


# edwin wijaya

## Paper Khoerul Umam

 Jabatan Fungsional

 tes Jafung

 Universitas Prof. Dr. Moestopo (Beragama)

---

### Document Details

Submission ID

trn:oid::1:3533250395

Submission Date

Apr 11, 2026, 4:09 AM GMT+7

Download Date

Apr 11, 2026, 4:11 AM GMT+7

File Name

layout\_finished\_1.docx

File Size

265.2 KB

20 Pages

8,500 Words

55,840 Characters

# 7% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

## Filtered from the Report

- Bibliography
- Quoted Text

## Match Groups

- 51 Not Cited or Quoted 6%**  
Matches with neither in-text citation nor quotation marks
- 2 Missing Quotations 0%**  
Matches that are still very similar to source material
- 0 Missing Citation 0%**  
Matches that have quotation marks, but no in-text citation
- 0 Cited and Quoted 0%**  
Matches with in-text citation present, but no quotation marks

## Top Sources

- 6% Internet sources
- 3% Publications
- 1% Submitted works (Student Papers)

## Integrity Flags

### 1 Integrity Flag for Review

- Hidden Text**  
89 suspect characters on 1 page  
Text is altered to blend into the white background of the document.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

### Match Groups

- 51 Not Cited or Quoted 6%**  
Matches with neither in-text citation nor quotation marks
- 2 Missing Quotations 0%**  
Matches that are still very similar to source material
- 0 Missing Citation 0%**  
Matches that have quotation marks, but no in-text citation
- 0 Cited and Quoted 0%**  
Matches with in-text citation present, but no quotation marks

### Top Sources

- 6% Internet sources
- 3% Publications
- 1% Submitted works (Student Papers)

### Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

<b>1</b>	Internet	<b>www.mdpi.com</b>	<b>1%</b>
<b>2</b>	Internet	<b>dergipark.org.tr</b>	<b>&lt;1%</b>
<b>3</b>	Internet	<b>link.springer.com</b>	<b>&lt;1%</b>
<b>4</b>	Internet	<b>www-emerald-com-443.webvpn.sxu.edu.cn</b>	<b>&lt;1%</b>
<b>5</b>	Internet	<b>www.jespk.net</b>	<b>&lt;1%</b>
<b>6</b>	Internet	<b>assajournal.com</b>	<b>&lt;1%</b>
<b>7</b>	Internet	<b>itrev.kemenkeu.go.id</b>	<b>&lt;1%</b>
<b>8</b>	Internet	<b>onlinelibrary.wiley.com</b>	<b>&lt;1%</b>
<b>9</b>	Student papers	<b>University Of Tasmania</b>	<b>&lt;1%</b>
<b>10</b>	Internet	<b>openjournal.unpam.ac.id</b>	<b>&lt;1%</b>

11	Internet	remittancesreview.com	<1%
12	Student papers	University of Wales Institute, Cardiff	<1%
13	Internet	iiste.org	<1%
14	Internet	journal.unm.ac.id	<1%
15	Internet	revistas.udc.gal	<1%
16	Student papers	Swiss School of Business and Management - SSBM	<1%
17	Internet	journal.uui.ac.id	<1%
18	Internet	www.allcommercejournal.com	<1%
19	Internet	rebus.us.edu.pl	<1%
20	Internet	www.openjournals.ijaar.org	<1%
21	Internet	files.eric.ed.gov	<1%
22	Internet	iieta.org	<1%
23	Internet	ijcat.com	<1%
24	Internet	jestp.com	<1%

25	Internet	mail.ajmesc.com	<1%
26	Internet	pmc.ncbi.nlm.nih.gov	<1%
27	Internet	www.irjms.com	<1%
28	Publication	Gyan Prakash, Amandeep Kaur. "AI and Sustainable Transformations", CRC Press,...	<1%
29	Publication	Honggen Xiao, Haiyan Song, Songshan (Sam) Huang. "Sustainable Tourism in Em...	<1%
30	Internet	ejournal.unibabwi.ac.id	<1%
31	Internet	ejournal.uniramalang.ac.id	<1%
32	Internet	f1000research.com	<1%
33	Internet	hpp.tbzmed.ac.ir	<1%
34	Internet	ijirss.com	<1%
35	Internet	irep.iium.edu.my	<1%
36	Internet	jcasc.com	<1%
37	Internet	jurnal.untagsmg.ac.id	<1%
38	Internet	nursing.jmir.org	<1%

39	Internet		
ojs.uph.edu			<1%
<hr/>			
40	Internet		
www.frontiersin.org			<1%
<hr/>			
41	Publication		
Krishna Koppa, Manita D. Shah, Srimantoorao S. Appadoo. "Empowering Inclusive..."			<1%
<hr/>			
42	Publication		
Md. Tanvir Alam Himel, Shahrin Ashraf, Tauhid Ahmed Bappy, Md Tanaz Abir, Md ...			<1%



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

Khoerul Umam<sup>1\*</sup>, Ardi Dwi Susandi<sup>2</sup>, Yohanes Surya<sup>3</sup>

<sup>1</sup> Universitas Muhammadiyah Prof. DR. HAMKA, Jakarta, 12130, Indonesia

<sup>2</sup> Universitas Terbuka, Tangerang Selatan, 12130, Indonesia

<sup>3</sup> GASING Academy, Jakarta, Indonesia

[khoerul.umam@uhamka.ac.id](mailto:khoerul.umam@uhamka.ac.id)

## Article Information

Submitted: NOV 05, 2025  
 Revised: March 04, 2026  
 Accepted: April 09, 2026

### Keywords

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

## 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

### How to cite

Umam, K., Susandi, A. D., & Surya, Y. (2026). Leveraging GASING pedagogy and ai adoption to enhance problem-solving skills: The mediating roles of learning motivation and mathematical creativity. *Al-Jabar: Pendidikan Matematika*, 17(2), 1-22.

### E-ISSN

2540-7562

### Published by

Mathematics Education Department, UIN Raden Intan Lampung

21

14

1

24

28

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 ( $\beta$ ),  $R^2$  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)

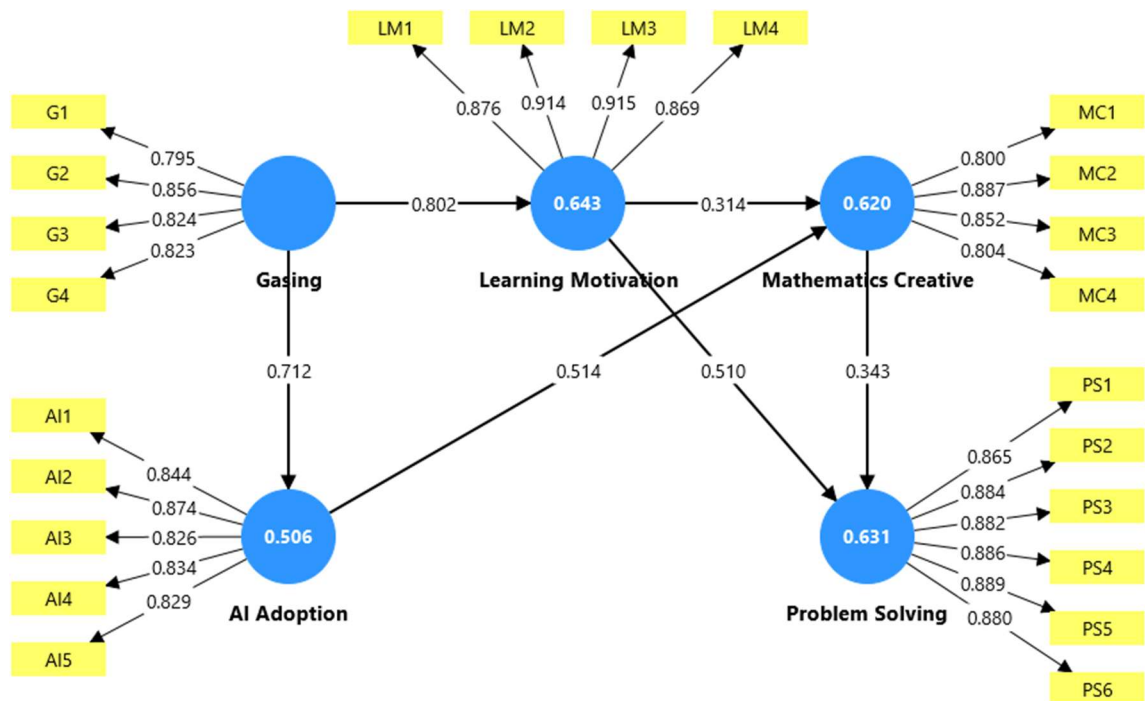
The themes emerging from the qualitative analysis are subsequently triangulated with the statistical outputs from SmartPLS. This integration aims to construct a comprehensive interpretation of how creativity, catalyzed by the AI-GASING synergy, functions as the primary mental mechanism enhancing student 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 ( $\beta = 0.802$ ) and AI Adoption ( $\beta = 0.712$ ) 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 ( $\beta = 0.514$ ). 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 ( $\beta = 0.510$ ) provides the impetus for engagement, it must be synthesized through Mathematical Creativity ( $\beta = 0.343$ ) 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 $\alpha$	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

1 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).

1 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	$\beta$	t-value	p-value	f <sup>2</sup>	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  $R^2$  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	$\beta$	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.

25

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