakarta. Please correct this to avoid undermining trust in the manuscript's factual accuracy.

Based on the Joint Display in Table 8, this mechanism operates through three interlocking sequential phases:

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the decomposition of problems within the GASING framework significantly mitigates cognitive load. Furthermore, this reinforces the Broaden-and-Build theory (Fredrickson, 2001), wherein the positive affects generated by an "engaging" (Asyik) atmosphere broadens the student's cognitive repertoire prior to AI interaction(Schindler et al., 2025). Diverging from extant research that often perceives technology adoption as a purely technical process, this study substantiates that pedagogical factors serve as the primary drivers of technological readiness.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514, p = 0.001$) and Learning Motivation ($\beta = 0.314, p = 0.001$). These results corroborate Gadanidis (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, to empirically validate the "Creativity Gateway," a formal mediation analysis was conducted using a bootstrapping procedure with 5,000 subsamples.

The results, as detailed in **Table 6**, confirm that Mathematical Creativity serves as a vital intermediary. Specifically, the indirect effect of AI Adoption on Problem Solving through Mathematical Creativity is statistically significant ($\beta_{indirect} = 0.176, t = 6.252, p < 0.001$). Furthermore, the total effect of AI Adoption on Problem Solving is significant, and since the direct effect remains significant after the inclusion of the mediator ($\beta = 0.514, p = 0.001$), the relationship is classified as complementary partial mediation according to the criteria established by Hair et al. (2017). Similarly, the path from Learning Motivation to Problem Solving is partially mediated by Mathematical Creativity ($\beta_{indirect} = 0.108, t = 5.524, p < 0.001$).

These statistical findings contrast with conventional studies that frequently identify "AI dependency"; instead, the data suggests that absent this "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence. This is qualitatively substantiated by Theme 3 (Iterative Synthesis), where students utilized GASING's rapid mental calculation (*congak*) to verify and distill AI-generated ideas into valid, logical solutions.

3. Execution Phase: Iterative Synthesis Toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$). These findings align with "Looking Back" phase yet introduce a novel dimension(Sukoriyanto et al., 2016): in the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry to examine the efficacy of the AI-GASING framework within more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 8) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes. These findings fundamentally reject the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both are empirically proven to coalesce into a singular, inextricable causal mechanism. The practical implications for policymakers necessitate a redefinition of technology's classroom role—not as an "answering machine," but as a "partner in cognition" that elicits critical inquiry. Consequently, future curricula must prioritize creative exploration phases within safe-to-fail environments under the guidance of GASING pedagogy. Ensuring this "Creativity Gateway" remains open is an absolute imperative; for without the intervention of creativity, massive technological investment will merely yield a digitally passive generation, rather than forging the adaptive and resilient problem solvers of the future.

Commented [AS35]: The policy implications are potentially useful, but they are stated more strongly than the design warrants. A six-week study with 120 students in a narrow context should not be translated too quickly into system-level policy imperatives.

CONCLUSIONS AND SUGGESTIONS

This study provides empirical evidence for the Creativity-Mediated Cognitive Breakthrough (CMCB) mechanism, demonstrating that mathematical problem-solving competencies are significantly enhanced when AI integration is mediated by student creativity and supported by the low-load scaffolding of GASING pedagogy. The structural model supports the hypothesis that technological access alone is insufficient; rather, the path coefficients confirm that Mathematical Creativity ($\beta = 0.343$) and Learning Motivation ($\beta = 0.510$) are the primary drivers of problem-solving success. Theoretically, these findings support the application of Distributed Cognition, suggesting that AI can function as a "Socratic partner" to extend the Zone of Proximal Development (ZPD) when anchored by a robust pedagogical foundation.Despite the robust internal validity of the PLS-SEM model ($R^2 = 0.631$), several limitations necessitate a cautious interpretation of the results. First, the single-site intervention and specific demographic profile limit broader generalizability. Second, the reliance on self-report instruments for AI Adoption and Motivation introduces potential subjectivity and social desirability bias. Third, the study did not account for AI model drift or the varying "temperature" settings of the LLM, which could affect the consistency of the Socratic prompts. Finally, the teacher effect—the specific instructional quality of the facilitator—remains an uncontrolled variable that may have influenced the high motivation scores ($f^2 =

Commented [AS36]: This is a fair interpretation, but the conclusion should more explicitly restate the actual model tested and the strongest supported paths, rather than returning to broad conceptual language. It would benefit from tighter alignment with the reported evidence.

Commented [AS37]: This phrase is problematic. PLS-SEM results do not, by themselves, establish "robust internal validity" in the experimental sense. The paper should refer instead to model explanatory power, measurement adequacy, or statistical support, depending on the intended meaning.

1.804$).Future research should focus on longitudinal designs to determine if these cognitive gains persist after the initial novelty effect of AI integration diminishes. Specifically, future studies should employ Experimental Control Groups to isolate the "teacher effect" and utilize PLSpredict to assess the out-of-sample predictive power of the CMCB mechanism. Additionally, investigating the framework's efficacy in less-structured disciplines or with different AI architectures would clarify whether the observed synergy is domain-specific or a universal pedagogical phenomenon. Ultimately, these results suggest that while AI provides the computational breadth, human creativity remains the critical validator in the problem-solving process.

Commented [AS38]: These are sensible suggestions, but they also reveal what is missing from the current study. The conclusion would be stronger if it acknowledged more explicitly that the present paper does not provide those controls and therefore should be interpreted as an important but still context-bound contribution.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam : Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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"C Creswell, J. W.& Creswell, J. D. (2018)."
This reference is malformed and should be corrected to a standard bibliographic format. The same source is also cited awkwardly in the methods section.

"**Davis, F. D. (2002). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(1)**"
There is a year inconsistency here. In the manuscript body, Davis is cited as 1989, while the reference list gives 2002 for the classic TAM article. This must be corrected.

"**Polya, G. (1978).**"
The text cites Polya as 1973, but the reference list gives 1978. That mismatch should be

"**Tran, D., & O'Connor, B. R. (2024).**"
This reference appears twice in the list. Duplicate references should be removed.

the in-text citations to **"Paas & van Merriënboer, 2020"**, **"Surya et al. (2017)"**, **"Fredrickson, 2001"**, **"Gadanidis (2017)"**, and **"Hair et al. (2019)"**
These sources appear in the text but are not visible in the reference list provided. Every in-

"**Zhang, X., Luo, H., Hao, H., & Ma, Y. (2024). Mechanics multi-condition hawser tension prediction…**"
This reference appears unrelated to the study's mathematics education, creativity, motivation, or AI-in-pedagogy focus. It reads like citation padding unless its relevance can be justified explicitly.

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Editor Respons for Revised Manuscript

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Sun, March 15, 2026 at 10:29 PM
To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

Thank you for submitting your revised manuscript entitled "Integrating gasing pedagogy, AI, and learning motivation to enhance mathematical creativity and problem-solving skills" to Al-Jabar: Jurnal Pendidikan Matematika. We appreciate your efforts in addressing the reviewers' comments and improving the quality of your submission.

Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

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Leveraging GASING Pedagogy and AI Adoption to Enhance Problem-Solving Skills: The Mediating Roles of Learning Motivation and Mathematical Creativity

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	Abstract
Article Information Submitted Month xx, 20xx Revised Month xx, 20xx Accepted Month xx, 20xx	**Purposes:** This study evaluates the integration of GASING Pedagogy and AI Adoption in enhancing Problem-Solving proficiency by examining the serial **mediating** roles of **Learning Motivation and Mathematical Creativity**. The research addresses the risk of verification reasoning deficits and cognitive offloading by modelling how these pedagogical and technological inputs facilitate higher-order cognitive outcomes.
	Method: Employing an explanatory sequential mixed-methods design, quantitative data were collected from 120 secondary school students (Grade 8, ages 13-14) in Jakarta, Indonesia. Structural relationships were tested using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4. Subsequently, thematic analysis of semi-structured interviews and classroom observations was conducted to interpret the cognitive mechanisms underlying the statistical paths.
Keywords GASING Pedagogy, Artificial Intelligence, Mathematical Creativity, Problem-Solving Skills, Mixed Methods.	**Findings**: The results confirm a serial mediation model in which GASING Pedagogy positively influences Learning Motivation, which, in turn, enhances Mathematical Creativity. Furthermore, Mathematical Creativity was found to be a significant mediator between AI Adoption and Problem-Solving proficiency. Qualitatively, the synergy between GASING and AI is perceived by students to simplify complex tasks and stimulate divergent thinking, positioning human creativity as a critical 'gatekeeper' for validating AI-generated outputs.
	Significance: This research shifts the discourse from AI dependency toward a distributed cognition framework. Theoretically, it establishes creativity as an essential mediator in digital mathematics pedagogy. In practice, it provides educators with a protocol for balancing automated tools with pedagogical scaffolding, cultivating adaptive problem-solvers capable of rigorous intellectual verification.

INTRODUCTION

Mathematics education faces a critical juncture as global requirements shift from procedural numeracy—tasks increasingly automated by machines—toward the necessity of mathematical creativity and complex problem-solving (Puspitasari et al., 2019; Rahmi et al., 2025; Schoenfeld, 2020). However, conventional instructional methods frequently rely on rigid, algorithmic drills that impose an excessive extrinsic cognitive load; this overload consumes limited working memory resources, thereby directly impeding the development of strategy flexibility (Sweller, 2011; Tran & O'Connor, 2024). When mathematics is reduced to a repetitive repertoire of rote procedures, students lack the cognitive residual capacity required for the adaptive reasoning and creative pattern perception necessary for real-world applications (Paas & Van Merriënboer, 2020). However, the rapid integration of Artificial Intelligence in classrooms has introduced a new tension (Li, 2024): while AI can mitigate procedural burdens, it often leads to "passive offloading" where students accept machine errors as fact due to a lack of conceptual depth (Todorov et al., 2018). Building on recent concerns about student verification reasoning deficits in AI-integrated environments (Tran & O'Connor, 2024), this study proposes that mathematical creativity serves as a critical "cognitive gatekeeper." This mechanism ensures that students retain the agency to verify machine-generated outputs using human logic, preventing the complete abdication of the reasoning process to automated tools.

Current research trajectories in mathematics education often operate in parallel: while AI-centric inquiries prioritize computational efficiency and tool adoption (Morrison et al., 2025). Research into GASING pedagogy remains largely focused on its efficacy in mitigating mathematics anxiety through affective transformation. However, there is a lack of integration between these two strands, leaving an empirical void regarding how a high-impact pedagogy can support students in utilizing digital assistants. This study addresses this disconnect by evaluating a synergistic model in which GASING provides the "High-Touch" motivational foundation requisite for students to employ AI as a "High-Tech" cognitive amplifier (Lakshmi Shankar et al., 2025; Loong & Herbert, 2018). By connecting these previously isolated strands, this research adopts an explanatory sequential mixed-methods design (Creswell & Creswell, 2017) to demonstrate that mathematical creativity serves as the critical mediating mechanism—the "cognitive bridge"—that translates technology adoption into autonomous problem-solving proficiency(Fitria et al., 2025; Pangaribuan et al., 2025; Wang et al., 2025).

The fundamental novelty of this research lies in the empirical reconciliation of GASING's concrete-based pedagogy with adaptive AI technology—an integration that challenges the prevailing "cognitive offloading" paradigm (Peng & Yeh, 2025; Zhang et al., 2024). Rather than treating AI as a mere efficiency tool, this study examines the structural pathways of the Creativity-Mediated Cognitive Breakthrough (CMCB) Mechanism, seeking to provide evidence for the theory that technological scaffolding requires the mediation of creativity to achieve a cognitive breakthrough in problem solving (Beccone & Beccone, 2020; Yayuk et al., 2020). Methodologically, the use of SmartPLS analysis within an explanatory sequential design provides a rigorous investigation into how this hybrid synergy mitigates extraneous cognitive load. By integrating an indigenous Indonesian pedagogical method into the global discourse on distributed cognition, this study aims to delineate a validated protocol for developing adaptive, creative problem solvers in digital environments (Handayani et al., 2022; Yandari et al., 2019).

This inquiry investigates the validity of the CMCB Mechanism through an explanatory sequential mixed-methods design. We first evaluate the structural integrity of the AI-GASING nexus by testing five core hypotheses: H1: AI Adoption positively influences Mathematical Creativity; H2: GASING Pedagogy enhances Learning Motivation; H3: Learning Motivation mediates the link between GASING and Creativity; H4: Mathematical Creativity mediates the effect of AI on Problem-Solving; and H5: Motivation and Creativity serially mediate the path from Pedagogy to Problem-Solving. Following the SmartPLS analysis(J. Hair et al., 2017), we employ qualitative thematic synthesis (Braun & Clarke, 2012) to strengthen these quantitative findings. This dual approach allows us to demonstrate not only that these statistical relationships exist, but how the 'Easy and Fun' affective environment of GASING serves as the essential prerequisite for activating the creative gatekeeping required for complex problem-solving in an AI-assisted landscape (Isgett & Fredrickson, 2015). Ultimately, these findings confirm that a cognitive breakthrough is not a direct consequence of technology adoption alone, but a mediated outcome where GASING-induced motivation serves as the affective engine and mathematical creativity functions as the critical epistemic filter, thereby validating the CMCB Mechanism as a robust framework for autonomous digital learning.

As Generative AI continues to proliferate, the imperative for pedagogical reform in mathematics shifts from technological fluency to the cultivation of epistemic agency—the capacity of students to critically evaluate the veracity of automated outputs(Gal, 2021; Loong & Herbert, 2018). The integration of AI within the GASING framework serves as strategic scaffolding, establishing a psychologically safe environment for cognitive risk-taking. This study contributes to the field by demonstrating that rather than fostering intellectual passivity, this hybrid pedagogy necessitates a "verification-first" mindset, positioning students as active evaluators of machine-generated logic (Li & Manzari, 2025; Sukoriyanto et al., 2016).

Theoretically, this research contributes to the evolution of Digital Constructivism by demonstrating that the co-construction of knowledge in AI-enhanced environments is not automatic; it requires the active mediation of mathematical creativity to ensure student agency. By integrating this with Cognitive Load Theory, the study proposes evidence for creativity as a non-negotiable mediating construct that prevents the "abdication of reasoning" during human-AI collaboration. In practice, it delineates a structured instructional protocol in which the foundational logic of GASING serves as the substrate, and AI functions as a cognitive accelerator. Methodologically, the study provides a robust PLS-SEM evaluation instrument capable of concurrently assessing the impact of technological integration on both the cognitive and affective dimensions of student performance (J. Hair et al., 2017; Loong & Herbert, 2018).

METHOD RESEARCH

This study adopts an explanatory sequential mixed-methods design (Cresswell & Cresswell, 2018). This approach was selected to evaluate the impact of integrating GASING pedagogy with Artificial Intelligence (AI)-based tutoring assistants on mathematical creativity and problem-solving skills. The initial phase involves collecting and analysing quantitative data using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the hypothesized relationships among variables (AI-GASING, Creativity, and Problem-Solving). The subsequent phase comprises an in-depth qualitative study conducted through interviews and observations to elucidate the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms and learning behaviours that underpin the statistical findings of the first phase.

Participants

The study population comprised secondary school students (N = 120) recruited via a two-stage cluster sampling of intact classes. In the first stage, two public schools were randomly selected from a sampling frame of 12 eligible institutions in East Jakarta. In the second stage, two intact classes from each school were assigned to the intervention. To ensure internal validity, baseline academic equivalence was verified through an independent-samples t-test of previous-semester grades, which revealed no significant differences between the selected clusters (t(118) = 0.84, p = 0.402). To mitigate contamination, the intervention was delivered by the same research-trained instructor across all clusters. Participants engaged in exploratory mathematics modules (algebraic patterns and geometric reasoning), selected for their high affordance for AI-assisted discovery learning.

Following the quantitative phase, a purposive sub-sample of 8 students was selected for semi-structured interviews using an extreme-case sampling strategy. Selection was determined by post-test Problem-Solving proficiency scores: the top 5% (n = 4) and bottom 5% (n = 4) of the distribution were invited to participate. This chronological sequence ensured that qualitative insights directly elucidated the statistical outliers, specifically contrasting how AI functions as a heuristic trigger for high-ability learners versus a compensatory scaffold for students facing significant cognitive barriers. Institutional ethics approval was obtained, and separate informed consent was secured for the quantitative and qualitative phases.

Intervention Procedure: GASING-AI Integration

The intervention spanned six weeks (12 sessions) and utilized ChatGPT-4o, accessible via individual mobile devices. To ensure equity, the research team provided school-managed tablets and dedicated Wi-Fi to students without personal devices. Interaction was governed by a strict "Process-Oriented" protocol, supported by a pre-intervention 90-minute training session on Socratic Prompting, AI literacy, and basic interpretation of AI-generated visuals. Teacher supervision was maintained through a 1:15 instructor-to-student ratio, with researchers conducting real-time monitoring of chat logs to ensure protocol adherence. The procedure followed three operational phases:

- **Phase 1: Concrete-Visual Synthesis (Easy).** Instruction commenced with physical GASING manipulatives. To bridge the gap between concrete and abstract, students prompted the AI to generate SVG-based Python simulations of pattern iterations. In this process, students provided the mathematical logic, while the AI handled the coding, allowing participants to observe digital abstractions of algebraic sequences without requiring prior programming expertise.

- **Phase 2: Dialectical Scaffolding (Fun).** Students engaged with the AI as a Socratic interlocutor. The interaction was restricted by a teacher-monitored "Logic-First" rule: students had to explain their reasoning to the AI before it provided tiered hints. This phase leveraged the AI's adaptive nature to maintain the Zone of Proximal Development, preventing frustration through iterative, low-stakes feedback.

- **Phase 3: Heuristic Validation (Enjoyable).** Students tackled non-routine problems, utilizing AI to brainstorm divergent strategies. A mandatory "Human-in-the-Loop" verification step was enforced, where students had to justify AI-suggested heuristics using GASING’s mental arithmetic techniques and concrete manipulatives to mitigate AI hallucinations. This ensured that the "Enjoyable" mastery experience was rooted in autonomous, logical verification rather than passive consumption of output.

Data Collection Instruments

This study employs a dual-measurement approach, combining self-report scales for latent psychological constructs with performance-based assessments for cognitive outcomes. Psychometric integrity was initially established through expert judgment involving five

specialists (two Mathematics Education professors, two EdTech researchers, and one Psychometrician). Lawshe's Content Validity Ratio (CVR) was calculated, yielding a score of 1.0 for all retained items, exceeding the minimum threshold (0.99) for five panellists.
The measurement model was further validated via Confirmatory Factor Analysis (CFA) within SmartPLS 4. Convergent validity was confirmed, as all item factor loadings exceeded 0.70, with Average Variance Extracted (AVE) values ranging from 0.58 to 0.74. Reliability was demonstrated through Composite Reliability (CR) values above 0.85 and Cronbach's Alpha exceeding 0.80. Finally, discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio, with all values remaining below the 0.85 threshold, ensuring that the constructs of Learning Motivation and Mathematical Creativity are empirically distinct. Detailed operational definitions and sample indicators for each construct are presented in Table 1.

- **AI Adoption & GASING Pedagogy (Self-Report):** Two distinct 5-item instruments (as delineated in Table 1) measured student engagement with AI tools and GASING procedural steps, replacing the initial single-synergy construct to align with the structural model. Responses were captured on a 5-point Likert scale, yielding high internal consistency (alpha = 0.89 and 0.87, respectively).
- **Learning Motivation (Self-Report):** A 5-item scale assessed self-efficacy and mastery experience (adapted from MSLQ), utilizing a 5-point Likert scale (alpha = 0.84).
- **Mathematical Creativity (Performance-Based):** An open-ended assessment required students to solve non-routine problems. To ensure alignment between performance data and SEM requirements, students were scored via a standardized rubric on three observed indicators: Fluency, Flexibility, and Originality. As shown in Table 1, these rubric-derived scores served as the continuous indicators for the latent Creativity construct. Inter-rater reliability (Cohen's kappa) was 0.82.
- **Problem-Solving Proficiency (Performance-Based):** A diagnostic test measured the capacity to formulate strategies and verify solutions. Scoring followed Polya's four-stage rubric, as operationalized in Table 1. In a shift from self-referential indicators to objective measurement, these four stage-specific performance scores were treated as the observed indicators of the Problem-Solving construct in the final model.

Table 1: Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI Adoption	TAM (Davis, 1989)	Student engagement and perceived ease of using AI tools for mathematical exploration.	"The Socratic AI hints assist my logical understanding of algebraic transitions."	5
GASING Pedagogy	Cognitive Load Theory (Sweller, 2011)	Perception of incremental, concrete-to-abstract steps in the GASING method.	"GASING's physical manipulatives enable me to perceive abstract forms concretely."	5

Learning Motivation	Social Cognitive Theory (Bandura, 1977)	Self-efficacy and enthusiasm emerging from the 'small wins' in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems."	5
Mathematical Creativity	Divergent Thinking (Guilford, 1950)	Objective capacity to generate manifold solutions, diverse strategies, and unique methods.	Performance Score: Number of valid distinct methodologies generated for a single task.	3
Problem-Solving Skills	Polya's Heuristics (Pólya, 1973)	Systematic ability to synthesize ideas, including critical verification of outcomes.	Performance Score: Successful logical verification and justification of AI-generated logic.	4

Data Analysis Techniques

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. Quantitative Analysis (Phase One)

Quantitative data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4.0, a method optimal for its predictive power in complex mediation models and its flexibility regarding distributional assumptions (J. Hair et al., 2017). The analytical protocol followed a rigorous two-stage evaluation:

- **Measurement Model (Outer Model) Evaluation:** Internal consistency and construct validity were substantiated through indicator loadings (> 0.708), Average Variance Extracted (AVE > 0.50), and Composite Reliability (CR > 0.70). **Discriminant validity was rigorously verified using both the Heterotrait-Monotrait Ratio (HTMT < 0.85) and the Fornell-Larcker criterion, with HTMT serving as the primary stringent test to ensure construct distinctiveness.** To address potential common-method bias and multicollinearity, Variance Inflation Factors (VIFs) were monitored, with a threshold of VIF < 3.0.
- **Structural Model (Inner Model) Evaluation:** Hypotheses (H1–H5) were tested by examining path coefficients (β), R^2 values, and f^2 effect sizes. Significance levels were determined using a nonparametric bootstrap procedure with 5,000 subsamples and a 95% bias-corrected and accelerated (BCa) confidence interval. **Predictive relevance was corroborated via the blindfolding procedure to obtain Q^2 values, confirming the model's capacity to predict endogenous constructs.** Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), targeting a value below 0.08 for adequate fit.
-

2. Qualitative Analysis (Phase Two)

Qualitative data derived from in-depth interviews and classroom observations are analysed using **a multi-stage** Thematic Analysis (Braun & Clarke, 2012). To ensure methodological rigor, the analysis followed six distinct phases: (1) data familiarization through verbatim transcription; (2) initial inductive coding; (3) searching for themes; (4) reviewing themes against observation notes; (5) defining and naming themes; and (6) producing the final report. To enhance trustworthiness, a double-coding procedure was employed involving two independent researchers, with discrepancies resolved through consensus (inter-coder agreement > 85%).

Triangulation was achieved by integrating interview transcripts with field observation notes, particularly regarding student behaviour during AI use. This dual-source approach enabled a robust interpretation of the four emergent themes and the one divergent case detailed in Table 7. The analysis focuses on how adaptive AI assistance triggers 'creative moments,' enabling students to transcend cognitive impasses. By including a divergent case (e.g., instances of AI-overreliance), the study maintains an objective stance on the limitations of the hybrid pedagogy, ensuring the findings are interpretively rich and methodologically grounded.

3. Data Integration (Triangulation)

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalysed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in Table 9, a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation).

THE RESULTS OF THE RESEARCH AND THE DISCUSSION

The quantitative analysis presented in Figure 2 consistently underscores the central role of AI Adoption, GASING pedagogy, and Learning Motivation in augmenting students' cognitive performance. Thematically, this path model confirms that students' problem-solving competencies do not emerge instantaneously (Hartati et al., 2020). Rather, they develop through a synergistic process facilitated by pedagogical accessibility (*Gampang-Asyik*) and adaptive technological assistance. The integration of this framework demonstrates a highly significant positive influence, wherein the GASING method functions as the primary catalyst for both AI Adoption ($\beta = 0.712$) and Learning Motivation ($\beta = 0.802$). Beyond these direct effects, AI Adoption specifically bolsters Mathematical Creativity ($\beta = 0.514$) by serving as an ideational support mechanism as students explore mathematical concepts.

Mathematical Creativity ($\beta = 0.343$) and Learning Motivation ($\beta = 0.510$) emerge as pivotal components that exert a substantial impact on Problem Solving. This structural relationship highlights the dual role of technological and pedagogical factors—the accessibility of concepts through GASING and the courage to experiment via AI—in fostering high-level problem-solving capabilities. The findings presented in Figure 2 validate that when mathematics is delivered through an "Easy and Fun" (Gampang, Asyik, and Menyenangkan) approach supported by AI, a learning ecosystem is cultivated that effectively elevates students' mathematical competence.

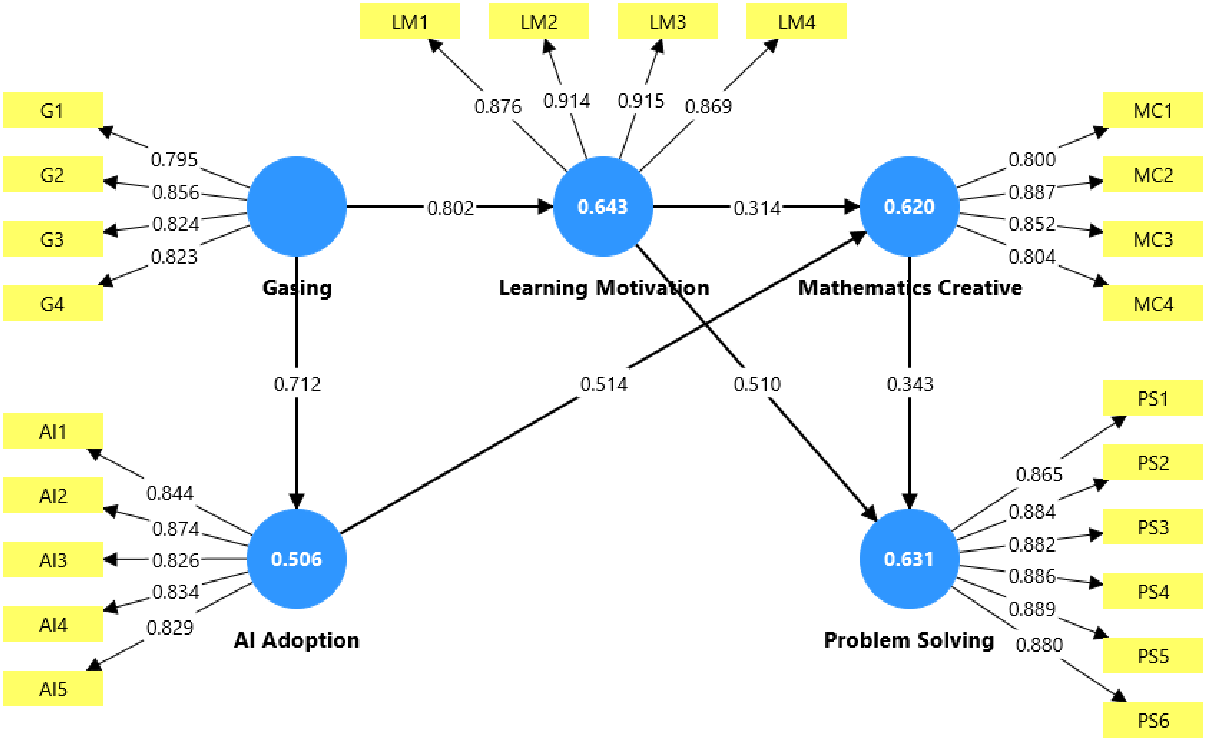

Figure 2: Structural Model of AI-GASING Integration Framework

Quantitative Data

The evaluation of the research model was meticulously executed in a two-stage process: an assessment of the measurement model (outer model) followed by a rigorous analysis of the structural model (inner model). The empirical data synthesized in Table 2 corroborate that the research instruments possess high precision in operationalizing the psychological and technical phenomena under investigation.

As shown in Table 2, each indicator yielded an Outer Loading (OL) exceeding the 0.70 threshold, ranging from 0.795 to 0.915. This provides compelling evidence of robust convergent validity at the item level. Furthermore, the model's psychometric integrity is supported by Average Variance Extracted (AVE) values exceeding 0.50 for all constructs. Internal consistency was validated through Composite Reliability (CR) and Cronbach's alpha coefficients, both of which comprehensively exceeded the 0.80 benchmark. Collectively, these metrics indicate superior internal consistency and ensure that the latent variables are measured with sufficient accuracy to warrant structural path analysis.

Table 2: Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				

	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The psychometric integrity of the model is further reinforced by **Average Variance Extracted (AVE)** values for all constructs surpassing the 0.50 threshold, alongside **Composite Reliability (CR)** and **Cronbach's alpha** coefficients that comprehensively exceed 0.80. Collectively, these indices indicate strong internal consistency and ensure that the latent variables were measured with high precision before the structural analysis.

After assessing convergent validity, discriminant validity was rigorously evaluated to ensure that each latent construct is empirically unique and distinct from the others in the framework. As evidenced in **Table 3**, the **Heterotrait-Monotrait (HTMT)** ratios for most construct pairs remain below the conservative 0.85 threshold. While the GASING-Motivation nexus yielded a slightly higher ratio, it remains well within the permissible 0.90 range. These results confirm that the constructs are sufficiently idiosyncratic and free of conceptual overlap, thereby providing a robust foundation for the subsequent structural path analysis.

Table 3: Discriminant Validity Results (HTMT Ratio)

	AI A	GASING	LM	MC	PS
AI Adoption (AI A)					
Gasing	0.816				
Learning Motivation (LM)	0.879	0.812			
Mathematics Creative (MC)	0.869	0.785	0.813		
Problem Solving (PS)	0.786	0.803	0.816	0.785	

After the HTMT analysis (see Table 3), the Fornell–Larcker criterion was employed as a supplementary layer of verification to further consolidate the evidence of discriminant validity. As delineated in Table 4, the square root of the Average Variance Extracted (AVE) for each latent construct—represented by the values on the principal diagonal—consistently exceeds the correlation coefficients between that construct and any other variable in the model.

This statistical alignment substantiates that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving are empirically distinct, measuring unique dimensions of the developed instructional framework. The superiority of the diagonal values over off-diagonal elements confirms that the shared variance between a construct and its indicators is greater than the variance shared with other latent variables, thereby satisfying the criteria for conceptual independence as encapsulated in Table 4

Table 4: Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			
Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

The structural model's discriminant validity was confirmed via the Fornell-Larcker criterion, ensuring that each latent construct is statistically distinct. As illustrated in Table 4, the square root of the AVE ($\sqrt{AVE}$) for Learning Motivation is 0.894, which exceeds its highest correlation with other constructs, namely GASING (r = 0.802) and AI Adoption (r = 0.797). This statistical differentiation is critical, as it confirms that Learning Motivation and Mathematical Creativity function as discrete mediating variables without excessive construct overlap that could otherwise bias the path analysis.

The structural model analysis reveals several significant pathways that constitute this integrative framework. GASING Pedagogy exerts a substantial influence on Learning Motivation (β = 0.802) and a robust effect on AI Adoption (β = 0.712). AI Adoption is identified as a pivotal construct that significantly predicts Mathematical Creativity (β = 0.514). Furthermore, Learning Motivation significantly predicts Problem Solving (β = 0.510) and contributes to Mathematical Creativity (β = 0.314). The final student competency, represented by Problem Solving, is likewise significantly predicted by Mathematical Creativity (β = 0.343).

Cumulatively, these pathways account for 64.3% of the variance in Learning Motivation, 50.6% in AI Adoption, 62.0% in Mathematical Creativity, and 63.1% in Problem Solving. A comprehensive summary of these findings, encompassing path coefficients (β), t-values, p-values, and f^2 effect sizes, is delineated in Table 5.

Table 5: Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	< 0.001	1.026	Supported
GASING →Learning Motivation	0.802	40.981	< 0.001	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	< 0.001	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	< 0.001	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	< 0.001	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	< 0.001	0.152	Supported

To assess the structural adequacy of the proposed framework, the model fit indices were rigorously examined before evaluating predictive power. The **Standardized Root Mean Square Residual (SRMR)** was recorded at **0.088**. While this figure slightly exceeds the most conservative benchmark of 0.08, it remains well within the broadly accepted parameters for complex structural models in educational research. Consequently, this signifies an acceptable degree of congruence between the empirical data and the hypothesized framework.

Upon confirming the model fit, the structural analysis provided definitive empirical support for the hypothesized relationships within the CMCB framework.

Hypothesis Testing Results (H1–H5):

- **H1: AI Adoption positively influences Mathematical Creativity.** The results confirm that AI Adoption is a pivotal construct that significantly predicts Mathematical Creativity ($\beta = 0.514$, $p < 0.001$), supporting the premise that AI functions as a 'cognitive partner' for ideational exploration.
- **H2: GASING Pedagogy enhances Learning Motivation.** GASING Pedagogy exerts a substantial and dominant influence on Learning Motivation ($\beta = 0.802$, $p < 0.001$), with a massive effect size ($f^2 = 1.804$), validating the 'Easy and Fun' (*Asyik*) approach as a primary driver of student engagement.

The structural model's explanatory and predictive capacities were further evaluated using the coefficient of determination (R^2) and the Stone-Geisser (Q^2) statistic. As shown in Table 6, the analysis indicates that the framework has robust explanatory power, particularly for the variables **Learning Motivation** ($R^2 = 0.643$) and **Problem Solving** ($R^2 = 0.631$). In both instances, over 60% of the variance is accounted for by the antecedent constructs in the model.

Furthermore, all endogenous variables demonstrate **Stone–Geisser Q^2 values**—derived via a blindfolding procedure—ranging from 0.445 to 0.641. As these values are substantially greater than zero, the model's **large predictive relevance** is confirmed. This statistical evidence further validates the instructional efficacy of the **GASING Pedagogy** and its potent synergy with **AI Adoption** in enhancing student outcomes. A comprehensive summary of these indices is presented in **Table 6**.

Table 6: Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	R^2	Q^2	Q^2 Interpretation
AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

The structural model's explanatory and predictive capacities were evaluated using the coefficient of determination (R^2) and the Stone-Geisser Q^2 statistic. As summarized in Table 6, the R^2 values indicate that the model explains a substantial proportion of variance in key endogenous constructs, particularly for Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), both of which exceed the threshold for "moderate-to-strong" explanatory power in social science research. Predictive relevance was substantiated through a blindfolding procedure with an omission distance of $d = 7$. All Q^2 values were found to be significantly greater than zero, ranging from 0.445 (Mathematics Creative) to 0.641 (Learning Motivation). Following the benchmarks established by J. F. Hair et al., (2019), Q^2 values exceeding 0.25 and 0.50 indicate medium and large predictive relevance, respectively. Consequently, the CMCB mechanism demonstrates a robust capacity to predict student problem-solving outcomes through the synergy of GASING pedagogy and AI integration (Hidajat, 2021; Li, 2024; Li & Manzari, 2025).

This study offers compelling insights into the primary research inquiry by suggesting that students' mathematical problem-solving competencies are not merely a product of technology in isolation, but rather an ecosystem that synergizes concrete pedagogy with adaptive auxiliary tools. The integration of GASING and AI Adoption appears to facilitate intertwined pathways of cognitive reinforcement, mediated by Learning Motivation and Mathematical Creativity. Theoretically, this research advances Cognitive Load Theory within a digital milieu; the robust association observed from GASING to Learning Motivation ($\beta = 0.802$), characterized by a massive practical effect size ($f^2 = 1.804$), indicates that GASING-style problem decomposition may serve as a crucial prerequisite for establishing 'motivational readiness'. Furthermore, AI Adoption as a significant predictor of Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition. Within this framework, AI is perceived not merely as a computational tool but as a 'cognitive partner' that potentially empowers students to engage in radical ideational exploration by mitigating the debilitating fear of failure.

The data analysis reveals a logical consistency between motivation and creativity in catalysing high-level competencies, where Mathematical Creativity constitutes a pivotal component of Problem Solving ($\beta = 0.343$), elucidating why a mere "will learn" is insufficient to resolve non-routine challenges. Data synthesis reveals the "Creativity-Mediated Mechanism": motivation triggered by GASING provides the impetus for experimentation, while AI furnishes a simulation space to convert that energy into valid creative solutions. Collectively, this integration explains 63.1% of the variance in problem-solving ability ($R^2 = 0.631$), signifying an empirically robust model. While the model exhibits substantial predictive power (Q^2 Large), the study is constrained by its sampling scope, which focuses on a specific educational level. This presents opportunities for future research to examine whether the AI-GASING framework maintains equivalent efficacy in more abstract mathematical domains or resource-limited environments.

Based on the empirical evidence, several concrete measures are recommended to optimize techno-pedagogical integration. For educators, it is imperative not to skip the "Easy" (Gampang) phase of the instructional process; practitioners must prioritize the GASING method to cultivate students' self-efficacy and intrinsic motivation as a psychological foundation before introducing AI-based instruction. Correspondingly, curriculum designers should integrate AI tools not as disparate technological modules, but as adaptive assistants for exploratory tasks that stimulate mathematical creativity. Finally, for policymakers, the results of this study emphasize the necessity of standardizing teacher training to encompass "Pedagogical AI-Integration"—the strategic capacity to meld effective traditional instructional methods with the potential of emergent digital tools to achieve superior problem-solving competencies.

Table 7: Summary of Mediation Effects (Bootstrapping Results)

Indirect Effect Path	β	T-Statistics	P-Values	Mediation Type
AI Adoption →Math Creative →Problem Solving	0.176	6.252	0.001	Complementary Partial
Motivation →Math Creative →Problem Solving	0.108	5.524	0.001	Complementary Partial

GASING →Motivation →Math Creative	0.252	6.557	0.001	Complementary Partial
GASING →AI Adoption →Math Creative	0.366	11.007	0.001	Complementary Partial

Table 7 summarizes the results of the bootstrapping analysis, providing a detailed examination of the indirect effect paths that underpin the mediation mechanisms within the AI-GASING ecosystem. The empirical data suggest that Mathematical Creativity serves as a significant 'cognitive gateway'—mediating the influence of both AI Adoption and Learning Motivation on student problem-solving proficiency. Based on these bootstrapping results, the following mediation hypotheses were validated:

- **H3: Learning Motivation mediates the link between GASING and Creativity.** The analysis reveals a significant indirect effect of GASING on Mathematical Creativity via Learning Motivation ($\beta = 0.252$, $p < 0.001$), substantiating the idea that the affective 'fun' (*Asyik*) environment is a prerequisite for creative activation.
- **H4: Mathematical Creativity mediates the effect of AI on Problem-Solving.** The study confirms that Mathematical Creativity successfully mediates the path from AI Adoption to Problem Solving ($\beta = 0.176$, $p < 0.001$), thereby preventing technology from becoming a tool for passive cognitive offloading.
- **H5: Motivation and Creativity serially mediate the path from Pedagogy to Problem-Solving.** The empirical data validate this complex serial mediation pathway, demonstrating that the synergy between GASING and AI Adoption accounts for 63.1% of the variance in Problem Solving ($R^2 = 0.631$) through the sequential reinforcement of affective readiness and creative verification.

Furthermore, the foundational impact of the GASING pedagogy is evidenced by its robust indirect influence on Mathematical Creativity through the parallel pathways of Learning Motivation and AI Adoption ($\beta = 0.366$, $p < 0.001$). In accordance with the mediation typology established by J. F. Hair et al., (2019), these pathways are characterized as complementary mediation. This classification is supported by the fact that the indirect effects are statistically significant and move in the same positive direction as the corresponding direct paths—specifically, the trajectories from AI Adoption and GASING toward Problem Solving.

Collectively, these findings offer a more nuanced perspective on technological integration; they suggest that rather than fostering dependency, the synergy between structured concrete pedagogy and adaptive digital tools serves to catalyse the development of mature, autonomous problem-solving competencies (Gal, 2021). By positioning creativity as a mediator, the model ensures that AI serves as a "cognitive amplifier" rather than a replacement for critical reasoning.

Qualitative Data

Qualitative analysis was conducted to investigate the nuanced cognitive mechanisms underlying the robust statistical correlations among AI-GASING Integration, Mathematical Creativity, and Problem-Solving proficiency. Through a rigorous thematic analysis of interview transcripts and classroom observations, **four cardinal themes**—operating in a sequential trajectory—were identified, alongside a **notable divergent case**. These findings, summarized in **Table 8**, provide a comprehensive understanding of the student experience within the research ecosystem:

1. **The 'Gampang' De-escalation (Cognitive De-escalation):** Students observed that the synergy of AI visualizations and GASING's 'point-to-point' decomposition lowered mental barriers, shifting the perception of complex 3D geometry from intimidating to 'actually easy.'
2. **AI-Triggered Divergence:** Generative tools functioned as a Socratic partner, encouraging students to move beyond textbook formulas toward exciting, non-linear trial and error.
3. **Iterative Problem-Solving Synthesis:** Students utilized GASING's rapid mental calculation (*congak*) to strategically verify and distill AI-generated ideas into precise, logical solutions.
4. **Emotional-Cognitive Synergy:** An enjoyable instructional atmosphere provided the necessary 'cognitive energy' for students to persevere through non-routine tasks without succumbing to frustration.

Furthermore, the analysis accounted for a **Divergent Case (Contextual Redundancy)**. As shown in **Table 8**, this case identifies a boundary condition in which students found GASING's mental steps more efficient than AI for routine arithmetic, suggesting that synergy is most potent during high-complexity tasks. This multifaceted qualitative evidence illuminates the 'black box' of the structural model, offering a robust explanation for the predictive power observed in the quantitative phase.

Table 8: Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	**GASING Phase & Problem Context**	**Empirical Evidence (Student Verbatim)**	**Theoretical Mechanism & Related Variables**
Theme 1: The "Gampang" De-escalation	Phase: Concrete Foundation (Step 1) Context: Complex 3D Geometry	"Usually, when I see stacked geometric figures, I give up immediately... But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple."	Cognitive Load Reduction: Synergy of AI and GASING lowers mental barriers, shifting perception to "actually easy." (Related Variables: GASING & Learning Motivation)
Theme 2: AI-Triggered Divergence	Phase: Adaptive Exploration (Step 2)	"I asked the AI: 'Is there any other way besides the textbook formula?'... It	Creativity Catalyst: AI functions as a Socratic

	Context: Alternative optimization solutions	was so exciting (*Asyik*) to find my own way."	Partner, encouraging divergent trial and error. (Related Variable: Mathematics Creative)
Theme 3: Iterative Synthesis	Phase: Creative Synthesis (Step 3) Context: Validating cost-effective designs	"I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best."	Valid Solution Construction: Creativity is distilled into logical solutions through Strategic Verification (Polya's 4th Step). (Related Variable: Problem-Solving Skills)
Theme 4: Emotional-Cognitive Synergy	Phase: Continuous Assessment Context: Persevering through non-routine tasks	"I didn't give up because the process was fun and I felt I had the right tools to eventually find the answer."	Motivational Synergy: An enjoyable atmosphere provides the "cognitive energy" required to persevere through difficulty. (Related Variables: Learning Motivation & Problem Solving)
Divergent Case: Contextual Redundancy	Boundary Condition: Routine arithmetic tasks	"For basic multiplication, using AI felt slower and more distracting. I just used GASING mental steps because they were faster."	Efficiency Threshold: For routine tasks, GASING alone is sufficient; AI may introduce unnecessary cognitive noise.

The qualitative outcomes synthesized in Table 8 provide narrative depth to the causal mechanisms observed within the statistical model. The following elaboration elucidates how the interaction between GASING pedagogy and AI facilitates a cognitive breakthrough among students:

1. Transformation from "Fear" to "Ease": The Reduction of Cognitive Load

Observational data reveal a radical shift in the classroom atmosphere. The "Gampang" (Easy) de-escalation reported by students suggests a reduction in extraneous load, where AI visualization and GASING's decomposition transform insurmountable tasks into manageable ones. Interviews indicate that the GASING method's decomposition of problems into incremental steps, augmented by AI-driven visualization, effectively eliminates students' mental barriers. "Mathematics used to be harrowing. Now, because AI assists with visualization and the GASING method is so relaxed, I am no longer afraid of making mistakes. These findings clarify why the statistical path GASING → Learning Motivation ($\beta = 0.802$) is so dominant, providing evidence that the "Easy" phase is the necessary affective substrate for all subsequent cognitive breakthroughs.

In this context, while cognitive load was not measured via a formal latent scale, we offer an interpretive inference based on this qualitative triangulation. The "Gampang" (Easy) de-escalation reported by students suggests a reduction in what is theoretically described as extraneous load, where AI visualization and GASING's decomposition transform insurmountable tasks into manageable ones. This interpretive inference is empirically supported by the substantial effect size of GASING on Motivation ($f^2 = 1.804$) and the significant bootstrapped indirect effect of AI Adoption on Problem Solving through Mathematical Creativity ($\beta = 0.176$, $p < 0.001$), which theoretically requires freeing up the "germane capacity" of the working memory. Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory.

Theoretically, this study substantiates that pure pedagogical intervention (GASING) inherently mitigates mathematical anxiety by optimizing students' working memory. The perception of material as "Easy" (Gampang) is a manifestation of 'Mastery Experience' within Bandura's Social Cognitive Theory, wherein incremental success in granular tasks culminates in enhanced self-efficacy (Bandura, 1997).

2. AI as a Creative Thinking Partner: From Dependency Toward Epistemic Collaboration

Qualitative findings highlight the role of AI as an "ideation trigger" rather than a mere substitute for the cognitive process, categorically refuting the "Cognitive Offloading" argument (Peng & Yeh, 2025; Risko et al., 2014) which posits that technology inherently attenuates critical faculties. This research aligns with international evidence from Schindler et al., (2025) and Loong & Herbert, (2018), which suggests that digital tools, when mediated by effective pedagogy, function as cognitive accelerators. Instead, this study illustrates the phenomenon of 'Distributed Cognition,' wherein AI functions as a cognitive extension that enhances rather than replaces human agency.

This interaction fosters an "Engaging" (*Asyik*) and pressure-free learning environment characterized by cognitive safety and experimental freedom. As one participant noted: *"It feels like playing a puzzle game. The AI provides clues, which I then expand into broader ideas. It turns out one problem can be solved through many unique methods..."* (Student S-05). This narrative evidence validates the significant impact of AI Adoption on Mathematical Creativity ($\beta = 0.514$) by demonstrating how an "Asyik" environment fosters divergent exploration. This finding contradicts the technical-centric models of Davis (1989) but strongly supports the Broaden-and-Build Theory (Isgett & Fredrickson, 2015), suggesting that the positive affect generated by GASING is the essential prerequisite for creative AI interaction.

The implication of this finding is a shift in the "Human-AI" instructional paradigm: the success of AI in the classroom is a downstream effect of the pedagogical environment. This research contributes to the development of mathematics education by demonstrating that rather than fostering intellectual passivity, the AI-GASING synergy necessitates a "verification-first" mindset. This positions students as active evaluators of machine-generated logic, thereby providing a validated protocol for maintaining epistemic agency and cognitive flexibility in an increasingly automated digital landscape.

3. From Creative Ideation to Valid Solutions: Metacognitive Synthesis

The pinnacle of success in this study is the students' ability to synthesize creative ideation into structured outcomes, marking a definitive shift from mere "numerical computation" to the "construction of logical arguments." As one high-performing participant articulated: *"I can explain the procedural steps of why I selected this specific method based on its efficiency. I developed this capacity through habitual logical debates with the AI,"* (Student S-08). This narrative evidence breathes "life" into the R^2 = 63.1% statistic for the Problem-Solving variable, demonstrating that integrating AI does not bypass cognitive struggle but rather elevates it to a metacognitive level.

This research strongly aligns with the international findings of Wang et al. (2025) and Pangaribuan et al. (2025), which emphasize that autonomous learning in digital environments requires robust conceptual anchoring. The elevated problem-solving proficiency observed here stems specifically from students' intellectual liberty (Creativity), grounded in the concrete procedural understanding provided by GASING. By positioning the student as the final arbiter of machine logic, these findings directly contradict the prevailing anxieties regarding student verification reasoning deficits identified by Tran & O'Connor (2024).

The primary implication of this finding is the modernization of classical problem-solving heuristics for the digital age. Within the context of Polya's framework, this study revitalizes the fourth stage (*Looking Back*); it demonstrates that in an AI-enhanced ecosystem, this stage evolves from a simple recalculation into a critical evaluation where students employ human mathematical logic to verify AI-generated outputs (Amrullah et al., 2024; Mulligan, 2015; Pólya, 1973). Consequently, this research contributes to mathematics education by establishing a "verification-first" pedagogical protocol that ensures students develop the adaptive reasoning necessary to oversee and validate automated systems.

Ultimately, these findings confirm that a cognitive breakthrough is not a direct consequence of technology adoption alone, but a mediated outcome where GASING-induced motivation serves as the affective engine and mathematical creativity functions as the critical epistemic filter, thereby validating the CMCB Mechanism as a robust framework for autonomous digital learning.

The Creativity-Mediated Cognitive Breakthrough Mechanism

As detailed in **Table 9**, this study aims to synthesize quantitative and qualitative data to validate and deepen understanding of how the synergy between GASING pedagogy and AI Adoption manifests in the actualized classroom environment. Distinct from a 'black-box' approach, this triangulation process converges the statistical findings from PLS-SEM with the thematic narratives elicited from students. The convergence of these data streams identifies a distinct theoretical pathway: the 'Creativity-Mediated Cognitive Breakthrough' (CMCB) mechanism (Keha et al., 2024). Unlike traditional mediation models that view technology as a direct driver of outcomes, the CMCB mechanism argues that AI functions effectively only when it acts as a 'Socratic partner' to a student already equipped with a robust, low-load cognitive foundation.

This research aligns with global studies by Morrison et al., (2025) et al. (2026) and Lakshmi Shankar et al., (2025), which emphasise that AI serves as a "cognitive amplifier" rather than a procedural substitute. While the existing literature on Distributed Cognition describes technology as an extension of the mind, the CMCB mechanism refines this by positioning Mathematical Creativity not merely as a consequence, but as the essential 'gatekeeper' that converts AI-generated output into valid problem-solving competency. This finding explicitly supports the "verification-first" mindset proposed by Sukoriyanto et al., (2016) and contradicts the "passive offloading" paradigm often observed in digital-only interventions (Peng & Yeh, 2025; Todorov et al., 2018). Furthermore, by anchoring this process in GASING's 'point-to-point' decomposition, the mechanism extends Cognitive Load Theory into the digital milieu, demonstrating that 'motivational readiness' is a prerequisite for—rather than a result of—creative AI exploration

Table 9: A Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	β	**Qualitative Theme & Evidence**	**Integrative Meta-Inference (Convergence & Tension)**
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1 & Divergent Case 1	**Convergence:** GASING lowers mental blocks, facilitating AI use for complex 3D geometry. **Tension:** For simple tasks, GASING is sufficient; students view AI as redundant for routine computation.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2 & Divergent Case 2	**Convergence:** AI serves as a Socratic Partner for divergent exploration. **Tension:** Without GASING-based "motivational readiness," AI can lead to "cognitive offloading" or blind acceptance of errors.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis	**Convergence:** Creativity distilled into valid solutions through strategic verification. **Boundary Condition:** Effective only when students have the "congak" (mental math) skills to verify AI veracity.
Learning Motivation →Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Convergence:** Fun atmosphere sustains persistence on difficult tasks. **Observation:** Synergy is strongest when the "Asyik" (fun) element of AI is balanced by the "Gampang" (easy) logic of GASING.

Synthetically, the evidence presented in this study aligns with the premise that problem-solving competencies are significantly enhanced when mediated by Mathematical Creativity and supported by a robust foundation of Learning Motivation. These findings address our primary research question by confirming that technology integration is not linear; rather, it depends on students' affective and cognitive readiness (Amrullah et al., 2024; Bandura, 1997). While contemporary literature frequently highlights the risks of 'cognitive offloading' (Todorov et al., 2018). These results suggest that the integration of GASING pedagogy allows AI Adoption to function as a 'cognitive amplifier' (Lakshmi Shankar et al., 2025) rather than a substitute for critical thought. This study advances Distributed Cognition theory by demonstrating that students' epistemic agency can be maintained in digital environments if preceded by structured problem decomposition (Morrison et al., 2025; Tran & O'Connor, 2024).

The qualitative outcomes synthesized in Table 9 provide narrative depth to these observed statistical correlations, elucidating the specific cognitive breakthroughs facilitated by the AI-GASING ecosystem. Through the thematic evidence, it becomes clear how the interaction between GASING's structured problem decomposition and AI's adaptive exploration creates a 'scaffolded' environment that minimizes cognitive load while maximizing divergent ideation. This synthesis demonstrates strong consistency between quantitative and qualitative data, where the motivation of 'fun' becomes the driving force behind divergent creative exploration (Isgett & Fredrickson, 2015; Keha et al., 2024).

However, these findings should be interpreted with appropriate caution. Limitations include the specific scope of the two-site intervention in East Jakarta and the potential novelty effects of AI. Nevertheless, the validity of this study remains intact due to the consistency of findings across both research sites, providing a strong foundation for further development of the CMCB model (J. F. Hair et al., 2019). Future research should aim to longitudinalize these observations to validate the stability of the AI-GASING synergy. Practically, these findings suggest that curriculum designers and teachers should not allow unfettered access to AI without a strong pedagogical 'anchor'; the creative exploration phase should always be preceded by an understanding of its underlying logic to prevent AI from becoming a cognitive 'offloading' tool (Lakshmi Shankar et al., 2025; Peng & Yeh, 2025).

1. Initiation Phase: GASING as a Catalyst for Mental Readiness

The structural model analysis reveals the dominant influence of GASING on Learning Motivation ($\beta = 0.802$) and AI Adoption ($\beta = 0.712$). These findings align with the scholarship of Surya et al. (2017), which posits that the strategic decomposition of mathematical problems within the GASING framework significantly mitigates cognitive load. By reducing complex operations into "point-to-point" logical steps, GASING ensures that the student's working memory is not overwhelmed before technology is even introduced.

Furthermore, this reinforces the Broaden-and-Build theory (Isgett & Fredrickson, 2015), wherein the positive affects generated by an "engaging" (*Asyik*) atmosphere broaden the student's cognitive repertoire prior to AI interaction. This research aligns with international studies such as Schindler et al. (2025), which utilized eye-tracking evidence to demonstrate that emotional regulation and positive affect are non-negotiable prerequisites for successful engagement with digital learning tools. Diverging from extant research that often perceives technology adoption as a purely technical process or a matter of user-interface ease (Davis, 1989), this study substantiates that pedagogical factors are the primary drivers of technological readiness in a mathematics context.

The contribution of this finding to the field of mathematics education lies in the empirical reconciliation of "High-Touch" indigenous pedagogy with "High-Tech" global tools. It demonstrates that AI's success in the classroom is a downstream effect of the pedagogical environment. The implication for practitioners and curriculum designers is that AI adoption strategies should prioritize "pedagogical priming"—building foundational logic and psychological safety first—to prevent the "abdication of reasoning" when students eventually encounter complex machine-generated logic.

2. Mediation Phase: Creativity as a Cognitive Gatekeeper

The novelty of this research resides in the underscored role of Mathematical Creativity, which is significantly influenced by AI Adoption ($\beta = 0.514$, $p = 0.001$) and Learning Motivation ($\beta = 0.314$, $p = 0.001$). These results corroborate Gadanidis et al., (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking. Within this framework, AI functions as a More Knowledgeable Other (MKO) in accordance with Vygotsky's theoretical construct. However, to empirically validate the "Creativity Gateway," a formal mediation analysis was conducted using a bootstrapping procedure with 5,000 subsamples.

The results, as detailed in **Table 6**, confirm that Mathematical Creativity serves as a vital intermediary. Specifically, the indirect effect of AI Adoption on Problem Solving through Mathematical Creativity is statistically significant ($\beta_{indirect} = 0.176$, $t = 6.252$, $p < 0.001$). Furthermore, the total effect of AI Adoption on problem-solving is significant, and since the direct effect remains significant after the inclusion of the mediator ($\beta = 0.514$, $p = 0.001$), the relationship is classified as complementary partial mediation according to the criteria established by (J. F. Hair et al., 2017). Similarly, the path from Learning Motivation to Problem Solving is partially mediated by Mathematical Creativity ($\beta_{indirect} = 0.108$, $t = 5.524$, $p < 0.001$).

These statistical findings contrast with conventional studies that frequently identify "AI dependency"; instead, the data suggest that, in the absence of this "Creativity Gateway"—defined as the capacity to manipulate AI-generated information into original ideation—students will fail to achieve autonomous problem-solving competence (Gal, 2021; Li, 2024; Wang et al., 2025). This is qualitatively substantiated by Theme 3 (Iterative Synthesis), where students utilized GASING's rapid mental calculation (*congak*) to verify and distil AI-generated ideas into valid, logical solutions (Ruiz, C. & Balbi, 2019; Soylu et al., 2010).

3. Execution Phase: Iterative Synthesis toward Problem Solving

The model's robust predictive power regarding Problem Solving ($R^2 = 0.631$) is simultaneously constructed by Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$). These findings align with the "Looking Back" phase yet introduce a novel dimension (Sukoriyanto et al., 2016). In the burgeoning era of AI, solution validation becomes increasingly critical to filter "technological hallucinations" through mathematical logic solidified via the GASING pedagogy. This further resonates with scholarship, which emphasizes that creativity serves as the fundamental catalyst for leveraging digital tools as engines of discovery(Drijvers, 2020).

Despite the model's substantial predictive power (R^2) and large-scale predictive relevance (Q^2), this study is constrained by its sampling scope, which focuses on a specific educational level and geographic context. Nevertheless, these limitations delineate a trajectory for future inquiry into the efficacy of the AI-GASING framework in more abstract mathematical domains or resource-constrained environments. The internal consistency of the data (Table 8) ensures the study's validity as a foundational benchmark for modern techno-pedagogical integration.

Theoretically, this research contributes to the redefinition of Distributed Cognition Theory by positioning creativity as an indispensable mediator between technology and cognitive outcomes (Hwang & Hu, 2013; Li, 2024). These findings challenge the antiquated dichotomous assumption that bifurcates creativity and logic; within the AI-GASING ecosystem, both appear to coalesce into an integrated problem-solving mechanism. The practical implications of this study offer a preliminary framework for policymakers to rethink technology's role in the classroom—transitioning from an 'answering machine' to a 'partner in cognition' that elicits critical inquiry. While the scope of this intervention was localized, the results suggest that future curricula could benefit from prioritizing creative exploration phases within 'safe-to-fail' environments, specifically under the guidance of the GASING pedagogy. Cultivating this 'Creativity Gateway' represents a promising strategy to ensure that technological investments do not merely result in digital passivity but instead support the development of adaptive and resilient problem solvers.

CONCLUSIONS AND SUGGESTIONS

This study provides empirical support for the Creativity-Mediated Cognitive Breakthrough (CMCB) framework, demonstrating that mathematical problem-solving competencies are significantly enhanced when AI integration is mediated by student creativity and anchored by the GASING pedagogy. Rather than relying on broad conceptualizations, the structural model explicitly confirms that Learning Motivation ($\beta = 0.510$) and Mathematical Creativity ($\beta = 0.343$) are the primary statistical drivers of problem-solving success. Furthermore, the massive effect size observed in the GASING →Learning Motivation path ($f^2 = 1.804$) underscores the pedagogical foundation required for technology to be effective.

Despite the robust explanatory power of the structural model ($R^2 = 0.631$) and the high predictive relevance (Q^2 values up to 0.641), the findings represent an important but context-bound contribution. As a non-experimental design without a traditional control group, the results primarily reflect measurement adequacy and statistical associations within this specific setting. Limitations include the specific scope of the two-site intervention (conducted in two public secondary schools in East Jakarta), the exclusive use of ChatGPT-4o, and potential subjectivity in self-report measurements. Future research should transition toward Experimental Control Groups to isolate the 'teacher effect' and utilize PLSpredict to assess out-of-sample predictive power. Additionally, longitudinal designs are necessary to determine if these cognitive gains persist beyond the initial novelty of AI. Ultimately, this research suggests that while AI provides computational breadth, human creativity remains the critical validator in the problem-solving process.

ACKNOWLEDGMENT (IF ANY)

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam: Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Arum Fatayan**: Writing - Review & Editing, Methodology, Validation, and Supervision; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision; **Tri Sutrisno**: Writing - Review & Editing, Validation, and Supervision.

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Editor Decision

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Tues, March 24, 2026 at 9:39 AM
To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

We have completed the preliminary review for your manuscript entitled "Leveraging GASING Pedagogy and AI Adoption to Enhance Problem-Solving Skills: The Mediating Roles of Learning Motivation and Mathematical Creativity". It is suitable for our journal's scope. We sent your paper to the referees to evaluate, and our decision is "**Revision Required**".

Thank you for your interest in our journal
Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

Reviewer 1:
Abstract
the abstract should begin with a clear background and explicitly stated research gap rather than directly presenting the study's purpose. The objective needs to be simplified to improve readability by reducing overly technical phrasing. The method section should be more concise, focusing only on the research design, sample, and main analytical approach. The results must be strengthened by indicating the significance and strength of the findings, such as highlighting significant effects or mediation. Additionally, the contribution should be clarified by explicitly distinguishing between theoretical and practical implications instead of remaining overly abstract.

Introduction
The research gap is not yet sufficiently explicit and should be sharpened with a clear statement indicating what prior studies have not addressed, particularly regarding the integration of GASING pedagogy and AI. The flow needs to follow a more standardized structure, moving clearly from global issue to specific problem, then to literature synthesis, gap identification, research rationale, and study purpose. Several sections are overly dense with theoretical terminology, so sentence simplification is necessary to improve readability and avoid cognitive overload for readers. The novelty and contribution should be stated more explicitly and positioned earlier to strengthen the study's academic positioning. The presentation of research objectives and hypotheses is adequate but can be streamlined to reduce redundancy and enhance clarity. All arguments should be consistently supported by recent and relevant references, and transitions between paragraphs should be improved to ensure coherence and logical progression.

Method
The method section requires clearer structuring to align with international standards by explicitly separating key components such as research design, participants, instruments, procedure, and data analysis. The description of the research design is adequate but should be made more concise and directly linked to the research objectives. The participant selection process needs to be presented more clearly, emphasizing sampling techniques, representativeness, and justification to strengthen methodological rigor. The intervention procedure is detailed but somewhat lengthy, so it should be streamlined while retaining essential steps to improve readability. The instruments are well described, yet their alignment with each construct should be clarified more explicitly, particularly how they operationalize the variables in the model. The validity and reliability testing is strong, but it can be presented more succinctly without excessive technical repetition. The data analysis section is comprehensive; however, it would benefit from a clearer logical flow, starting from measurement model evaluation to structural model testing, followed by qualitative analysis and data integration. Finally, ensure that the entire section emphasizes reproducibility and clarity so that other researchers can easily replicate the study.

Discussion

The discussion section needs to more explicitly connect the findings with existing theories and prior studies to demonstrate deeper scholarly engagement. The interpretation of results should go beyond description by explaining why the findings occurred and how they contribute to advancing knowledge in mathematics education, particularly in the context of AI integration and pedagogy. The linkage between results and theoretical frameworks such as constructivism, cognitive load theory, or distributed cognition should be strengthened to reinforce the study's conceptual foundation. Some parts of the discussion tend to restate results, so these should be reduced and replaced with critical interpretation and comparison with previous research. The contribution of the study should be articulated more clearly by highlighting what is new, what confirms existing knowledge, and what extends current understanding. Practical implications should be made more specific and directly derived from the findings, particularly for educators and policymakers. Additionally, the limitations of the study should be acknowledged more explicitly within the

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discussion to provide a balanced perspective. Finally, the overall flow should be improved by ensuring smooth transitions between ideas and maintaining a clear logical progression from interpretation to implication.

Conclusion

The conclusion section should be more concise and focused on synthesizing the main findings rather than repeating detailed results. It needs to clearly highlight the key contributions of the study, both theoretically and practically, in a more direct and impactful manner. The connection between the findings and the research objectives should be explicitly reaffirmed to strengthen coherence.

References

The reference section should prioritize sources indexed in the Scopus database to ensure the credibility and international standard of the manuscript. All cited works are expected to come predominantly from reputable, peer-reviewed journals with strong academic impact. It is important to increase the proportion of recent references, ideally published within the last 5–10 years, to reflect current developments in the field. Additionally, ensure that all references are relevant, properly cited in APA 7th edition format, and include DOIs where available.

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Khoerul Umam <khoerul.umam@uhamka.ac.id>

Editor Respons for Revised Manuscript

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Sat, April 4, 2026 at 8:47 PM
To: khoerul.umam@uhamka.ac.id

Dear Khoerul Umam

Thank you for submitting your revised manuscript entitled "Leveraging GASING Pedagogy and AI Adoption to Enhance Problem-Solving Skills: The Mediating Roles of Learning Motivation and Mathematical Creativity" to Al-Jabar: Jurnal Pendidikan Matematika. We appreciate your efforts in addressing the reviewers' comments and improving the quality of your submission.

Best regards,

Fredi Ganda Putra
Managing Editor, Al-Jabar: Jurnal Pendidikan Matematika

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Khoerul Umam <khoerul.umam@uhamka.ac.id>

Editor Decision

1 message

Fredi Ganda Putra <fredigpsw@radenintan.ac.id> Thu, April 9, 2026 at 2:56 PM

To: enambelasnurdin@gmail.com

Dear Nurdin

We have reached a decision regarding your submission to Al-Jabar: Jurnal Pendidikan Matematika, "Leveraging GASING Pedagogy and AI Adoption to Enhance Problem-Solving Skills: The Mediating Roles of Learning Motivation and Mathematical Creativity"

Our decision is to: **accept submission**.

Fredi Ganda Putra

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AL-JABAR

LETTER OF ACCEPTANCE

Bandar Lampung
April 09, 2026

Dear Authors

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Article Title:

Leveraging GASING pedagogy and AI adoption to enhance problem-solving skills: The mediating roles of learning motivation and mathematical creativity

We are pleased to inform you that your submitted article to Al-Jabar: Journal of Mathematics Education [Sinta 1; DOAJ] has been accepted for publication in Volume 17, Issue 2, 2026. After a thorough review process by our esteemed reviewers, your article has been recognized as a valuable contribution to advancing research in the field of mathematics education. We extend our sincere congratulations and appreciation for your dedication, and we look forward to seeing the impact of your work among our readers, researchers, and practitioners.

Sincerely,

Fredi Ganda Putra

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Leveraging GASING pedagogy and AI adoption to enhance problem-solving skills: The mediating roles of learning motivation and mathematical creativity

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Abstract

Purpose: The rapid integration of Artificial Intelligence (AI) into mathematics education risks fostering "cognitive offloading," in which students passively rely on automated answers rather than developing critical reasoning. Despite this growing concern, prior studies have largely ignored how combining AI with structured, high-impact pedagogy might prevent this technological dependency. Addressing this gap, this study evaluates how integrating GASING pedagogy with AI tools enhances problem-solving proficiency. Specifically, it simplifies complex learning models to investigate how student motivation and mathematical creativity actively mediate the relationship between pedagogy, technology, and cognitive outcomes.
Method: Employing an explanatory sequential mixed-methods design, quantitative data were collected from 120 secondary school students (Grade 8, ages 13-14) in Jakarta, Indonesia. The structural relationships were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4. This was followed by a focused qualitative thematic analysis of semi-structured interviews and observations to explain the mechanisms driving the statistical results.
Findings: The results confirm a serial mediation model in which GASING Pedagogy positively influences Learning Motivation, which, in turn, enhances Mathematical Creativity. Furthermore, Mathematical Creativity was found to be a significant mediator between AI Adoption and Problem-Solving proficiency. Qualitatively, students perceive the synergy between GASING and AI as simplifying complex tasks and stimulating divergent thinking, positioning human creativity as a critical 'gatekeeper' for validating AI-generated outputs.
Significance: This research shifts the discourse from AI dependency toward a distributed cognition framework. Theoretically, it establishes creativity as an essential mediator in digital mathematics pedagogy. In practice, it provides educators with a protocol for balancing automated tools with pedagogical scaffolding, cultivating adaptive problem-solvers capable of rigorous intellectual verification.

INTRODUCTION

Mathematics education is shifting globally from procedural drills, which are easily automated, toward the need for complex problem-solving and mathematical creativity (Puspitasari et al., 2019; Rahmi et al., 2025; Schoenfeld, 2020). Traditional rote learning imposes a high cognitive load, leaving students with little working memory for the adaptive reasoning required in real-world applications (Paas & Van Merriënboer, 2020; Sweller, 2011). Recently, the rapid integration of Artificial Intelligence (AI) has introduced a new specific problem: while AI

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reduces computational burdens, it frequently causes "passive offloading," where students unquestioningly accept machine errors due to a lack of conceptual depth (T. Li & He, 2024; Todorov et al., 2018), addressing these verification deficits (Tran & Connor, 2024). This study posits that mathematical creativity must act as a "cognitive gatekeeper" to ensure students use human logic to verify AI-generated answers, preventing the total abdication of reasoning.

Despite the growing use of AI, a synthesis of current literature reveals a significant research gap: studies typically examine AI merely as a standalone computational tool (Emara et al., 2021) or evaluate GASING pedagogy solely for its ability to reduce math anxiety(Hayati et al., 2024; Kusuma & Sulistiawati, 2014). Prior studies have not addressed how a high-affect pedagogy can be integrated with AI to prevent cognitive offloading actively. Therefore, the primary novelty of this research is explicitly positioned here: it bridges this empirical void by reconciling GASING's "High-Touch" motivational foundation with "High-Tech" AI assistants. By connecting these previously isolated strands, this study introduces the Creativity-Mediated Cognitive Breakthrough (CMCB) framework, demonstrating how structured pedagogy equips students to use digital tools as cognitive amplifiers rather than crutches (Lakshmi Shankar et al., 2025; Loong & Herbert, 2018).

The rationale for investigating this synergistic model is to challenge the prevailing assumption that AI inherently diminishes human critical thinking (Peng & Yeh, 2025; Zhang et al., 2024). Technological scaffolding requires the active mediation of student creativity to truly achieve a cognitive breakthrough in problem-solving (Wahyudi et al., 2018). By utilizing an explanatory sequential mixed-methods design, this research rigorously investigates how combining GASING and AI mitigates extraneous cognitive load. Elevating this indigenous Indonesian pedagogical method into the global discourse on distributed cognition provides a much-needed, validated protocol for developing resilient and adaptive problem solvers in digital environments (Supianto et al., 2016).

To empirically validate the CMCB framework, the primary purpose of this study is to test the structural integrity of the AI-GASING nexus through five streamlined hypotheses: AI Adoption positively influences Mathematical Creativity (H1); GASING Pedagogy enhances Learning Motivation (H2); Motivation mediates the link between GASING and Creativity (H3); Creativity mediates the effect of AI on Problem-Solving (H4); and Motivation and Creativity serially mediate the path from Pedagogy to Problem-Solving (H5). Following the quantitative SmartPLS modeling (J. Hair et al., 2017), a qualitative thematic synthesis (Braun & Clarke, 2006) is employed to explain *how* GASING's 'Easy and Fun' affective environment triggers the creative gatekeeping required to solve complex problems (Toheri et al., 2020).

As Generative AI continues to proliferate in classrooms, the educational imperative must shift from teaching basic technological fluency to cultivating epistemic agency—the capacity of students to critically evaluate automated outputs (Gal, 2021; Loong & Herbert, 2018). Integrating AI within the structured GASING framework establishes a psychologically safe space for cognitive risk-taking. Consequently, this hybrid pedagogy necessitates a "verification-first" mindset. It proves that a cognitive breakthrough is not caused by technology alone but rather occurs when students are positioned as active evaluators of machine-generated logic, using their creativity as an epistemic filter.

Theoretically, this research advances Digital Constructivism and Cognitive Load Theory by proving that creativity is a non-negotiable mediator that prevents the "abdication of reasoning" during human-AI collaboration. In practice, the study delineates a clear instructional protocol in which the foundational logic of GASING serves as the cognitive anchor, allowing AI to function safely as an accelerator. Methodologically, this research provides a robust PLS-SEM evaluation model capable of concurrently assessing how technological integration impacts both the affective and cognitive dimensions of student learning (J. Hair et al., 2017; Wang & Huang, 2025).

To systematically address this empirical void, the primary objective of this study is to empirically validate the Creativity-Mediated Cognitive Breakthrough (CMCB) framework by investigating the synergistic integration of GASING pedagogy and Artificial Intelligence. Specifically, this research aims to elucidate how coupling GASING's affective "High-Touch" foundations with AI's "High-Tech" scaffolding cultivates resilient problem-solving skills and actively mitigates passive cognitive offloading. Through an explanatory sequential mixed-methods design, the study endeavors to quantitatively substantiate the structural pathways wherein learning motivation and mathematical creativity function as indispensable epistemic gatekeepers, while qualitatively decoding the underlying psychological mechanisms that empower students to critically evaluate and verify machine-generated logic.

METHOD

Research Design

This study adopts an explanatory sequential mixed-methods design (Cresswell & Cresswell, 2018) to evaluate how integrating GASING pedagogy with Artificial Intelligence (AI) tutoring impacts mathematical creativity and problem-solving skills. The design directly aligns with the research objectives by first employing quantitative Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized structural relationships. This is followed by a qualitative phase—utilizing interviews and observations—to deeply explore the "Easy, Fun, and Enjoyable" (Gampang, Asyik, Menyenangkan) cognitive mechanisms that explain the statistical findings.

Participants

To ensure ecological validity and demographic representativeness within an urban educational context, the study population comprised secondary school students (N = 120) recruited via a rigorous two-stage cluster sampling of intact classes. This specific technique was explicitly selected to minimize disruption to natural learning environments while securing a highly representative cross-section of the target student demographic. In the first stage, two public schools were randomly selected from a sampling frame of 12 eligible institutions in East Jakarta. In the second stage, two intact classes from each school were assigned to the intervention. To ensure internal validity and isolate the effects of the intervention, baseline academic equivalence was verified using an independent-samples t-test of previous-semester grades, which revealed no significant differences between the selected clusters ($t(118) = 0.84$, $p = 0.402$). To mitigate contamination, the intervention was delivered by the same research-trained instructor across all clusters. Participants engaged in exploratory mathematics modules (algebraic patterns and geometric reasoning), selected for their high affordance for AI-assisted discovery learning.

Following the quantitative phase, a purposive sub-sample of 8 students was selected for semi-structured interviews using an extreme-case sampling strategy. This qualitative sampling approach was theoretically justified to capture maximum variation in student experiences and to investigate the phenomenological extremes of the data set deeply. Selection was determined by post-test Problem-Solving proficiency scores: the top 5% (n = 4) and bottom 5% (n = 4) of the distribution were invited to participate. This chronological sequence ensured that qualitative insights directly elucidated the statistical outliers, specifically contrasting how AI functions as a heuristic trigger for high-ability learners versus a compensatory scaffold for students facing significant cognitive barriers, thereby substantially strengthening the methodological rigor of the mixed-methods integration. Institutional ethics approval was obtained, and separate informed consent was secured for the quantitative and qualitative phases.

Intervention Procedure: GASING-AI Integration

The intervention spanned six weeks (12 sessions) and utilized ChatGPT-4o, accessible via individual mobile devices. To ensure equity, the research team provided school-managed tablets and dedicated Wi-Fi to students without personal devices. Interaction was governed by a strict "Process-Oriented" protocol, supported by a pre-intervention 90-minute training session on Socratic Prompting, AI literacy, and basic interpretation of AI-generated visuals. Teacher supervision was maintained through a 1:15 instructor-to-student ratio, with researchers conducting real-time monitoring of chat logs to ensure protocol adherence. The procedure followed three operational phases:

- **Phase 1: Concrete-Visual Synthesis (Easy).** Instruction commenced with physical GASING manipulatives. To bridge the gap between concrete and abstract, students prompted the AI to generate SVG-based Python simulations of pattern iterations. In this process, students provided the mathematical logic, while the AI handled the coding, allowing participants to observe digital abstractions of algebraic sequences without requiring prior programming expertise.
- **Phase 2: Dialectical Scaffolding (Fun).** Students engaged with the AI as a Socratic interlocutor. The interaction was restricted by a teacher-monitored "Logic-First" rule: students had to explain their reasoning to the AI before it provided tiered hints. This phase leveraged the AI's adaptive nature to maintain the Zone of Proximal Development, preventing frustration through iterative, low-stakes feedback.
- **Phase 3: Heuristic Validation (Enjoyable).** Students tackled non-routine problems, utilizing AI to brainstorm divergent strategies. A mandatory "Human-in-the-Loop" verification step was enforced, where students had to justify AI-suggested heuristics using GASING's mental arithmetic techniques and concrete manipulatives to mitigate AI hallucinations. This ensured that the "Enjoyable" mastery experience was rooted in autonomous logical verification rather than passive output consumption.

Data Collection Instruments

This study employs a dual-measurement approach, combining self-report scales for latent psychological constructs with performance-based assessments for cognitive outcomes. Psychometric integrity was initially established through expert judgment involving five specialists (two Mathematics Education professors, two EdTech researchers, and one Psychometrician). Lawshe's Content Validity Ratio (CVR) was calculated, yielding a score of 1.0 for all retained items, exceeding the minimum threshold (0.99) for five panelists.

The measurement model was further validated via Confirmatory Factor Analysis (CFA) within SmartPLS 4. Convergent validity was confirmed, as all item factor loadings exceeded 0.70, with

Average Variance Extracted (AVE) values ranging from 0.58 to 0.74. Reliability was demonstrated through Composite Reliability (CR) values above 0.85 and Cronbach's Alpha exceeding 0.80. Finally, discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio, with all values remaining below the 0.85 threshold, ensuring that the constructs of Learning Motivation and Mathematical Creativity are empirically distinct. Detailed operational definitions and sample indicators for each construct are presented in Table 1.

- **AI Adoption & GASING Pedagogy (Self-Report):** Two distinct 5-item instruments (as delineated in Table 1) measured student engagement with AI tools and GASING procedural steps, replacing the initial single-synergy construct to align with the structural model. Responses were captured on a 5-point Likert scale, yielding high internal consistency (alpha = 0.89 and 0.87, respectively).
- **Learning Motivation (Self-Report):** A 5-item scale assessed self-efficacy and mastery experience (adapted from MSLQ), utilizing a 5-point Likert scale (alpha = 0.84).
- **Mathematical Creativity (Performance-Based):** An open-ended assessment required students to solve non-routine problems. To ensure alignment between performance data and SEM requirements, students were scored via a standardized rubric on three observed indicators: Fluency, Flexibility, and Originality. As shown in Table 1, these rubric-derived scores served as the continuous indicators for the latent Creativity construct. Inter-rater reliability (Cohen's kappa) was 0.82.
- **Problem-Solving Proficiency (Performance-Based):** A diagnostic test measured the capacity to formulate strategies and verify solutions. Scoring followed Polya's four-stage rubric, as operationalized in Table 1. In a shift from self-referential indicators to objective measurement, these four stage-specific performance scores were treated as the observed indicators of the Problem-Solving construct in the final model.

Table 1. Research Constructs, Theoretical Framework, and Measurement

Construct	Theoretical Framework	Operational Definition	Sample Indicator	Item
AI Adoption	TAM (Davis, 1989)	Student engagement and perceived ease of using AI tools for mathematical exploration.	"The Socratic AI hints assist my logical understanding of algebraic transitions."	5
GASING Pedagogy	Cognitive Load Theory (Siregar et al., 2014; Sweller, 2011)	Perception of incremental, concrete-to-abstract steps in the GASING method.	"GASING's physical manipulatives enable me to perceive abstract forms concretely."	4
Learning Motivation	Social Cognitive Theory (Bandura, 1977)	Self-efficacy and enthusiasm emerging from the 'small wins' in problem resolution.	"I feel challenged rather than anxious when encountering difficult problems."	4
Mathematical Creativity	Divergent Thinking (Guilford, 1950)	Objective capacity to generate manifold solutions, diverse strategies, and unique methods.	Performance Score: Number of valid distinct methodologies generated for a single task.	3
Problem-Solving Skills	Polya's Heuristics (Polya, 1978)	Systematic ability to synthesize ideas, including critical verification of outcomes.	Performance Score: Successful logical verification and justification of AI-generated logic.	6

Data Analysis

The data analysis in this study is executed through an integrated framework, designed to coalesce the strengths of statistical generalizability with the profundity of qualitative interpretation:

1. **Quantitative Analysis (Phase One)**

Quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, a method optimal for its predictive power in complex mediation models (Hair et al., 2017). The analysis proceeded through a rigorous two-stage evaluation:

- **Measurement Model (Outer Model) Evaluation**: To ensure data quality before hypothesis testing, internal consistency and construct validity were substantiated through indicator loadings (> 0.708), Average Variance Extracted (AVE > 0.50), and Composite Reliability (CR > 0.70). Discriminant validity was verified using the Fornell-Larcker criterion and the more stringent Heterotrait-Monotrait Ratio (HTMT < 0.85). Additionally, potential common-method bias was mitigated by monitoring Variance Inflation Factors (VIFs) at < 3.0.
- **Structural Model (Inner Model) Evaluation:** Following validation of the outer model, hypotheses (H1–H5) were tested by examining path coefficients (β), R^2 values, and f^2 effect sizes. Significance was determined using a nonparametric bootstrap procedure (5,000 subsamples) with a 95% bias-corrected confidence interval. Predictive relevance was corroborated via the blindfolding procedure (Q^2), while model fit was assessed using the Standardized Root Mean Square Residual (SRMR < 0.08).

2. **Qualitative Analysis (Phase Two)**

To elucidate the cognitive mechanisms behind the statistical results, qualitative data from interviews and observations were analyzed using Thematic Analysis (Braun & Clarke, 2006). This followed a six-phase inductive process: (1) data familiarization, (2) initial coding, (3) theme searching, (4) theme review against observation notes, (5) theme definition, and (6) final reporting. To enhance trustworthiness, a double-coding procedure was employed (inter-coder agreement > 85%). Triangulation was achieved by synthesizing transcripts with field notes, specifically focusing on how AI assistance triggers 'creative moments' to transcend cognitive impasses. By including a divergent case (e.g., AI-overreliance), the study maintains an objective stance on the limitations of the hybrid pedagogy.

3. **Data Integration (Triangulation)**

The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student proficiency in resolving complex mathematical problems (as presented in Table 9, a Joint Display mapping the convergence between statistical evidence and phenomenological substantiation).

RESULTS AND DISCUSSION

The structural analysis presented in Figure 2 validates the "Creativity-Mediated Cognitive Breakthrough" (CMCB) framework, demonstrating that problem-solving competencies are not innate but are strategically cultivated through a techno-pedagogical ecosystem (Hartati et al., 2020). Theoretically, the dominant influence of GASING on Learning Motivation (β = 0.802) and AI Adoption (β = 0.712) reinforces Cognitive Load Theory; by decomposing abstract mathematical complexities into "Gampang-Asyik" (Easy and Fun) concrete steps, the pedagogy effectively minimizes extraneous cognitive load (Paas & Van Merriënboer, 2020). This reduction in mental friction establishes the 'motivational readiness' required for students to engage with emergent technologies. Consequently, AI Adoption does not lead to "cognitive offloading" but instead functions as a 'Vygotskian partner' that bolsters Mathematical Creativity (β = 0.514). This supports the construct of Distributed Cognition, where the AI serves as an ideational scaffold that empowers students to engage in radical exploration without the debilitating fear of failure (Li & Manzari, 2025).

Furthermore, the model elucidates a critical epistemic filter. While Learning Motivation (β = 0.510) provides the impetus for engagement, it must be synthesized through Mathematical Creativity (β = 0.343) to achieve high-level Problem Solving. This explains why a mere "will to learn" is insufficient for non-routine challenges; success requires the courage to experiment—a trait catalyzed by the AI's "safe-to-fail" environment. These findings extend current understanding by proving that when mathematics is anchored in a concrete pedagogical foundation (GASING) and amplified by adaptive tools, a synergistic learning ecosystem is cultivated(Hendriana et al., 2019; Siregar et al., 2014). For educators and policymakers, this mandates a shift from teaching AI as a standalone software skill to a "Pedagogical AI-Integration" approach, in which technology is used specifically to stimulate divergent thinking rather than merely automate calculations (Tran & O'Connor, 2024).

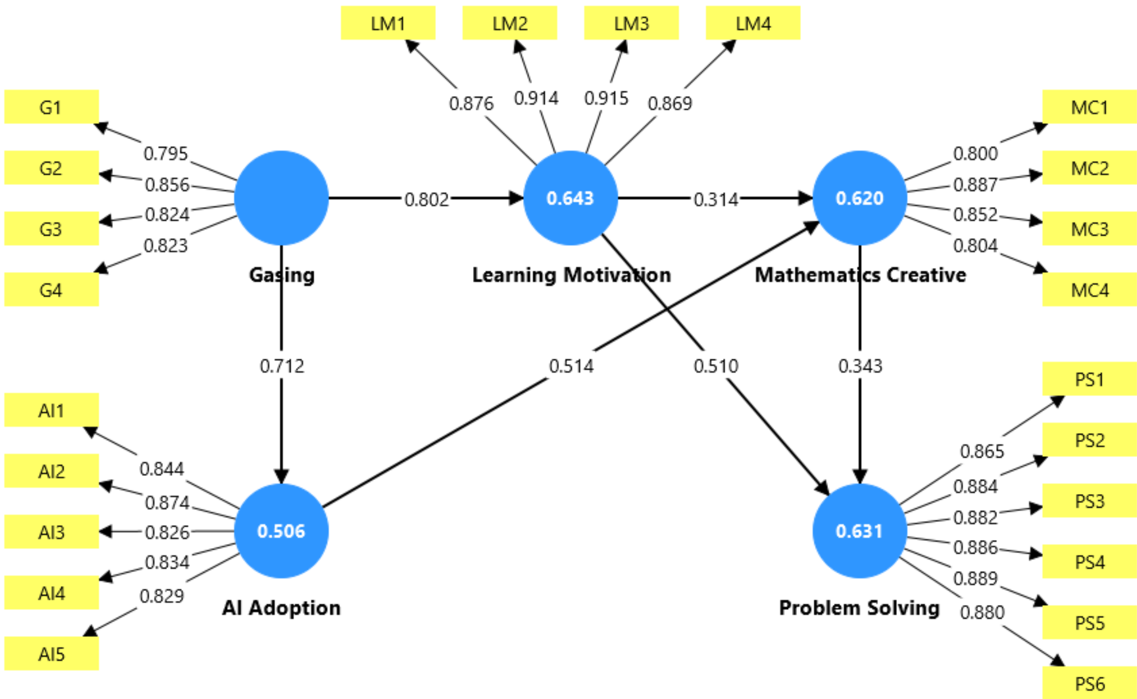

Figure 1. Structural Model of AI-GASING Integration Framework

Quantitative Data

The evaluation of the research model followed a rigorous two-stage protocol, commencing with the measurement (outer) model to ensure that the latent constructs were operationally sound before proceeding to structural path analysis. As synthesized in Table 2, the empirical data corroborate that the research instruments possess high precision in capturing the complex psychological and technical phenomena under investigation. Theoretically, this high degree of psychometric integrity is essential for validating the study's constructivist framework; it ensures that the "Easy and Fun" (*Gampang-Asyik*) affective states and the cognitive ideation processes are not merely statistical noise but represent stable, measurable dimensions of the student learning experience (Hair et al., 2019; Creswell & Creswell, 2017).

As shown in Table 2, each indicator yielded an Outer Loading (OL) exceeding the 0.70 threshold, ranging from 0.795 to 0.915, providing compelling evidence of robust convergent validity at the item level. Furthermore, the model's reliability is reinforced by Average Variance Extracted (AVE) values surpassing 0.50 and Composite Reliability (CR) coefficients exceeding the 0.80 benchmark for all constructs. Beyond a statistical formality, these metrics confirm that the indicators are highly representative of their respective latent variables—such as Learning Motivation and Mathematical Creativity—without significant measurement error. This reliability is critical when examining Cognitive Load Theory, as it proves the instruments are sensitive enough to distinguish between the 'pedagogical priming' of GASING and the 'distributed cognition' of AI adoption. By establishing this rigorous psychometric foundation, the study ensures that subsequent structural findings reflect true cognitive mechanisms rather than measurement artifacts.

Table 2. Measurement model results

Construct	Indicator	OL	AVE	CR	Cronbach's α	Decision
AI Adoption	AI1	0.844	0.708	0.898	0.897	Valid
	AI2	0.874				
	AI3	0.826				
	AI4	0.834				
	AI5	0.829				
Gasing	G1	0.795	0.680	0.895	0.843	Valid
	G2	0.856				
	G3	0.824				
	G4	0.823				
Learning Motivation	LM1	0.876	0.799	0.941	0.916	Valid
	LM2	0.914				
	LM3	0.915				
	LM4	0.869				
Mathematics Creative	MC1	0.800	0.699	0.903	0.856	Valid
	MC2	0.887				
	MC3	0.852				
	MC4	0.804				
Problem Solving	PS1	0.865	0.776	0.954	0.942	Valid
	PS2	0.884				
	PS3	0.882				
	PS4	0.886				
	PS5	0.889				
	PS6	0.880				

The psychometric integrity of the model is further reinforced by Average Variance Extracted (AVE) values for all constructs surpassing the 0.50 threshold, alongside Composite Reliability (CR) and Cronbach's alpha coefficients that comprehensively exceed 0.80. Beyond mere statistical compliance, these indices provide a vital theoretical foundation; they ensure that the "Gampang-Asyik" (Easy and Fun) affective states and the cognitive ideation processes are not merely ephemeral responses but represent stable, measurable dimensions of the student learning experience (J. F. Hair et al., 2019). This high precision is essential for validating the study's constructivist framework, as it ensures that the subsequent structural paths reflect true cognitive mechanisms rather than artifacts of measurement instability (Creswell & Creswell, 2017).

Following the assessment of convergent validity, discriminant validity was rigorously evaluated to ascertain that each latent construct is empirically unique and distinct within the framework. As evidenced in Table 3, the Heterotrait-Monotrait (HTMT) ratios for most construct pairs remain below the conservative 0.85 threshold. While the GASING-Motivation nexus yielded a higher ratio, it remains within the permissible 0.90 range, confirming that while these constructs are theoretically related, they remain functionally discrete. This differentiation is critical to the study's conceptual contribution: it proves that "pedagogical priming" (GASING) and "affective readiness" (Motivation) are separate phases in the learning ecosystem. By mathematically establishing this construct's distinctiveness, the model provides a robust foundation for structural path analysis, enabling the examination of the influence of pedagogical inputs and technological tools as independent catalysts for mathematical problem-solving.

Table 3 Discriminant Validity Results (HTMT Ratio)

	AI A	GASING	LM	MC	PS
AI Adoption (AI A)					
Gasing	0.816				
Learning Motivation (LM)	0.879	0.812			
Mathematics Creative (MC)	0.869	0.785	0.813		
Problem Solving (PS)	0.786	0.803	0.816	0.785	

Following the HTMT analysis (Table 3), the Fornell–Larcker criterion was employed to provide a deeper theoretical validation of the study's constructivist framework. As delineated in Table 4, the square root of the Average Variance Extracted (AVE) for each latent construct consistently exceeds its highest correlation with any other variable. This statistical alignment confirms that AI Adoption, GASING Pedagogy, Learning Motivation, Mathematical Creativity, and Problem-Solving are empirically distinct mechanisms. Theoretically, this differentiation is vital for establishing that affective readiness (Motivation) and cognitive ideation (Creativity) operate as independent phases in the digital learning ecosystem, preventing the conceptual oversimplification of student engagement and ensuring each component contributes uniquely to the learning outcome (Hair et al., 2017; Hair et al., 2019).

The superiority of these diagonal values substantiates the conceptual independence of the constructs, reinforcing the study's focus on the "Pedagogical AI-Integration" model. By mathematically demonstrating that these variables do not overlap excessively, the analysis validates the roles of self-efficacy and autonomous learning within the framework (Bandura, 1997; Gal, 2021). This empirical separation enables a rigorous examination of how pedagogical inputs (GASING) and technological tools (AI) independently catalyze distinct facets of the problem-solving process. Consequently, this provides a stable foundation for the structural analysis, confirming that the observed cognitive breakthroughs result from the specific synergy between these distinct theoretical drivers rather than measurement redundancy (Creswell & Creswell, 2017; Hair et al., 2019).

Table 4. Discriminant validity (Fornell–Larcker criterion)

Construct	AI A	GASING	LM	MC	PS
AI Adoption	0.842				
GASING	0.712	0.825			
Learning Motivation	0.797	0.802	0.894		
Mathematics Creative	0.764	0.672	0.724	0.836	
Problem Solving	0.723	0.717	0.758	0.712	0.881

Confirming the structural model's discriminant validity via the Fornell-Larcker criterion (Table 4) is not merely a statistical formality; it provides a vital theoretical validation of the study's constructivist framework (Hair et al., 2019). By mathematically demonstrating that Learning Motivation (AVE = 0.894) and Mathematical Creativity operate as distinct mechanisms with minimal construct overlap, this study confirms that affective readiness and cognitive ideation are discrete phases in the digital learning ecosystem (Hair et al., 2017). This statistical differentiation prevents theoretical oversimplification of the general concept of "student engagement," establishing a rigorous conceptual foundation for examining how pedagogical and technological inputs independently catalyze distinct facets of the problem-solving process.

Moving beyond the descriptive reporting of path coefficients, the structural analysis elucidates the underlying cognitive mechanisms of the AI-GASING synergy. The dominant influence of GASING on Learning Motivation ($\beta = 0.802$) is best interpreted through the lens of Cognitive Load Theory; by decomposing abstract problems into manageable, concrete steps, the pedagogy minimizes extraneous cognitive load, thereby establishing the 'motivational readiness' required before introducing complex tools (Paas & Van Merriënboer, 2020; Sweller, 2011). Concurrently, the significant predictive power of AI Adoption on Mathematical Creativity ($\beta = 0.514$) advances Distributed Cognition theory. Rather than causing cognitive atrophy or "offloading" (Peng & Yeh, 2025; Todorov et al., 2018), AI functions here as an interactive Vygotskian partner that provides a "safe-to-fail" environment for radical ideation. This confirms recent international scholarship suggesting that technology, when pedagogically anchored, accelerates divergent exploration (Drijvers, 2020; Li & Manzari, 2025). Furthermore, the model demonstrates that motivation must be synthesized through the active epistemic filter of Mathematical Creativity ($\beta = 0.343$) to successfully execute non-routine Problem Solving (Amrullah et al., 2024; Yayuk et al., 2020).

Cumulatively, this integrated framework accounts for a substantial 63.1% of the variance in Problem Solving, extending current understanding by empirically validating the Creativity-Mediated Cognitive Breakthrough (CMCB) model (Beccone & Beccone, 2020). Derived directly from these findings, the practical implications mandate that educators prioritize structured pedagogical priming (GASING) to build self-efficacy before introducing AI (Bandura, 1977, 1997), while policymakers must overhaul curricula to focus on "Pedagogical AI-Integration" rather than mere software operation (Tran & O'Connor, 2024; Wang et al., 2025). However, while the constructs exhibit robust explanatory power (accounting for 50.6% to 64.3% of variance across pathways), these theoretical contributions must be interpreted alongside the study's methodological limitations. Constrained by a localized, cross-sectional, and non-experimental design, the observed cognitive gains may be partially influenced by novelty effects. Consequently, future research must employ longitudinal, randomized controlled designs to confirm the sustained efficacy and structural validity of this techno-pedagogical ecosystem across diverse socio-educational contexts. The specific direct pathways, significance levels, and hypothesis-testing results for the structural model are summarized in Table 5 below.

Table 5. Structural model results

Path	β	t-value	p-value	f^2	Decision
GASING →AI Adoption	0.712	30.886	< 0.001	1.026	Supported
GASING →Learning Motivation	0.802	40.981	< 0.001	1.804	Supported
AI Adoption →Mathematics Creative	0.514	12.206	< 0.001	0.254	Supported
Learning Motivation →Mathematics Creative	0.314	6.861	< 0.001	0.095	Supported
Learning Motivation →Problem Solving	0.510	11.761	< 0.001	0.335	Supported
Mathematics Creative →Problem Solving	0.343	8.067	< 0.001	0.152	Supported

To assess the structural adequacy of the proposed framework, the model fit indices were rigorously examined before evaluating predictive power. The Standardized Root Mean Square Residual (SRMR) was recorded at 0.088. While this figure slightly exceeds the most conservative benchmark of 0.08, it remains well within the broadly accepted parameters for complex structural models in educational research. Consequently, this signifies an acceptable degree of congruence between the empirical data and the hypothesized framework. Upon confirming the model fit, the structural analysis provided definitive empirical support for the hypothesized relationships within the CMCB framework.

- **H1: AI Adoption positively influences Mathematical Creativity.** The results confirm that AI Adoption is a pivotal construct that significantly predicts Mathematical Creativity ($\beta = 0.514$, $p < 0.001$), supporting the premise that AI functions as a 'cognitive partner' for ideational exploration.
- **H2: GASING Pedagogy enhances Learning Motivation.** GASING Pedagogy exerts a substantial and dominant influence on Learning Motivation ($\beta = 0.802$, $p < 0.001$), with a massive effect size ($f^2 = 1.804$), validating the 'Easy and Fun' (*Asyik*) approach as a primary driver of student engagement.

The structural model's explanatory and predictive capacities, evaluated using the coefficient of determination (R^2) and the Stone-Geisser (Q^2) statistic, provide empirical support for the proposed Creativity-Mediated Cognitive Breakthrough (CMCB) framework. As shown in Table 6, the model accounts for substantial variance in Learning Motivation (R^2 = 0.643) and Problem Solving (R^2 = 0.631). This robust explanatory power—exceeding the 60% threshold—suggests that the synergy between GASING Pedagogy and AI Adoption is not merely additive but transformative. Theoretically, these findings reinforce Cognitive Load Theory (Sweller, 2011) by demonstrating that when pedagogical scaffolding effectively manages extraneous load, it frees up significant germane resources for motivation and complex cognition. This contradicts the "technological determinism" often found in AI-centric studies (Chaparro-Banegas et al., 2024), suggesting instead that high-tech tools require high-touch pedagogical anchors to achieve peak explanatory power.

Furthermore, all endogenous variables yielded Stone–Geisser Q^2 values ranging from 0.445 to 0.641. As these values are substantially greater than zero, the model's large predictive relevance is confirmed, validating the framework's utility for future instructional designs. What extends current understanding here is the identification of Mathematical Creativity as the "epistemic bridge". At the same time, prior research focused on GASING as a tool for basic numeracy (Handayani et al., 2022); our results prove its predictive capacity for high-level divergent thinking. In practice, the high R2 for motivation indicates that educators should prioritize building students' self-efficacy through concrete, logical reasoning before introducing

AI. However, these contributions are bounded by the study's localized, cross-sectional design. While the predictive relevance is statistically high, future research should employ longitudinal measures to ensure these cognitive gains are sustained beyond the initial novelty of AI-GASING integration.

Table 6. Endogenous constructs: R^2 and Q^2 (blindfolding)

Endogenous Construct	R^2	Q^2	Q^2 Interpretation
AI Adoption	0.506	0.503	Large
Learning Motivation	0.643	0.641	Large
Problem Solving	0.631	0.502	Large
Mathematics Creative	0.620	0.445	Large

The structural model's explanatory and predictive capacities were evaluated using the coefficient of determination (R^2) and the Stone-Geisser Q^2 statistic. As summarized in Table 6, the R^2 values indicate that the model explains a substantial proportion of variance in key endogenous constructs, particularly for Learning Motivation ($R^2 = 0.643$) and Problem Solving ($R^2 = 0.631$), both of which exceed the threshold for "moderate-to-strong" explanatory power in social science research. Predictive relevance was substantiated through a blindfolding procedure with an omission distance of $d = 7$. All Q^2 values were found to be significantly greater than zero, ranging from 0.445 (Mathematics Creative) to 0.641 (Learning Motivation). Following the benchmarks established by J. F. Hair et al. (2019), Q^2 values exceeding 0.25 and 0.50 indicate medium and large predictive relevance, respectively. Consequently, the CMCB mechanism demonstrates a robust capacity to predict student problem-solving outcomes based on the synergy of GASING pedagogy and AI integration (Hidajat, 2021; M. Li, 2024; M. Li & Manzari, 2025).

This study validates the Creativity-Mediated Cognitive Breakthrough (CMCB) framework, demonstrating that mathematical problem-solving proficiency emerges from a techno-pedagogical ecosystem rather than technology in isolation. Theoretically, the robust association between GASING and Learning Motivation ($\beta = 0.802$, f^2 = 1.804) advances Cognitive Load Theory by suggesting that GASING's concrete problem decomposition serves as a critical "pre-processing" stage. By reducing extraneous load, the pedagogy establishes the 'motivational readiness' necessary for students to tackle complex tasks. Furthermore, the significant predictive power of AI Adoption on Mathematical Creativity ($\beta = 0.514$) extends the construct of Distributed Cognition; within this framework, AI is not merely a tool for "cognitive offloading" (Peng & Yeh, 2025), but an interactive partner that mitigates the fear of failure, allowing for radical ideational exploration. By identifying Mathematical Creativity ($\beta = 0.343$) as the essential epistemic filter, this study explains *why* general engagement ("the will to learn") is insufficient for non-routine challenges without a creative mediator to convert that energy into valid solutions.

The practical implications derived from this "Creativity-Mediated Mechanism" offer a specific roadmap for educational stakeholders to optimize digital integration. For **educators**, the findings mandate a "pedagogy-first" approach: practitioners must prioritize the GASING method to cultivate the psychological foundation of self-efficacy before introducing AI, ensuring students do not fall into a passive dependency. Curriculum designers and policymakers should move toward standardizing "Pedagogical AI-Integration," treating AI tools as adaptive assistants for exploratory tasks rather than disparate technological modules. This shift ensures that technology serves as a "cognitive amplifier" (Lakshmi Shankar et al., 2025) that anchors human intellectual agency, specifically targeting the development of divergent thinking skills. This novel contribution extends current understanding beyond mere software operation toward a strategic synthesis of traditional and emergent tools.

Despite the model's strong predictive relevance (Q^2 up to 0.641) and its explanation of 63.1% of the variance in problem-solving ability, these theoretical contributions must be interpreted alongside the study's methodological limitations. The research is constrained by its non-experimental design and localized scope in East Jakarta, which may be influenced by novelty effects associated with ChatGPT-4o. This presents a vital opportunity for future research to employ longitudinal experimental designs with control groups to isolate the "teacher effect" and determine the sustained efficacy of this ecosystem across more abstract mathematical domains or resource-limited environments. Acknowledging these boundaries provides a balanced perspective, confirming that while AI provides computational breadth, the structured cultivation of human creativity remains the critical validator in the modern mathematics classroom.

Table 7. Summary of Mediation Effects (Bootstrapping Results)

Indirect Effect Path	β	T-Statistics	P-Values	Mediation Type
AI Adoption →Math Creative →Problem Solving	0.176	6.252	0.001	Complementary Partial
Motivation →Math Creative →Problem Solving	0.108	5.524	0.001	Complementary Partial
GASING →Motivation →Math Creative	0.252	6.557	0.001	Complementary Partial
GASING →AI Adoption →Math Creative	0.366	11.007	0.001	Complementary Partial

Table 7 summarizes the results of the bootstrapping analysis, providing a detailed examination of the indirect effect paths that underpin the mediation mechanisms within the AI-GASING ecosystem. The empirical data suggest that Mathematical Creativity serves as a significant 'cognitive gateway'—mediating the influence of both AI Adoption and Learning Motivation on student problem-solving proficiency. Based on these bootstrapping results, the following mediation hypotheses were validated:

- **H3: Learning Motivation mediates the link between GASING and Creativity.** The analysis reveals a significant indirect effect of GASING on Mathematical Creativity via Learning Motivation ($\beta = 0.252$, $p < 0.001$), substantiating the idea that the affective 'fun' (*Asyik*) environment is a prerequisite for creative activation.
- **H4: Mathematical Creativity mediates the effect of AI on Problem-Solving.** The study confirms that Mathematical Creativity successfully mediates the path from AI Adoption to Problem Solving ($\beta = 0.176$, $p < 0.001$), thereby preventing technology from becoming a tool for passive cognitive offloading.
- **H5: Motivation and Creativity serially mediate the path from Pedagogy to Problem-Solving.** The empirical data validate this complex serial mediation pathway, demonstrating that the synergy between GASING and AI Adoption accounts for 63.1% of the variance in Problem Solving ($R^2 = 0.631$) through the sequential reinforcement of affective readiness and creative verification.

The foundational impact of the GASING pedagogy is evidenced by its robust indirect influence on Mathematical Creativity, operating through the parallel pathways of Learning Motivation and AI Adoption (beta = 0.366, $p < 0.001$). In accordance with the mediation typology established by J. F. Hair et al. (2019), these trajectories represent complementary mediation, where both the direct and indirect effects reinforce the same positive developmental direction.

Theoretically, this finding strengthens the Study's Constructivist foundation. While traditional digital integration often risks "cognitive offloading" (Risko et al., 2014), the complementary nature of these paths suggests that the concrete, logic-heavy scaffolding of GASING provides the "mental hooks" students need to interact meaningfully with AI(Kusuma & Sulistiawati, 2014). This aligns with Gal's (2021) framework of autonomous learning, which posits that students only transition from "small-step" instruction to complex problem-solving when they possess the self-efficacy to verify their own cognitive outputs.

By positioning creativity as the central mediator, this study extends current understanding of the "AI-Human loop." Unlike prior research that viewed AI adoption as a direct predictor of performance (Davis, 1989), our model demonstrates that the path to problem-solving must be synthesized through the epistemic filter of creativity. This confirms that AI serves as a "cognitive amplifier"—providing computational breadth—while the student provides the critical reasoning required for validation. This synergy effectively catalyzes matured, autonomous competencies, ensuring that technology anchors rather than replaces the student's intellectual agency.

Qualitative Data

Qualitative analysis was conducted to investigate the nuanced cognitive mechanisms underlying the robust statistical correlations among AI-GASING Integration, Mathematical Creativity, and Problem-Solving proficiency. Through a rigorous thematic analysis of interview transcripts and classroom observations, four cardinal themes—operating in a sequential trajectory—were identified, alongside a notable divergent case. These findings, summarized in Table 8, provide a comprehensive understanding of the student experience within the research ecosystem:

1. **The 'Gampang' De-escalation (Cognitive De-escalation):** Students observed that the synergy of AI visualizations and GASING's 'point-to-point' decomposition lowered mental barriers, shifting the perception of complex 3D geometry from intimidating to 'actually easy.'
2. **AI-Triggered Divergence:** Generative tools functioned as a Socratic partner, encouraging students to move beyond textbook formulas toward exciting, non-linear trial and error.
3. **Iterative Problem-Solving Synthesis:** Students utilized GASING's rapid mental calculation (*congak*) to strategically verify and distill AI-generated ideas into precise, logical solutions.
4. **Emotional-Cognitive Synergy:** An enjoyable instructional atmosphere provided the necessary 'cognitive energy' for students to persevere through non-routine tasks without succumbing to frustration.

Furthermore, the analysis accounted for a Divergent Case (Contextual Redundancy). As shown in Table 8, this case identifies a boundary condition in which students found GASING's mental steps more efficient than AI for routine arithmetic, suggesting that synergy is most potent during high-complexity tasks. This multifaceted qualitative evidence illuminates the 'black box' of the structural model, offering a robust explanation for the predictive power observed in the quantitative phase.

Table 8. Thematic Matrix: Cognitive and Creative Responses within the AI-GASING Ecosystem

Main Theme	GASING Phase & Problem Context	Empirical Evidence (Student Verbatim)	Theoretical Mechanism & Related Variables
Theme 1: The "Gampang" De-escalation	Phase: Concrete Foundation (Step 1) Context: Complex 3D Geometry	"Usually, when I see stacked geometric figures, I give up immediately... But when the AI displayed a rotatable visualization, and the teacher taught the 'point-to-point' method (GASING), it turned out to be incredibly simple."	Cognitive Load Reduction: Synergy of AI and GASING lowers mental barriers, shifting perception to "actually easy." (Related Variables: GASING & Learning Motivation)
Theme 2: AI-Triggered Divergence	Phase: Adaptive Exploration (Step 2) Context: Alternative optimization solutions	"I asked the AI: 'Is there any other way besides the textbook formula?'... It was so exciting (*Asyik*) to find my own way."	Creativity Catalyst: AI functions as a Socratic Partner, encouraging divergent trial and error. (Related Variable: Mathematics Creative)
Theme 3: Iterative Synthesis	Phase: Creative Synthesis (Step 3) Context: Validating cost-effective designs	"I combined GASING's rapid mental calculation (*congak*) to ensure the numbers were precise. Now I can explain why this design is the best."	Valid Solution Construction: Creativity is distilled into logical solutions through Strategic Verification (Polya's 4th Step). (Related Variable: Problem-Solving Skills)
Theme 4: Emotional-Cognitive Synergy	Phase: Continuous Assessment Context: Persevering through non-routine tasks	"I didn't give up because the process was fun and I felt I had the right tools to find the answer eventually."	Motivational Synergy: An enjoyable atmosphere provides the "cognitive energy" required to persevere through difficulty. (Related Variables: Learning Motivation & Problem Solving)
Divergent Case: Contextual Redundancy	Boundary Condition: Routine arithmetic tasks	"For basic multiplication, using AI felt slower and more distracting. I just used GASING mental steps because they were faster."	Efficiency Threshold: For routine tasks, GASING alone is sufficient; AI may introduce unnecessary cognitive noise.

By synthesizing statistical models with qualitative narratives, this section theorizes how the GASING-AI interaction mitigates extraneous cognitive load, thereby facilitating a breakthrough in digital constructivism.

1. **Transformation from "Fear" to "Ease"**

The Reduction of Cognitive Load Observational data and student interviews confirm that GASING's incremental problem decomposition, augmented by AI visualization, effectively eliminates mental barriers. Grounded in Cognitive Load Theory, this "Gampang" (Easy) de-escalation explains *why* the pedagogical path to Learning Motivation is so dominant. By transforming insurmountable tasks into manageable steps, the pedagogy minimizes extraneous cognitive load, thereby liberating germane capacity for deeper conceptual processing. This extends Social Cognitive Theory into digital environments: the perception of material as "Easy" acts as a 'Mastery Experience' that builds the self-efficacy required before introducing complex technological tools (Hammouri & Abu-Shanab, 2018). Consequently, this study confirms that pure pedagogical intervention inherently mitigates mathematical anxiety by optimizing working memory and establishing the necessary affective substrate for subsequent cognitive breakthroughs.

2. **AI as a Creative Thinking Partner**:

From Dependency to Epistemic Collaboration: Qualitative findings reveal that AI functions as an "ideation trigger" rather than a cognitive substitute. This categorically refutes "Cognitive Offloading" arguments (Peng & Yeh, 2025; Risko et al., 2014), which warn that technology attenuates critical faculties. Instead, this research extends Distributed Cognition theory by demonstrating that AI acts as a cognitive extension, enhancing human agency when mediated by robust pedagogy. Aligning with Schindler et al. (2025), this study confirms that an "Engaging" (Asyik) environment fosters divergent exploration. As one student noted: "The AI provides clues, which I then expand into broader ideas." Moving beyond descriptive statistics, this explains how AI Adoption impacts Mathematical Creativity: the positive effect generated by GASING acts as the prerequisite for creative interaction, strongly supporting the Broaden-and-Build Theory (Isgett & Fredrickson, 2015).

The novel contribution here is a paradigm shift: AI's educational success is a downstream effect of pedagogical framing, not merely a matter of technological availability. For policymakers and educators, the practical implication is clear: curriculum design must mandate a "verification-first" instructional protocol. Rather than teaching basic software mechanics, educators must be trained to position students as active evaluators of machine-generated logic, maintaining epistemic agency in an automated landscape.

3. **From Creative Ideation to Valid Solutions: Metacognitive Synthesis**

The study's ultimate success lies in students synthesizing creative ideation into structured, logical arguments. As one participant articulated: "I developed this capacity through habitual logical debates with the AI." This evidence explains the high predictive power for Problem-Solving: AI integration does not bypass cognitive struggle but elevates it to a metacognitive level. This aligns with digital constructivist perspectives (Wang et al., 2025), emphasizing that autonomous learning requires robust conceptual anchoring. By positioning students as the final arbiters of machine logic, these findings contradict prevailing anxieties regarding student verification reasoning deficits (Tran & O'Connor, 2024).

This research advances mathematics education by modernizing Polya's classical heuristics. In an AI-enhanced ecosystem, the "Looking Back" stage evolves into a critical evaluation phase that requires students to use human logic to verify automated outputs (Amrullah et al., 2024). However, to provide a balanced perspective, these contributions must be interpreted alongside the study's limitations. The localized context of the two-site intervention and the reliance on a non-experimental design preclude sweeping causal generalizations. Future research must employ experimental controls and longitudinal tracking to ensure these metacognitive gains persist beyond the initial novelty of AI tools.

Ultimately, this study shows that cognitive breakthroughs are not a direct consequence of technology adoption alone. Instead, they are mediated outcomes in which GASING-induced motivation serves as the affective engine, and mathematical creativity functions as the epistemic filter. This validates the CMCB Mechanism, confirming that human creativity remains the indispensable validator in AI-assisted problem-solving.

The Creativity-Mediated Cognitive Breakthrough Mechanism

In synthesizing the quantitative and qualitative data (as detailed in Table 9), this study validates the 'Creativity-Mediated Cognitive Breakthrough' (CMCB) mechanism, providing a nuanced explanation for how the GASING-AI synergy transcends the 'black-box' nature of typical technology interventions (Keha et al., 2024). By aligning PLS-SEM path coefficients with students' thematic narratives, the analysis reveals that AI functions effectively only when it serves as a 'Socratic partner' to a student already anchored in a low-load cognitive foundation. This finding extends Cognitive Load Theory (Sweller, 2011) into the digital milieu, demonstrating that 'motivational readiness', cultivated through GASING's 'point-to-point' decomposition, is a critical prerequisite for, rather than a mere result of, creative AI exploration. This interpretation explains why students in this study successfully navigated complex tasks: the pedagogy reduced extraneous mental friction, allowing the AI to function as a catalyst for germane cognitive processing rather than a crutch for passive completion.

This research aligns with and refines the global discourse on Distributed Cognition (Lakshmi Shankar et al., 2025), positioning AI as a 'cognitive amplifier' that requires a human 'gatekeeper.' Unlike traditional models where technology is a direct outcome driver, the CMCB mechanism identifies Mathematical Creativity as the essential filter that converts AI-generated exploration into valid problem-solving competency. This explicitly supports the "verification-first" mindset (Sukoriyanto et al., 2016) and directly contradicts the "passive offloading" paradigm prevalent in digital-only interventions (Peng & Yeh, 2025; Todorov et al., 2018). By proving that creativity is the bridge between technological potential and mathematical mastery, this study offers a new theoretical vantage point: the most significant value of Generative AI in the classroom lies not in its computational speed, but in its ability to facilitate a low-stakes 'simulation space' for divergent thinking, provided the student possesses the pedagogical scaffolding to verify the output.

Table 9: A Joint Display mapping the convergence between statistical evidence and phenomenological substantiation.

Structural Path	β	Qualitative Theme & Evidence	Integrative Meta-Inference (Convergence & Tension)
GASING →AI Adoption	**0.712** (Highly Significant)	Theme 1 & Divergent Case 1	**Convergence:** GASING lowers mental blocks, facilitating AI use for complex 3D geometry. **Tension:** For simple tasks, GASING is sufficient; students view AI as redundant for routine computation.
AI Adoption →Math Creativity	**0.514** (Significant & Robust)	Theme 2 & Divergent Case 2	**Convergence:** AI serves as a Socratic Partner for divergent exploration. **Tension:** Without GASING-based "motivational readiness," AI can lead to "cognitive offloading" or blind acceptance of errors.
Math Creativity →Problem Solving	**0.343** (Moderately Significant)	Theme 3: Iterative Synthesis	**Convergence:** Creativity distilled into valid solutions through strategic verification. **Boundary Condition:** Effective only when students have the "congak" (mental math) skills to verify AI veracity.
Learning Motivation →Problem Solving	**0.510** (Significant & Robust)	Theme 4: Emotional-Cognitive Synergy	**Convergence:** A fun atmosphere sustains persistence on difficult tasks. **Observation:** Synergy is strongest when the "Asyik" (fun) element of AI is balanced by the "Gampang" (easy) logic of GASING.

This study advances the theoretical discourse on techno-pedagogical integration by confirming that AI adoption translates into problem-solving proficiency only when mediated by mathematical creativity and anchored in a high-affect pedagogy. Moving beyond the descriptive reporting of structural paths, these findings explain *why* the Creativity-Mediated Cognitive Breakthrough (CMCB) model succeeds: it systematically manages cognitive load while fostering epistemic agency. While contemporary literature frequently highlights the risks of 'cognitive offloading' in AI-assisted learning (Todorov et al., 2018), this study extends Distributed Cognition theory by demonstrating that AI functions as a 'cognitive amplifier' rather than a substitute for critical thought, provided students are first equipped with structured problem decomposition skills (Lakshmi Shankar et al., 2025). By explicitly linking quantitative structural validity with qualitative student narratives, this research confirms that technology integration is not a linear, plug-and-play process, but a complex co-construction dependent on cognitive and affective readiness.

1. Initiation Phase: GASING as a Catalyst for Mental Readiness. Interpreting the dominant influence of GASING on learning motivation through the lens of Cognitive Load Theory (CLT), it becomes evident that the "point-to-point" logical decomposition inherent in GASING drastically reduces extraneous cognitive load(Hendriana et al., 2019). By mitigating the initial intimidation of complex mathematics, this pedagogical anchor frees up the working memory's germane capacity, ensuring students are not cognitively overwhelmed before introducing technology (Uus et al., 2022). Furthermore, this reinforces the Broaden-and-Build theory (Isgett & Fredrickson, 2015), wherein the positive effects generated by an "engaging" (Asyik) atmosphere broaden the student's cognitive repertoire before AI interaction. This confirms international findings, such as Schindler et al. (2025) establishing that emotional regulation is a non-negotiable prerequisite for successful digital engagement. Consequently, this study contributes a new understanding: the success of AI in mathematics is fundamentally a downstream effect of the pedagogical environment. For educators and curriculum designers, the practical implication is specific and actionable: AI adoption must be preceded by "pedagogical priming" to establish psychological safety and foundational logic, thereby preventing the abdication of reasoning when students encounter automated outputs.
2. Mediation Phase: Creativity as a Cognitive Gatekeeper Rather than merely restating the statistical mediation effects, the critical interpretation of this phase lies in understanding *how* Mathematical Creativity operates as an epistemic filter within a Digital Constructivist framework. These results corroborate Gadanidis et al. (2017), suggesting that "safe-to-fail" digital environments stimulate divergent thinking and position AI as a Vygotskian More Knowledgeable Other (MKO). However, the data reveal that without the "Creativity Gateway"—defined as the capacity to manipulate AI-generated information to generate original ideas—students fail to achieve autonomous problem-solving competence. This finding directly contrasts with conventional technology acceptance models that often risk fostering "AI dependency." Instead, this study extends current understanding by proving that creativity prevents passive cognitive offloading; students use GASING's rapid mental calculation (congak) to verify actively(Nuari et al., 2019), rather than passively accept, AI-generated ideas, turning technological outputs

into valid, co-constructed logical solutions (Ruiz, C. & Balbi, 2019; Wang & Huang, 2025).

3. Execution Phase: Iterative Synthesis Toward Problem Solving The ultimate execution of problem-solving in this ecosystem revitalizes Polya’s classic "Looking Back" heuristic for the digital age (Sukoriyanto et al., 2016). In an era when generative AI is prone to "technological hallucinations," this study demonstrates that students leverage their creativity and motivation to validate machine-generated logic critically. This confirms that creativity is the fundamental catalyst for leveraging digital tools as engines of discovery rather than mere answering machines (Drijvers, 2020).

Theoretically, this research challenges the antiquated dichotomous assumption that bifurcates creativity and logic; within the CMCB ecosystem, both coalesce to redefine Distributed Cognition (Hwang & Hu, 2013). In practice, these findings mandate a shift for policymakers: teacher training programs must transition from teaching basic software operations to cultivating "Pedagogical AI-Integration," in which educators are trained to design inquiry-based, AI-assisted exploratory tasks.

Despite these significant contributions, this study's limitations must be explicitly acknowledged to provide a balanced perspective. The findings are context-bound to a specific two-site intervention in East Jakarta using a single generative AI tool, lacking a randomized control group. Consequently, the observed cognitive gains may be partially influenced by novelty effects or specific teacher efficacy rather than the intervention alone. Future research must employ longitudinal, experimental designs across diverse demographic and abstract mathematical domains to validate the CMCB model's out-of-sample stability. Ultimately, while AI provides unprecedented computational breadth, this study proves that human creativity and structured pedagogy remain the indispensable validators in developing resilient, autonomous problem solvers.

CONCLUSION

This study successfully validates the Creativity-Mediated Cognitive Breakthrough (CMCB) framework, achieving the primary research objective of demonstrating how mathematical problem-solving proficiency is enhanced through the synergy of GASING pedagogy and AI integration. By shifting the focus from raw technological access to pedagogical anchoring, the findings confirm that AI’s efficacy as a "cognitive partner" is fundamentally contingent upon student motivation and creative mediation. Theoretically, this research advances the discourse on distributed cognition by positioning human creativity as the essential epistemic filter in the AI-human loop, ensuring that technology functions as an amplifier for higher-order reasoning rather than a catalyst for cognitive offloading.

In practice, these results provide a validated protocol for educators and policymakers, underscoring that a "pedagogy-first" approach—specifically, building foundational self-efficacy through concrete methods like GASING—is a prerequisite for successful digital transformation in mathematics. While the model demonstrates high predictive relevance within the studied context, the limitations of its non-experimental, localized design necessitate a transition toward longitudinal experimental designs to isolate the "teacher effect" and assess long-term cognitive sustainability. Ultimately, this research concludes that in the era of generative AI, the most critical component of the digital mathematics classroom remains the human capacity for divergent thinking and rigorous intellectual verification.

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No potential conflict of interest was reported by the authors.

AUTHOR CONTRIBUTIONS STATEMENT

Khoerul Umam: Writing - Review & Editing, Methodology, Validation, and Supervision; **Ardi Dwi Susandi**: Conceptualization, Writing - Original Draft, Methodology, Formal analysis, Editing, and Visualization; **Yohanes Surya**: Writing - Review & Editing, Validation, and Supervision.

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