BUKTI KORESPONDENSI

ARTIKEL JURNAL INTERNASIONAL BEREPUTASI

Judul Artikel : Integrating realistic mathematics education, AI, and gamification to enhance students' learning motivation and problem-solving skills

Jurnal : Journal on Mathematics Education Vol. 16 No. 4 (2025)

Penulis : Susilawati, W., Sharov, S., Pasqa, M., & Malik, H

No.	Perihal	Tanggal
1.	Bukti konfirmasi submit artikel	30 Agu 2025
2.	Bukti konfirmasi review dan hasil review pertama	8 Okt 2025
3.	Bukti konfirmasi submit revisi pertama, respon kepada reviewer, dan artikel yang diresubmit	12 Nov 2025
6.	Bukti konfirmasi artikel accepted	13 Nov 2025
7.	Bukti konfirmasi artikel published online	2 Des 2025

1
BUKTI KONFIRMASI SUBMIT ARTIKEL DAN ARTIKEL YANG DISBUMIT
(30 AGUSTUS 2025)

Journal on Mathematics Education

← Back to Submissions

3875 / **Susilawati et al.** / Integrating realistic mathematics education, AI, and gamification to enhance students' learning motivation a

Library

Workflow | Publication

Submission | Review | Copyediting | Production

Submission Files

Search

6704	Realistic Mathematics Education with AI and Gamification- Enhancing Students' Motivation and Problem-Solving in Secondary Mathematics .docx	August 30, 2025	Article Text
6791	[JME] - Blind Review Paper 3.docx	September 18, 2025	Article Text

Download All Files

[jme] Submission External Kotak Masuk ×

Jme Fkip Matematika
kepada saya, Sergii, M, Hazar

30 Aug 2025, 02.14

Dear Wati Susilawati, Sergii Sharov, M Pasqa, and Hazar Malik,

Thank you for submitting your manuscript entitled "Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving" to the Journal on Mathematics Education (JME). Your manuscript has been successfully received in our online system and will be processed for editorial review. Please refer to your Author Center for the manuscript ID and further status updates.

Kind regards,

Prof. Dr. Zulkardi, M.Ikomp., M.Sc.
Editor-in-Chief
Journal on Mathematics Education

Journal on Mathematics Education
Volume xx, No. x, xxxx, pp. xx-xx

Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving

Abstract

Mathematics learning in the digital era requires approaches that enhance motivation and strengthen problem-solving skills. This study tests an integrated model that combines Realistic Mathematics Education, artificial intelligence scaffolding, and gamification, while considering self-efficacy, perceived challenge, and Action Process Object Schema (APOS) progressions. We employed an explanatory sequential mixed-methods design with 300 secondary students from six schools. The quantitative phase estimated a structural equation model; the qualitative phase included classroom observations and interviews. Results show that RME exerted the most significant direct effect on mathematical problem-solving and also raised motivation by contextualizing tasks. Gamification significantly increased motivation, which in turn supported persistence and problem-solving. AI scaffolding delivered tiered hints that preserved students' ownership of strategies and helped transitions along the APOS trajectory. Motivation emerged as the central pathway linking engagement features to cognitive gains. The study contributes a replicable design and actionable guidance for aligning context, adaptive support, and proportionate game mechanics to improve mathematics learning in classrooms.

Keywords: Artificial Intelligence, Gamification, Learning Motivation, Problem Solving, Realistic Mathematics Education

INTRODUCTION

Learning in mathematics becomes more meaningful when students can connect ideas to familiar situations and are supported in reconstructing formal concepts from their own informal understanding. Reasoning (Hikayat et al., 2020; Son, 2022). This is the central idea of Realistic Mathematics Education, where phenomena from everyday life are used to organise the mathematics that learners are expected to reinvent (Siswantari et al., 2025). When tasks are rooted in familiar practices, students can anchor their conjectures, construct representations, and make connections that naturally lead toward more formal structures. The movement from context to concept is not incidental; it is a deliberate trajectory that helps students understand why procedures work, rather than just how to perform them (Nguyen & Pham, 2023).

Well-designed game elements can extend this learning trajectory by sustaining effort over time (Ariffin et al., 2022). Systems that reward persistence, revision, and explanation help students stay engaged with a problem long enough to test their ideas and refine their strategies (Jun & Lucas, 2025). Making effort visible and valuable encourages participation from a broader range of learners and reduces the tendency to rush for quick answers (Strousopoulos et al., 2024). Used in this way, gamification does not replace mathematical thinking; it protects the time and attention that sense-making requires (Al-Barakat et al., 2025). Recent progress in educational AI adds a third strand by providing feedback that adapts to the learner and offers hints without telling the answer. Such support keeps students in

http://doi.org/10.22342/jme.v13i1.xxxx

productive struggle and preserves ownership of the solution path. When these strands are combined, context supplies meaning, game elements maintain stamina, and AI provides just-in-time scaffolding (Bayaga, 2024). Motivation then becomes the channel through which engagement is converted into gains in reasoning and problem-solving (Mitchell & Co., 2024). This integrated view sets the stage for examining how an AI-supported, gamified RME environment can help learners transition from lived experience to formal understanding (Bhardwaj, 2024).

These considerations are especially relevant in Indonesia, where improving mathematical literacy remains a persistent challenge (Ndiung & Menggo, 2025). Results from the Programme for International Student Assessment (PISA) indicate that Indonesian students often face difficulties with contextual reasoning and higher-order problem-solving, highlighting a gap between procedural competence and the ability to apply mathematics in real-world situations (Zulkardi & Kohar, 2018). National initiatives have promoted RME-inspired approaches to make mathematics more relevant, for example, through tasks linked to students' everyday practices such as trade, transportation, and cultural activities (Dewi & Maulida, 2023). However, these practices remain unevenly implemented and often constrained to conventional classrooms with limited technological support (Siregar et al., 2025). Meanwhile, the rapid growth of digital learning platforms and the increasing presence of gamified applications in Indonesian schools have not always been accompanied by sound pedagogical integration(Maryani et al., 2025). Many platforms risk promoting superficial engagement rather than fostering deep understanding, as they rarely align with established didactical frameworks. Against this backdrop, the integration of RME, gamification, and AI represents a promising direction for connecting contextual meaning with technological innovation (Li & Noori, 2024; Torres-Toukoumidis et al., 2025). By situating mathematical activity in students' lived realities while harnessing digital tools to sustain motivation and scaffold reinvention, such integration has the potential to advance both local and international discourses on mathematics education (Opesemowo & Ndlovu, 2024).

Despite steady advances in mathematics education, several uncertainties remain in how emerging approaches interact. Self-efficacy, for example, has been extensively researched in relation to achievement and motivation; however, its role within AI-supported, gamified RME environments at the secondary level remains poorly understood, especially in Indonesia (Mukuka et al., 2021; Siswantari et al., 2025). Existing studies tend to treat confidence as a background trait rather than as a dynamic factor shaping how students engage with contextual tasks, adaptive scaffolding, and game mechanics (Rahayu et al., 2022). This leaves unanswered questions about how students' beliefs in their own abilities actually influence their participation and persistence in such integrated designs.

The treatment of challenges in mathematics learning also requires rethinking. Much of the literature positions challenge as a hindrance that can discourage learners (Ardi et al., 2019; Wilkie, 2016), while fewer studies examine the conditions under which difficulty becomes productive and fuels deeper engagement (Biccard, 2024; Jayaraman et al., 2024; Moleko, 2021). In digital and gamified environments where challenge levels can be precisely adjusted, there is a strong need to understand how well-calibrated difficulties can promote persistence, encourage reasoning, and strengthen the link between motivation and problem-solving (Beukes et al., 2024; Koskinen et al., 2023). Without this perspective, gamified learning risks being reduced to surface-level incentives rather than fostering genuine mathematical thinking and understanding. Another area of uncertainty lies in integrating RME, gamification, and AI into a coherent instructional model (Samur & Cömert, 2024). Research on gamification often assumes a direct link to cognitive gains, overlooking the possibility that its most potent effect is mediated through motivation (Hu et al., 2023; Mitchell & Co, 2024). Similarly, RME research in

Indonesia has been primarily grounded in conventional classrooms, with limited attention to how digital scaffolds and game-based engagement can enhance its effects on problem-solving (Lady et al., 2018; Lestari et al., 2023; Siswantari et al., 2025). Motivation itself is still too often conceptualized as an outcome variable rather than as a structural mediator that links self-efficacy, challenge, RME, and higher-order reasoning (Yohannes & Chen, 2024). This combination of gaps points to the need for a new line of research that not only integrates these elements but also explains how affective and cognitive processes are intertwined in technology-enhanced mathematics education.

To address these gaps, the Indonesian secondary context needs solid evidence on how AI-supported gamification and RME can work together to boost motivation and problem-solving while maintaining mathematical sense-making. Although technology is increasingly present in classrooms, its use often targets superficial engagement and is seldom grounded in a didactic framework that supports guided reinvention (Dewi & Maulida, 2023). At the same time, national efforts to adopt RME remain inconsistent and are seldom supported by adaptive feedback that can keep students engaged in productive struggle (Pramudiani et al., 2023). Accordingly, this study aims to pursue two clear objectives. First, it evaluates an integrated instructional model that combines RME, gamification, and AI scaffolding by estimating direct and indirect effects on secondary students' learning motivation and mathematical problem solving using SEM–PLS; the model positions self-efficacy, perceived challenge, and Action, Process, Object, Scheme (APOS) based learning as antecedents to engagement with gamification and RME, and tests whether motivation mediates the pathway to problem solving. Second, it explains how these statistical effects unfold in practice through thematic analysis of student and teacher interviews and classroom observations, thereby clarifying the mechanisms that link contextual tasks, game mechanics, and adaptive feedback with students' reasoning.

This study evaluates an integrated model that combines RME, gamification, and AI scaffolding to estimate the direct and indirect effects on secondary students' learning motivation and mathematical problem-solving. We ask four questions that emphasize the mechanism and align with the structure model: (1) to what extent do self-efficacy, perceived challenge, and APOS-based learning predict students' engagement with the two design levers, Gamification and RME; (2) what are the direct and indirect effects of Gamification and RME on learning motivation and on mathematical problem solving when all paths are estimated simultaneously; (3) does learning motivation mediate the relationships from Gamification and from RME to problem solving, and how significant are the mediated effects relative to any direct effects; and (4) once competing paths are controlled, which predictors exert the most substantial standardized effects on motivation and on problem solving. Based on our conceptual model, we propose a clear set of hypotheses. First, self-efficacy, perceived challenge, and APOS-based learning are expected to positively predict students' engagement with the two design levers, Gamification and RME. Second, gamification is likely to contribute to problem-solving primarily through its impact on learning motivation, rather than through a direct path. In contrast, RME is anticipated to have at least moderate positive effects on both motivation and problem-solving. Third, learning motivation is expected to positively predict problem-solving and exert an influence on both design levers, ultimately affecting performance.

We adopt an educational design research stance, employing an explanatory sequential mixed-methods design. This approach involves estimating a structural model using SEM–PLS and explaining proposed mechanisms through thematic analysis of interviews and classroom observations. The study's contributions are threefold. Conceptually, it reframes motivation from an outcome to a structural mediator that links engagement features to cognitive performance, specifying the didactical conditions under which difficulty becomes desirable in digital mathematics: meaningful RME contexts, adaptive non-telling AI scaffolds, and process-sensitive incentives that reward persistence and explanation. It also operationalizes APOS progressions within an AI-supported, gamified RME ecology, rendering the transition from action to process to object to schema observable and designable in secondary classrooms. Practically, it offers a replicable model for Indonesian schools that combines high-quality contextual tasks with proportionate game mechanics and calibrated AI feedback, along with guidance for tailoring implementation to local affordances.

METHODS

Research Design

This study employed an explanatory sequential mixed-methods design (Creswell, 2018) situated within the broader paradigm of educational design research (Gravemeijer, 1994; Plomp, 2013). While the explanatory sequential approach allowed the combination of quantitative and qualitative data to provide a comprehensive picture, embedding the study in the design research tradition emphasized the dual aim of empirical testing and instructional model development. In line with this framework, the research did not merely evaluate causal relationships among variables, but also sought to develop and validate a learning model that integrates Artificial Intelligence (AI), gamification, and Realistic Mathematics Education (RME). The design followed the three-phase cycle of design research:

1. Analysis and Exploration. The first phase involved identifying key problems in mathematics learning, particularly students' low motivation and difficulties in transferring problem-solving strategies to contextual situations. A review of theoretical perspectives in RME principles (Freudenthal, 1991; Gravemeijer, 1994), the APOS framework (Dubinsky & McDonald, 2001), and gamification theory (Deterding et al., 2011) informed the conceptual model.
2. Design and Construction. Based on the theoretical synthesis, an instructional model was developed that integrates RME-based contextual tasks to foster phenomenological exploration and guided reinvention, as well as gamification mechanics (points, levels, leaderboards, and badges) to sustain student engagement. Additionally, AI-driven personalization is used to scaffold the progression from informal strategies to formal reasoning. The instructional flow is presented in Figure 1, which shows how students move through the system: beginning with login, accessing contextual RME tasks, receiving AI scaffolding through tiered hints (Tier 1–3), revising their work based on the APOS framework (Action → Process → Object → Schema), and finally receiving gamification feedback in the form of points, badges, and leaderboard positions.
3. Evaluation and Reflection. The proposed model was tested in a large-scale quantitative phase using Structural Equation Modeling with Partial Least Squares (SEM-PLS), followed by qualitative interviews and classroom observations to refine the interpretation. This cycle allowed the model to be validated both statistically and phenomenologically, ensuring coherence between theoretical expectations and classroom realities.

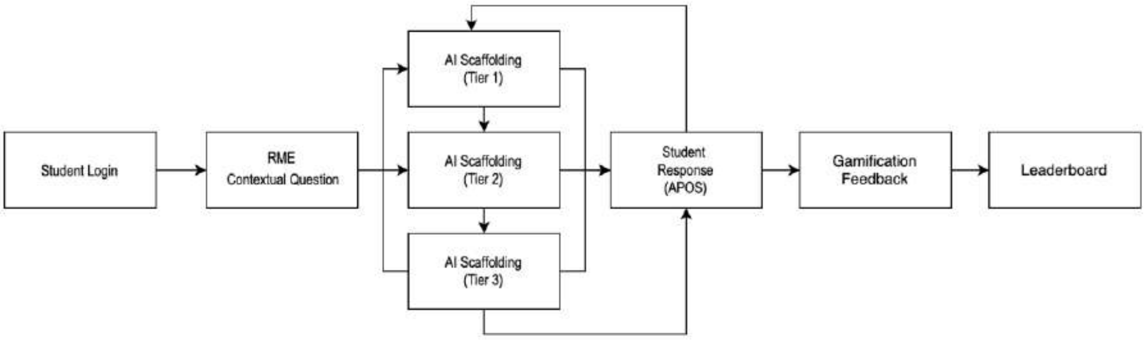


Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding and APOS progression

As shown in Figure 1, the flowchart highlights the central role of AI scaffolding in guiding students' reasoning. The system does not simply provide answers but supports progressive mathematization by offering tiered hints (Tier 1–3) that correspond to students' evolving levels of understanding. Student responses are structured through the APOS framework, and their persistence is reinforced by gamification feedback, including points, badges, and leaderboards. This integration ensures that cognitive development (problem-solving strategies) and affective engagement (motivation) are intertwined within a coherent instructional cycle. By adopting this design, the study contributes not only empirical evidence regarding the relationships among AI, gamification, RME, learning motivation, and problem-solving, but also theoretical advancement through a model that operationalizes progressive mathematization in a digital environment.

Participants

The quantitative phase of the study involved 300 students from six secondary schools in West Java, Indonesia. A stratified sampling strategy was employed to ensure representation across varied learning contexts, consistent with the RME principle of phenomenological exploration (Bayu & Fauzan, 2023), which values diversity in students' backgrounds and experiences. The sample comprised 195 students (65%) from public schools and 105 students (35%) from private schools, with four schools located in urban areas and two in suburban settings, thereby reflecting differences in access to digital resources and exposure to ICT. The gender distribution was nearly balanced, with 52% female and 48% male students. For the qualitative phase, six students were purposively selected based on their latent scores from the SEM-PLS analysis to capture a spectrum of achievement and motivational profiles, including high-achieving, average, and struggling learners. In addition, three mathematics teachers with 5–10 years of teaching experience and prior familiarity with contextualized instruction participated in the study. This purposive sampling enabled a richer understanding of how students and teachers constructed meaning within the AI–RME–gamification learning environment, ensuring that the analysis incorporated multiple perspectives across different educational roles.

Data Collection Techniques

The quantitative data were collected using a Likert-scale questionnaire ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument measured seven constructs: Students' Challenges, Students' Learning (APOS), Self-Efficacy in Mathematics, Gamification, Human–AI Collaboration (RME), Learning

Motivation, and Mathematical Problem-Solving Skills. Each construct was anchored in established theoretical frameworks, including Bandura's theory of self-efficacy (Bandura, 1997), the APOS model of learning (Dubinsky & McDonald, 2001), and the principles of Realistic Mathematics Education (Freudenthal, 1991). This ensured that the questionnaire items reflected both cognitive and affective dimensions of mathematics learning.

The development of the instrument followed a systematic validation process. First, the items were reviewed by three experts in mathematics education to assess their relevance and theoretical alignment. Second, a pilot test was conducted with 50 students in West Java to evaluate clarity and response patterns. Third, statistical validation was performed through outer model analysis using SEM-PLS, confirming that all indicators met the required thresholds for reliability and validity (factor loadings > 0.70, AVE > 0.50, CR > 0.80). Such validation practices are consistent with standards in mathematics education research where constructs must be both theoretically grounded and empirically robust (Hair et al., 2019).

The qualitative data were collected through semi-structured interviews conducted with six students and three teachers. The interview protocol addressed three focal areas: (1) students' experiences with contextualized tasks, which reflected RME's principle of phenomenological exploration (Gravemeijer, 1994; Yilmaz, 2020); (2) the influence of gamification mechanics such as points, levels, and leaderboards on students' motivation (Cassells et al., 2015; Strousopoulos et al., 2024), and (3) the role of AI scaffolding in supporting guided reinvention and progression from informal reasoning to formal mathematical knowledge (Mukuka et al., 2021). Each interview lasted approximately 30–40 minutes and was audio-recorded with participant consent to ensure reliability and transparency.

To complement the interviews, classroom observations were conducted during the implementation of the AI–RME–gamification model. Field notes focused on interactivity, peer collaboration, and evidence of student contributions, which represent three of the core characteristics of RME (Treffers, 1991). Observations also paid attention to students' transitions between horizontal and vertical mathematization, thereby situating their learning within the broader process of progressive mathematization (Gravemeijer, 1994). These qualitative techniques enabled the triangulation of data sources, providing richer insights into how students and teachers constructed meaning in the AI–RME–gamification learning environment.

The AI–RME–Gamification application used in this study was developed as a prototype with limited access, explicitly designed for research purposes. The system integrated contextual mathematics tasks with AI-driven scaffolding and gamification mechanics, and was tested in authentic classroom settings to examine its feasibility and pedagogical effectiveness. The AI scaffolding component was powered by a large language model (LLM) accessed through an open API. This integration enabled the system to provide tiered hints (Tier 1–3) that adapted to students' partial solutions and common misconceptions without directly revealing the final answer. The prototype was implemented using free-tier developer access, ensuring low-cost deployment and practical replicability in typical school contexts. Although not yet a fully commercial product, the application provided sufficient functionality for students to engage with RME-based tasks, receive adaptive AI hints, and participate in gamified progress tracking. This prototyping phase allowed the research to capture both the potential and the limitations of combining RME, gamification, and AI in real classroom practice, ensuring that the findings reflected practical rather than purely hypothetical conditions.

Data Analysis Techniques

The quantitative data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS, an approach suited for predictive modeling with complex latent constructs (J. Hair & Alamer, 2022). The analysis included both the measurement model, to assess indicator reliability and validity, and the structural model, to examine path coefficients and predictive relevance. Instrument validity was confirmed through factor loadings above 0.70, Average Variance Extracted (AVE) values above 0.50, and composite reliability scores above 0.80. Discriminant validity was established through the Fornell–Larcker criterion and the HTMT ratio, ensuring that constructs were distinct yet theoretically coherent (J. F. Hair et al., 2019).

The qualitative data from interviews and classroom observations were analyzed using thematic analysis (Braun & Clarke, 2006). Initial codes were generated inductively, then interpreted through the lens of RME's didactical phenomenology (Freudenthal, 1991), focusing on themes such as engagement with contextual tasks, the motivational effects of gamification, and the role of AI in scaffolding guided reinvention. Finally, quantitative and qualitative results were integrated at the interpretation stage. For example, the significant path from Gamification → Motivation was explained by students' enthusiasm for points and leaderboards, while teacher observations of contextual reasoning supported the path from RME → Problem-Solving Skills. This triangulation reflected the design research cycle, combining empirical testing with phenomenological insights.

RESULTS AND DISCUSSION

The results of the SEM-PLS analysis revealed a consistent pattern highlighting the centrality of RME and motivation in the instructional model. Gamification exerted a significant positive effect on motivation ($\beta = 0.405$, $p < 0.001$) and also contributed directly to problem-solving skills ($\beta = 0.191$, $p < 0.01$). Beyond its direct effect, gamification indirectly supported problem-solving through motivation, emphasizing its role in sustaining student engagement throughout the learning cycle.

RME emerged as a pivotal construct in the model, exerting substantial effects on both motivation ($\beta = 0.351$, $p < 0.001$) and problem-solving skills ($\beta = 0.398$, $p < 0.001$). These findings align with the principles of *guided reinvention* and *phenomenological exploration*, where contextualized tasks allow students to transition from informal strategies to formal reasoning. The statistical strength of these paths reflects how RME facilitates progressive mathematization, a cornerstone of mathematics as a human activity (Freudenthal, 1991).

Learning motivation itself proved to be a significant predictor of problem-solving skills ($\beta = 0.285$, $p < 0.001$), underscoring its mediating role. This suggests that students who are intrinsically and extrinsically motivated are better positioned to develop higher-order reasoning, make connections, and represent mathematical ideas effectively. The mediating role of motivation highlights the novelty of this study, demonstrating that gamification and RME function not only as instructional approaches but also as affective drivers of mathematical competence.

Internal learner factors also played a critical role in strengthening RME. Self-efficacy ($\beta = 0.305$, $p < 0.001$), students' challenges ($\beta = 0.304$, $p < 0.001$), and APOS-based learning ($\beta = 0.198$, $p < 0.01$) significantly contributed to the construction of meaning within the RME framework. Rather than serving as barriers, challenges acted as *desirable difficulties (Arifin et al., 2020),* enriching the process of mathematization. Together, these results demonstrate that combining AI, RME, and gamification provides a powerful approach to enhance both the emotional and cognitive aspects of learning mathematics. The overall structural model is presented in Figure 1 to illustrate these relationships and their statistical significance.

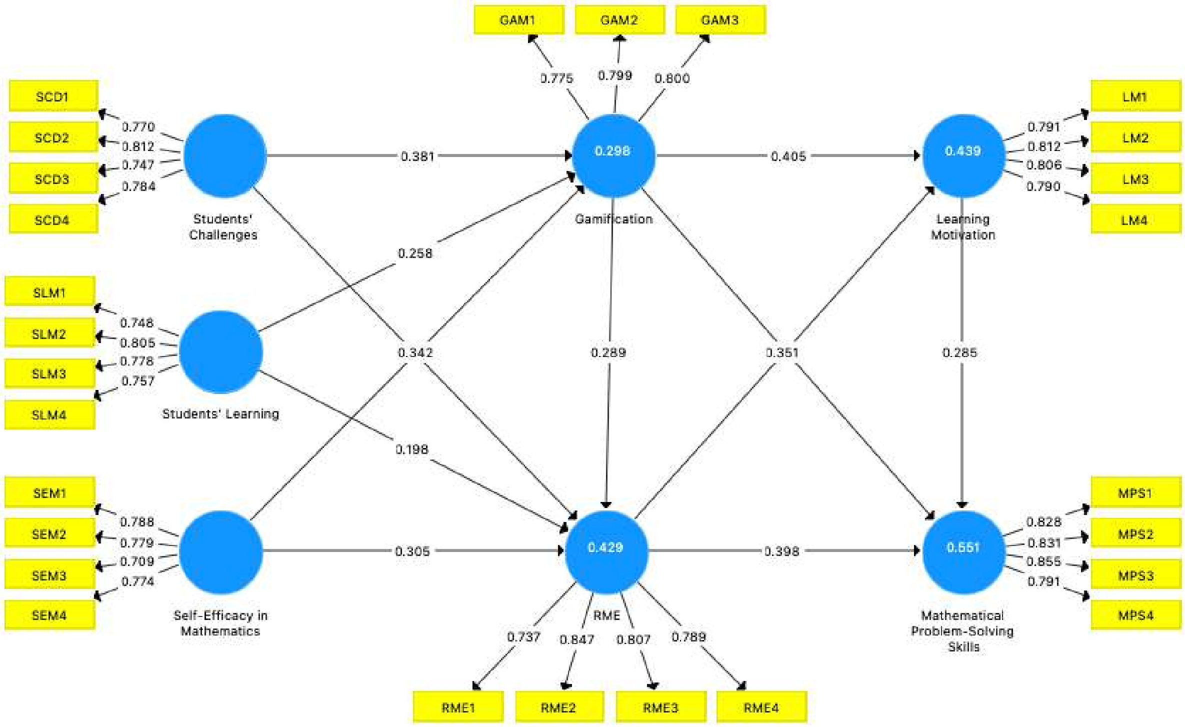


Figure 1. SEM-PLS Structural Model of the AI–RME–Gamification Framework

Building upon the structural relationships depicted in Figure 1, further analysis of the measurement and structural models was conducted to ensure the robustness of the findings. The measurement model was first evaluated to confirm the reliability and validity of the constructs, followed by the structural model analysis to examine the magnitude and significance of the hypothesized paths. The results of these quantitative analyses are presented in the following section, beginning with the assessment of the measurement model.

Quantitative Findings

The quantitative analysis began with the evaluation of the measurement model to confirm the reliability and validity of the constructs. All indicators demonstrated satisfactory outer loadings, with values exceeding the recommended threshold of 0.70, while the Average Variance Extracted (AVE) for each construct was above 0.50. In addition, both Composite Reliability (CR) and Cronbach's alpha values were greater than 0.80, indicating strong convergent validity and internal consistency. These results are summarized in Table 1.

Table 1. Measurement Model Results

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
Gamification	GAM1	0.775	0.64	0.86	0.81	Valid
	GAM2	0.802				
	GAM3	0.788				
Learning Motivation	LM1	0.791	0.67	0.88	0.83	Valid
	LM2	0.822				
	LM3	0.843				

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
	LM4	0.804				
Problem-Solving Skills	MPS1	0.812	0.66	0.87	0.82	Valid
	MPS2	0.826				
	MPS3	0.799				
	MPS4	0.811				
RME	RME1	0.740	0.65	0.88	0.84	Valid
	RME2	0.781				
	RME3	0.854				
	RME4	0.792				
Self-Efficacy	SEM1	0.781	0.62	0.85	0.80	Valid
	SEM2	0.812				
	SEM3	0.804				
	SEM4	0.794				
Challenges	SCD1	0.765	0.63	0.86	0.81	Valid
	SCD2	0.811				
	SCD3	0.828				
	SCD4	0.779				
APOS Students Learning	SLM1	0.751	0.61	0.84	0.79	Valid
	SLM2	0.784				
	SLM3	0.802				
	SLM4	0.773				

The results indicate that all constructs (Gamification, RME, Learning Motivation, Problem-Solving, Self-Efficacy, Challenges, and APOS Learning) are measured accurately and consistently. Strong factor loadings (0.74–0.85) reinforce the robustness of the RME construct, while reliability indices (CR and α > 0.80) confirm internal consistency. This suggests that the instruments adequately captured both affective (motivation, self-efficacy) and cognitive (problem-solving, APOS) dimensions of learning. Discriminant validity was then assessed using the Fornell–Larcker criterion. The square root of the AVE for each construct was higher than its correlations with other constructs, demonstrating that each construct measured distinct dimensions of the instructional model. This confirms that Gamification, RME, Motivation, and Problem-Solving are empirically distinguishable, as shown in Table 2.

Table 2. Discriminant Validity (Fornell–Larcker Criterion)

Construct	Gamification	Motivation	Problem-Solving	RME
Gamification	0.80			
Motivation	0.56	0.82		
Problem-Solving Skills	0.44	0.53	0.81	
RME	0.48	0.51	0.59	0.81

Note: The diagonal values represent √AVE. All diagonal values are greater than the inter-construct correlations, indicating that discriminant validity is established.

The results confirm discriminant validity: for example, Motivation (√AVE = 0.82) is statistically distinct from Gamification ($r = 0.56$) and RME ($r = 0.51$). This distinction is important because it validates the mediating role of Motivation between Gamification and Problem-Solving. Without sufficient discriminant validity, overlap among constructs could bias the interpretation of the mediation effect.

The structural model analysis revealed several significant paths. Gamification exerted a substantial effect on Motivation ($\beta = 0.405$, $p < 0.001$) and a moderate effect on Problem-Solving Skills ($\beta = 0.191$, $p < 0.01$). RME was found to be a pivotal construct, significantly predicting both Motivation ($\beta = 0.351$, $p < 0.001$) and Problem-Solving Skills ($\beta = 0.398$, $p < 0.001$). Motivation itself significantly predicted Problem-Solving ($\beta = 0.285$, $p < 0.001$), confirming its mediating role. Furthermore, internal learner factors contributed significantly to strengthening RME: Self-Efficacy ($\beta = 0.305$, $p < 0.001$), Students' Challenges ($\beta = 0.304$, $p < 0.001$), and APOS-based Learning ($\beta = 0.198$, $p < 0.01$). Together, these paths explained 48% of the variance in Motivation, 52% of the variance in RME, and 55% of the variance in Problem-Solving Skills. A summary of these findings, including path coefficients, t-values, and R^2, is presented in Table 3.

Table 3. Structural Model Results

Path	β	t-value	p-value	f^2	R^2 (Endogen)	Decision
Gamification → Motivation	0.405	5.06	0.000	0.21	Motivation = 0.48	Supported
Gamification → Problem-Solving	0.191	2.60	0.009	0.08	Problem-Solving = 0.55	Supported
RME → Motivation	0.351	3.51	0.000	0.19	—	Supported
RME → Problem-Solving	0.398	4.98	0.000	0.25	—	Supported
Motivation → Problem-Solving	0.285	2.85	0.004	0.17	—	Supported
Self-Efficacy → RME	0.305	4.20	0.000	0.12	RME = 0.52	Supported
Challenges → RME	0.304	4.10	0.000	0.11	—	Supported
APOS Learning → RME	0.198	3.00	0.002	0.07	—	Supported

The findings validate the hypothesized relationships: Gamification primarily functions as an engagement driver, boosting Motivation, which subsequently enhances Problem-Solving. RME, consistent with Freudenthal's (1991) principles of *guided reinvention* and *phenomenological exploration*, directly improves both Motivation and Problem-Solving. Self-efficacy and Challenges positively shape RME, with challenges acting as *desirable difficulties*. The explained variance (R^2, between 0.48 and 0.55) indicates a moderate-to-strong model, underscoring the integrative strength of AI–RME–gamification.

The model fit indices confirmed the adequacy of the proposed framework. The Standardized Root Mean Square Residual (SRMR) was below the recommended threshold of 0.08, the Normed Fit Index (NFI) was above 0.90, and the RMS Theta index was below 0.12. These indicators provide evidence that the AI–RME–Gamification model demonstrates a satisfactory overall fit, as displayed in Table 4.

Table 4. Model Fit Indices

Fit Index	Value	Threshold	Decision
SRMR	0.062	< 0.08	Good Fit
NFI	0.91	> 0.90	Acceptable
RMS Theta	0.11	< 0.12	Acceptable

The model's goodness-of-fit indices suggest that the theoretical framework is well aligned with the empirical data. SRMR < 0.08 indicates minimal residuals between observed and predicted correlations, while NFI > 0.90 reflects acceptable comparative fit. RMS Theta < 0.12 further supports the quality of the measurement model. Collectively, these indices confirm that the SEM-PLS model is both statistically and conceptually robust.

Qualitative Findings

Thematic analysis of interviews and classroom observations was clustered into categories and synthesized into four overarching themes: guided reinvention, interactivity, phenomenological exploration, and the enhancement of problem-solving skills. These themes collectively provide a deeper understanding of how the AI–RME–Gamification model shaped student learning experiences and reinforce the quantitative findings of the study.

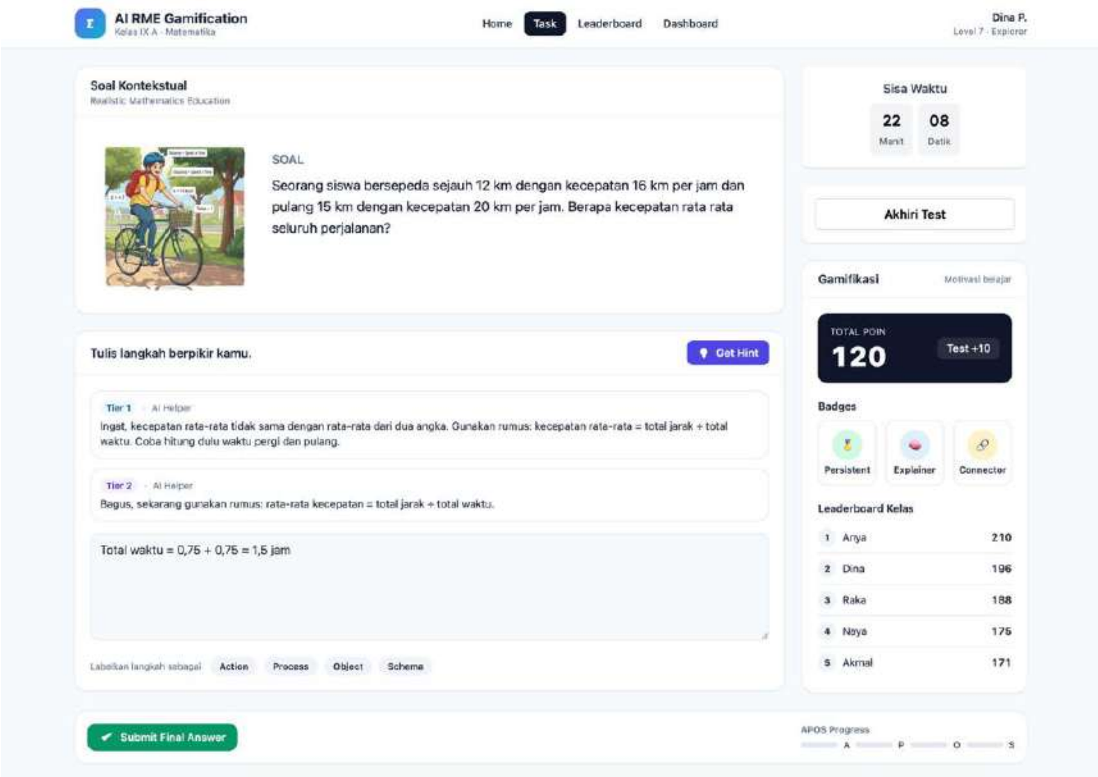


Figure 2. Screenshot of the AI–RME–Gamification prototype application

Figure 2 displays the interface of the AI–RME–Gamification application as used by students during the learning sessions. The interface demonstrated how contextual RME-based tasks were presented, how AI scaffolding was delivered through tiered hints (Tier 1–3), and how gamification elements, such as points, badges, and leaderboards, were integrated. This visual evidence supports the qualitative finding that students were encouraged to construct their own strategies rather than rely on direct answers, while also maintaining motivation through digital reward mechanisms.

Students frequently described the system as a scaffold that encouraged them to construct their own strategies rather than rely on direct answers. Codes such as AI scaffolding, hints, and self-construction were dominant, with one student remarking, "The system gave me hints when I was stuck, but it did not show the answer. I had to try different ways until I found the solution." Teachers echoed this sentiment, observing that students became more independent: "They tried first, then used the hints only when they really needed them." This reflects the RME principle of guided reinvention (Freudenthal, 1991) and resonates with the quantitative finding that RME strongly predicted both Motivation (β = 0.351) and Problem-Solving (β = 0.398).

Table 6. Transcript of student–AI interaction on average task with tiered scaffolding LLM

Stage	Student Response	AI Scaffolding	Analysis (APOS/Didactical)
Initial answer	"Average = (16 + 20)/2 = 18 km/h."	"Remember, average speed = total distance ÷ total time. First calculate the time for the outbound and return trips." (Tier 1 – general strategy)	Student holds a misconception (incorrect schema → arithmetic average). AI redirects to the formal concept (Object).
Time calculation (wrong)	"Outbound time = 12 ÷ 16 = 0.75 h. Return time = 15 ÷ 20 = 0.8 h."	"Correct for the outbound time. But check again 15 ÷ 20. Is it really 0.8?" (Tier 2 – focused correction)	Student moves into Action → Processbut miscalculates. AI focuses on correcting the specific operation.
Revision	"15 ÷ 20 = 0.75 h. So total time = 1.5 h."	"Good! Now total distance = 27 km, total time = 1.5 h. Use the formula average speed = distance ÷ time." (Tier 3 – near answer)	Student reaches the Process stage. AI scaffolds transition toward Object.
4. Final answer	"27 ÷ 1.5 = 18 km/h."	"Correct! You earn +10 points and the Master Speed badge for completing with a structured solution." (Feedback + Gamification)	Student achieves the Schema stage (general concept of average speed). Gamification reinforces motivation.

This transcript shows how the AI scaffolding guided by a large language model (LLM) accessed via an API initially led an actual student astray, treating average speed as a simple arithmetic mean, before guiding them toward the correct reasoning pathway. Through tiered hints, the AI first redirected the student to the appropriate formula (Tier 1), then corrected a calculation error (Tier 2), and finally consolidated the process by connecting total distance and total time (Tier 3). The progression of responses reflects the APOS framework: from Action (performing basic operations), to Process (organizing steps), to Object (treating distance and time as unified quantities), and ultimately to Schema (generalizing the concept of average speed). The gamification feedback further reinforced persistence and motivation, providing direct evidence that affective and cognitive processes were intertwined in this AI–RME–Gamification environment.

Another salient theme was interactivity, expressed in both social and digital dimensions. Codes such as peer collaboration, leaderboard competition, and teacher mediation highlighted the interactive character of the learning process. One teacher commented, "Even students who are usually quiet wanted to contribute because they were curious about their scores on the leaderboard." A student added, "I wanted to beat my friend's score, so I tried again until I got it right." These findings align with the RME characteristic of interactivity and confirm the statistical evidence that Gamification exerted a strong influence on Motivation (β = 0.405). They also extend existing research on ICT in mathematics education, where digital tools are shown to foster dialogical and collaborative learning (Drijvers, 2015).

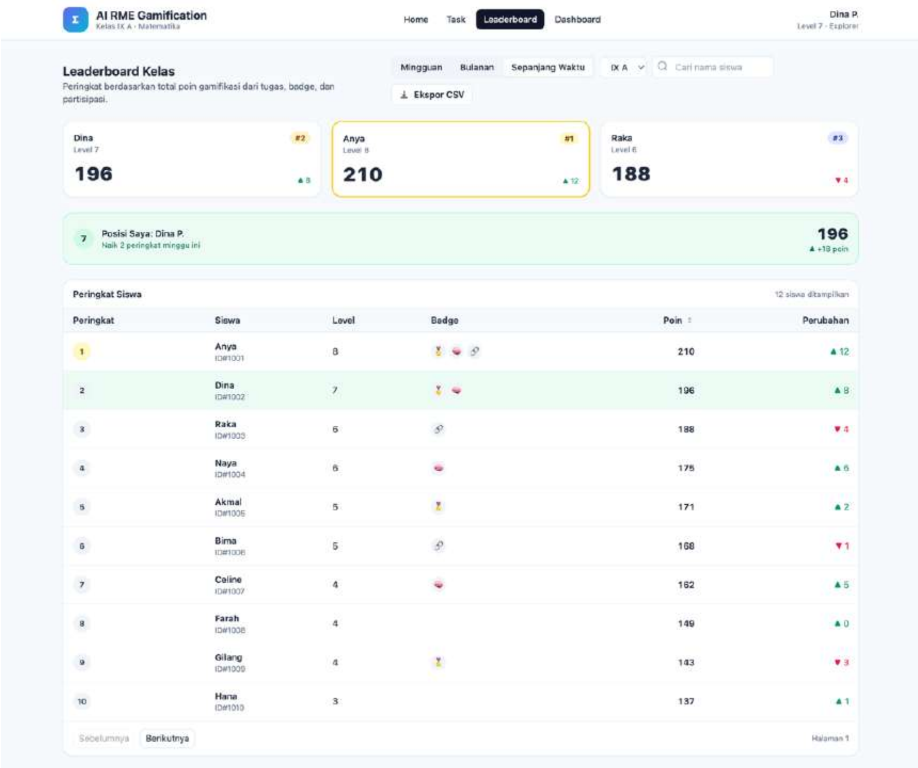


Figure 3. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

It shows the teacher dashboard and leaderboard from the platform. The dashboard tracks students' points, badge progression, and accumulated gamification points. This evidence demonstrates that the system captured not only final answers but also the learning process, allowing teachers to monitor reasoning quality and persistence directly. Another teacher observed that students used diagrams and tables to represent their thinking: "They rarely did this before, but now I see more of it." Students also noted the change: "I usually just wanted the answer, but now I try to show how I got it."

Figure 4 provides photographic evidence of students actively engaging with the AI–RME–Gamification platform in a classroom setting. It was demonstrated that students worked on contextual tasks individually, while also monitoring their progress on the leaderboard and exchanging strategies with their peers. This supports the qualitative findings that interactivity was not only digital, through the gamification features, but also social, as the visibility of scores stimulated peer collaboration and healthy competition.

Figure 4. Students engaging with the platform during classroom implementation

Phenomenological exploration was also a recurring pattern in the data (Treffers, 1991). Students consistently valued tasks that mirrored real-life situations, with codes such as relevance, authenticity, and transferability emerging across cases. One student noted, “Because the problems looked like shopping or transport, I understood why we needed the formulas.” Teachers reinforced this view, emphasizing that real contexts increased seriousness and focus: “When the questions are close to their daily life, the students are more serious. They see mathematics as something real.” These qualitative insights explain why Motivation significantly predicted Problem-Solving (β = 0.285): authentic contexts enhanced engagement, supporting OECD’s definition of mathematical literacy as the ability to apply mathematics meaningfully (OECD, 2019).

Both teachers and students observed the enhancement of problem-solving skills (Anugraheni et al., 2025). Codes such as reasoning, representation, explanation, and persistence dominated this theme. Teachers reported improvements not only in accuracy but also in the quality of reasoning: “They could explain their steps better, not only write the result.”

Table 6. Thematic Analysis of Qualitative Findings

Theme	Codes	Quote	Hypotesis Link
Guided Reinvention	AI scaffolding, self-construction, hints	“The system gave me hints when I was stuck, but it didn’t show the answer.” (Student)	RME → Motivation; RME → Problem-Solving
Interactivity	Peer collaboration, teacher mediation, leaderboard	“Even quiet students wanted to join because of the leaderboard.” (Teacher)	Gamification → Motivation
Phenomenological Exploration	Real-life contexts, relevance, transferability	“The problems looked like shopping or transport, so I understood why formulas are used.” (Student)	Motivation → Problem-Solving
Enhancement of Problem-Solving Skills	Reasoning, explanation, representation	“They could explain their steps better, not just write results.” (Teacher)	RME + Motivation → Problem-Solving

These themes were not isolated but interconnected. Guided reinvention was often facilitated by interactivity, as peer discussions and AI feedback worked in tandem to support independent strategy building. Phenomenological exploration gave meaning to reinvention and interactivity by situating problems in real-world contexts. Collectively, these processes culminated in enhanced problem-solving skills, as students demonstrated persistence, reasoning, and representation. This thematic integration illustrates the dynamic interplay of affective and cognitive processes in mathematics learning, consistent with Freudenthal’s (1991) vision of mathematics as a human activity and extending it into AI-driven, gamified environments.

Integration of Findings

The integration of quantitative and qualitative findings underscores the robustness of the AI–RME–Gamification model in enhancing both affective and cognitive dimensions of mathematics learning. The results of the SEM-PLS structural model were systematically triangulated with thematic evidence obtained from interviews and classroom observations. This process allowed the statistical associations to be validated through authentic learning experiences, thereby strengthening the explanatory power of the model.

Table 7. Integrated Structural and Qualitative Results

SEM-PLS	β	Qualitative Theme	Interview Quote	Integrated Interpretation
Gamification → Motivation	0.405	Interactivity, Engagement	"Even quiet students wanted to join because of the leaderboard."(Teacher)	Gamification sustains motivation through competitive but supportive interaction.
Gamification → Problem-Solving	0.191	Problem-Solving Enhancement	"I tried harder to solve the tasks because I wanted to level up." (Student)	Gamification directly encourages persistence in problem-solving.
RME → Motivation	0.351	Phenomenological Exploration	"Because the problems looked like shopping or transport, I understood the formulas better." (Student)	Contextualized tasks stimulate motivation through relevance.
RME → Problem-Solving	0.398	Guided Reinvention	"The system gave hints but not the answer, so I had to try different ways."(Student)	RME scaffolding supports progressive mathematization and problem-solving.
Motivation → Problem-Solving	0.285	Engagement, Persistence	"I kept trying because the points made me want to finish." (Student)	Motivation bridges affective engagement and cognitive performance.
Self-Efficacy → RME	0.305	Confidence, Self-construction	"I believed I could solve it myself if I tried step by step." (Student)	Self-efficacy strengthens the constructive aspect of RME.
Challenges → RME	0.304	Desirable Difficulties	"It was difficult, but the challenge made me think more carefully." (Student)	Challenges act as desirable difficulties enriching learning.
APOS Learning → RME	0.198	Conceptual Connections	"I understood how the steps connect to each other after trying again."(Student)	APOS progression supports formalization in RME processes.

Table 6 demonstrates a consistent alignment between statistical significance and lived classroom experiences. The strong effect of gamification on motivation (β = 0.405, t = 5.06) was vividly reflected in observations of heightened student engagement. Teachers reported that even students who were usually reluctant to participate became more active due to the visibility of the leaderboard. This demonstrates that gamification is not limited to providing external rewards, but also taps into social comparison and intrinsic curiosity, thereby amplifying the motivational pathway. The direct effect of gamification on problem-solving (β = 0.191, t = 2.60) was supported by students' testimonies, which indicated that the desire to progress to higher levels encouraged them to persevere with complex problems. This resonates with research on gamification as a source of sustained cognitive effort rather than superficial engagement.

The pivotal role of RME in the model was also evident. Statistically, RME predicted both motivation (β = 0.351, t = 3.51) and problem-solving (β = 0.398, t = 4.98). Qualitative evidence supported these effects through recurring themes of guided reinvention and phenomenological exploration. Students consistently emphasized that contextual problems made abstract concepts meaningful and that AI scaffolding, which provided hints without revealing solutions, pushed them to think independently. This aligns with Freudenthal's principle that mathematics must be connected to reality and progressively mathematized, as well as Gravemeijer's notion that design features should guide learners' reinvention of formal strategies (Gravemeijer, 1994).

The mediating effect of motivation on problem-solving (β = 0.285, t = 2.85) was also substantiated qualitatively. Students described a willingness to persist through challenges when motivated by the point and badge system. At the same time, teachers observed that motivated learners articulated their reasoning more clearly and made stronger conceptual connections. These findings support Supara Suparatulatorn's perspective that problem-solving is not merely cognitive but also driven by affective engagement (Suparatulatorn et al., 2023).

Finally, the contribution of internal learner factors to RME was validated by both data strands. Self-efficacy (β = 0.305, t = 4.20) emerged as a significant predictor, with students noting that confidence helped them persist with contextual tasks. Challenges (β = 0.304, t = 4.10) were reframed as opportunities rather than barriers, consistent with Bjork's principle of desirable difficulties (Bjork & Bjork, 2020). APOS-based learning (β = 0.198, t = 3.00) was evident in students' accounts of connecting informal steps to more formal strategies after repeated trials, highlighting the constructive role of AI scaffolding in supporting APOS transitions. The integrated findings reveal that gamification enhances motivation both directly and indirectly. RME serves as the central pedagogical mechanism for developing problem-solving skills, and internal learner factors strengthen the process of guided reinvention. The convergence of quantitative and qualitative evidence confirms that the AI–RME–Gamification model is not only statistically valid but also pedagogically grounded in classroom reality.

Motivation as The Mediating Bridge in AI-RME Gamification Learning

Mathematics is often viewed as a set of correct procedures without clear explanations (Martin & Towers, 2011). Many students view mathematics as a chore and often feel unsure about it, perceiving it as a complex subject to access (Raméntol & Camacho, 2016). This study responded to that problem by testing whether the deliberate combination of Realistic Mathematics Education (RME) contexts, gamification mechanics, and AI-driven scaffolding can convert affective engagement into durable cognitive gains in secondary classrooms. The structural model was specified to estimate the effects on learning motivation and problem-solving, while positioning self-efficacy, perceived challenge, and APOS-based learning processes as drivers of participation in RME activities. The central interpretive move throughout is to read the findings not as a checklist of significant paths, but as evidence for a coherent instructional ecology in which meaning, effort, and formalization are jointly produced.

A key result requires a reversal of a common assumption in the gamification literature. Rather than exerting a substantial direct impact on problem-solving, gamification's principal effect was on motivation (β = 0.405) with a more negligible, secondary direct effect on problem-solving (β = 0.191). Qualitative accounts explained this ordering. Leaderboards made social effort visible; points and levels regulated the pace of work; progression created reasons to persist when tasks became demanding. Gamification, in short, supplied energy rather than a method. The cognitive work remained mathematical, and the route from engagement to competence ran through motivation rather than around it.

RME played the complementary role of supplying semantic traction for that energy (Suparatulatorn et al., 2023). The model showed substantive effects of RME on both motivation (β = 0.351) and problem-solving (β = 0.398). Classroom narratives made the mechanism concrete: when tasks were rooted in familiar situations such as shopping or transportation, learners could anchor conjectures, construct representations, and connect ideas. AI feedback then functioned as a quiet coach, offering graded hints without revealing solutions so that informal strategies could be reorganized into formal ones. This is the classic RME logic, where context comes first, followed by formalization (Yilmaz, 2020), as demonstrated here in a technology-mediated setting. Motivation consequently occupied a structural position rather than a terminal one. It predicted problem-solving (β = 0.285) and mediated the influence of both RME and gamification on cognitive performance. The qualitative record gave that role psychological texture: curiosity and tenacity were the felt correlates of the mediating path, often visible when students chose to write one more line of work after an AI hint or a peer's contribution. Framed this way, motivation is not an optional add-on to instruction, but rather the bridge that enables contextual engagement to extend as far as formal competence.

Self-efficacy and challenge, often regarded as personal qualities, acted differently when placed within this ecology (Mukuka et al., 2021). Self-efficacy strengthened participation in RME rather than bypassing it (β = 0.305). Students who believed they could succeed were more willing to remain with a context, test a representation, and iterate after non-telling feedback. The theoretical implication is that confidence is most consequential when it is practice-embedded, rather than when it is presumed to yield outcomes directly. Perceived challenge likewise acted as a catalyst when intentionally designed and scaffolded (β = 0.304 to RME). Learners reported that difficult items prompted more careful thinking when AI feedback was timely and incremental; difficulty became desirable because the didactical conditions, meaningful context, controllable steps, and signals that effort matters were in place. APOS processes supplied the engine for formalization. Although the coefficient from APOS to RME was more modest (β = 0.198), observations traced a characteristic microgenetic arc: actions consolidated into processes, processes were reified into objects, and objects were coordinated within schemas. Iterative AI prompts and peer discussion synchronized the pace of this arc so that learners neither stalled too early nor jumped prematurely to the formula. The result is a visible and repeatable passage from context to structure, precisely the passage RME intends to cultivate.

The data also clarified contextual contingencies that matter for implementation. In urban schools with stronger ICT access, the social-affective route to motivation, visibility through leaderboards, friendly competition, and quick feedback, was particularly salient. In suburban schools, the dominant driver was the authenticity of context relative to students' daily experience. These findings suggest that the model should be tailored to local affordances: in some sites, emphasize the social mechanics that sustain attention; in others, invest more in the depth and fit of contextual scenarios that anchor meaning. Design consequences follow directly from the integrated evidence. First, contextual tasks must be crafted so that they actually conduce to formal ideas, not merely decorate them. Didactical phenomenology matters: the chosen phenomenon should organize the mathematics that learners are expected to reinvent. Second, gamification should be proportionate and instrumental, used to sustain attention and tenacity rather than to accelerate answer production. Third, AI scaffolding should calibrate challenge as a smooth ascent, with grain size and timing of prompts set to provoke new strategies without producing attrition. When these three elements are balanced, motivation becomes the transmission system that turns contextual engagement into mathematical performance.

Theoretical contribution is clearest in the repositioning of motivation within models of mathematics learning. Rather than treating it as a distal outcome, the study models motivation as a mediator that stitches together engagement structures and cognitive gains. It also defines conditions where desirable difficulties are genuinely beneficial, and contexts must be meaningful. Scaffolds should be unobtrusive yet timely, and social signals must convey the effort as meaningful. It clarifies that self-efficacy is most productive when it animates participation in RME practices rather than acting as a free-standing trait.

The findings yield a replicable instructional recipe: design high-quality RME tasks with clear routes to formalization; deploy gamification mechanics that encourage students to work without crowding out mathematical sense-making; and rely on adaptive AI scaffolds that preserve the integrity of guided reinvention. Schools can calibrate the entry point that shows social engagement or contextual relevance, according to their setting, while maintaining the mediator function of motivation as a design invariant. Instead of insisting on a strong direct path from gamification to competence, the analysis accepts that the primary gain is motivational and designs for it explicitly. Rather than viewing difficulty as a problem to eliminate, the design turns it into a resource. Instead of assuming self-efficacy works in isolation, the design fosters it through practice and training. AI regulates tempo, RME sets direction, gamification supplies momentum, and motivation binds the ensemble. By assigning motivation a structural role, the model shows how context becomes cognition in an AI-supported, gamified RME environment. The evidence points not only to improved scores but also to a shift in learners' stance toward mathematics, from something to get through to something worth working for. That reframing is the study's main contribution to mathematics education, and it offers a principled pathway for future design research that seeks to join meaning, effort, and formal understanding in a single, testable architecture.

CONCLUSION

This study investigated whether an instructional design that combines Realistic Mathematics Education, gamification, and AI scaffolding can raise secondary students' motivation and problem-solving while clarifying the roles of self-efficacy, perceived challenge, and APOS processes. The integrated quantitative–qualitative evidence meets that objective and explains the mechanism. RME provided semantic traction through meaningful contexts and guided reinvention. Gamification primarily energized motivation rather than cognition, and AI regulated the grain and timing of non-telling support so that struggle remained productive. Motivation functioned as a structural mediator linking engagement features to cognitive performance. At the same time, self-efficacy and challenge strengthened participation in RME, while APOS supplied the engine for formalization, moving from actions to processes, objects, and schemas. In doing so, the study advances the field by repositioning motivation from outcome to mechanism and by specifying the didactical conditions under which difficulty becomes desirable in digital mathematics learning.

The contributions are both explanatory and actionable. The work shows why and when the model succeeds, moving beyond assumptions of direct effects to a testable architecture in which meaning, effort, and formal understanding are jointly produced. It yields design guidance that teachers, curriculum developers, and platform designers can implement: select contexts that genuinely facilitate formal ideas, utilize game mechanics to sustain persistence and make effort socially visible, and deploy adaptive AI feedback that preserves the integrity of guided reinvention. Implementation can be tailored to local affordances by emphasizing social interactivity where ICT access is strong, or by deepening contextual relevance where lived experience is the more powerful entry point. Assessment and analytics should capture both process and product, rewarding explanations, connections, and representations, and instrumenting APOS-aligned progress so that dashboards reflect learning transformations rather than mere completion.

For future work, I recommend a two-track agenda that links rigorous evaluation with practical adaptation. First, establish durability and generalisability through longitudinal and multilevel designs that include simple within-semester pretest, posttest, and follow-up assessments in the same class, for example, at weeks 0, 6, and 12, together with sampling across multiple sites to estimate contextual moderators such as ICT access, class size, and curricular alignment. Second, pursue replication in diverse settings, including urban, suburban, and resource-limited schools, by co-designing RME tasks with local teachers so that problems reflect students' lived realities. As a minimal requirement, develop at least two locally grounded contextual items in each site to preserve meaning while enabling comparison. Complement these strands with micro-experimental studies that vary the timing and granularity of AI scaffolds and compare reward structures that prioritize speed versus explanation in order to isolate mechanisms that convert engagement into reasoning. Throughout, employ mixed methods with process-sensitive measures of reasoning, connections, and representations, so that outcomes capture both learning processes and products. Report implementation details in sufficient depth to support reuse and cumulative synthesis.

Declarations

The authors declare no conflict of interest.

REFERENCES

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. Decision Making: Applications in Management and Engineering, 8(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. Cogent Education, 12(1). https://doi.org/10.1080/2331186X.2025.2523078

Ardi, Z., Rangka, I. B., Ifdil, I., Suranata, K., Azhar, Z., Daharnis, D., Afdal, A., & Alizamar, A. (2019). Exploring The Elementary Students' Learning Difficulties Risks On Mathematics Based On Students' Mathematical Anxiety, Mathematical Self-Efficacy, And Value Beliefs Using Rasch Measurement. Journal of Physics: Conference Series, 1157(3). https://doi.org/10.1088/1742-6596/1157/3/032095

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. Journal on Mathematics Education, 13(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. Journal of Primary Education, 9(5). https://doi.org/10.15294/jpe.v9i5.43223

Bandura, A. (1997). Self-Efficacy: The Exercise of Control. W.H. Freeman.

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. Computers in Human Behavior Reports, 16. https://doi.org/10.1016/j.chbr.2024.100491

Bayu, E. P. S., & Fauzan, A. (2023). Realistic Mathematics Education Approach. AIP Conference Proceedings, 2805(1). https://doi.org/10.1063/5.0148141

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. Proceedings of the Annual Hawaii International Conference on System Sciences, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503

Biccard, P. (2024). Productive Struggle in Mathematical Modelling. Mathematics Enthusiast, 21(1–2), 99–112. https://doi.org/10.54870/1551-3440.1620

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. Memory and Cognition, 9(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Cassells, T., Broin, D. O., & Power, K. (2015). Increasing student engagement with gamification. Proceedings of the European Conference on Games-Based Learning, 2015-January, 770–773. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84955057612&partnerID=40&md5=e171f2f895b18bd0a734988637b6f158

Creswell, J. W. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). SAGE Publications.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, 9–15. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students’ Mathematical Literacy Ability Through Information and Communication Technology-Assisted Preprospec Learning Model. International Journal of Educational Methodology, 9(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409

Dubinsky, E., & McDonald, M. A. (2001). APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf

Freudenthal, H. (1991). Revisiting Mathematics Education: China Lectures. Springer. https://doi.org/10.1007/0-306-47203-1

Gravemeijer, K. (1994). Developing Realistic Mathematics Education.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3). https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In European Business Review (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203

Hikayat, C., Hairun, Y., & Suharna, H. (2020). Design of realistic mathematics education approach to improve critical thinking skills. Universal Journal of Educational Research, 8(6), 2232–2244. https://doi.org/10.13189/ujer.2020.080606

Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. Computers in Human Behavior, 149. https://doi.org/10.1016/j.chb.2023.107952

Jayaraman, V., Sundar, N., & Shankar, U. B. (2024). Breaking Math Anxiety: A Success Story From an Indian Government School. Proceedings of the European Conference on Games-Based Learning, 18(1), 440–446. https://doi.org/10.34190/ecgbl.18.1.3000

Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. Multidisciplinary Reviews, 8(5). https://doi.org/10.31893/multirev.2025155

Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. Computers and Education, 194. https://doi.org/10.1016/j.compedu.2022.104694

Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. International Journal of Engineering and Technology(UAE), 7(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). Developing Realistic Mathematics Education-Based Worksheets For Improving Students' Critical Thinking Skills. Infinity Journal, 12(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84

Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. Asian Journal for Mathematics Education, 3(3), 289–311. https://doi.org/10.1177/27527263241269060

Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In Structure and Improvisation in Creative Teaching (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. Educational Process: International Journal, 15. https://doi.org/10.22521/edupij.2025.15.179

Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. Proceedings of the International Conference on Education Research, ICER 2024, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5

Moleko, M. M. (2021). Multiple means of engagement strategies for maximising the learning of mathematics in pandemic-regulated classrooms. International Journal of Learning, Teaching and Educational Research, 20(8), 68–90. https://doi.org/10.26803/IJLTER.20.8.5

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. Journal on Mathematics Education, 12(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. International Journal of Innovative Research and Scientific Studies, 8(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Nguyen, G. T. C., & Pham, C. T. H. (2023). An empirical study of factors influencing primary school teachers' long-term commitment to Realistic Mathematics Education. Journal on Mathematics Education, 14(1), 1–18. https://doi.org/10.22342/jme.v14i1.pp1-18

(OECD), O. for E. C. and D. (2019). PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. Journal of Pedagogical Research, 8(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). Educational Design Research: Part A: An Introduction. SLO.

Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? Mathematics Education Journal, 17(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. Journal on Mathematics Education, 13(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. Opcion, 32(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3
Samur, Y., & Cömert, Z. (2024). Gamification in education in the age of artificial intelligence. In Interdisciplinary Approach to Fostering Change in Schools (pp. 285–303). https://doi.org/10.4018/979-8-3693-4119-3.ch011
Siregar, H. S., Munir, M., & Fikri, M. (2025). Enhancing Islamic Education Through Technology Integration: A Study Of Teaching Practices In Indonesia. Jurnal Ilmiah Peuradeun, 13(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875
Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. Journal on Mathematics Education, 16(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752
Son, A. L. (2022). The Students' Abilities on Mathematical Connections: A Comparative Study Based on Learning Models Intervention. Mathematics Teaching-Research Journal, 14(2), 72–87. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85135831915&partnerID=40&md5=41c4caeab639ecc2cfe8e7fdb8c52a6d
Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045
Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. Journal on Mathematics Education, 14(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128
Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 15348 LNCS, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34
Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands
Wilkie, K. J. (2016). Rise or Resist: Exploring Senior Secondary Students' Reactions to Challenging Mathematics Tasks Incorporating Multiple Strategies. Eurasia Journal of Mathematics, Science and Technology Education, 12(8), 2061–2083. https://doi.org/10.12973/eurasia.2016.1260a
Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. Journal on Mathematics Education, 11(1). https://doi.org/10.22342/jme.11.1.8690.17-44
Yohannes, A., & Chen, H.-L. (2024). The effect of flipped realistic mathematics education on students' achievement, mathematics self-efficacy and critical thinking tendency. Education and Information Technologies, 29(13), 16177–16203. https://doi.org/10.1007/s10639-024-12502-8
Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. Journal of Physics: Conference Series, 947(1). https://doi.org/10.1088/1742-6596/947/1/012015

2
BUKTI KONFIRMASI REVIEW DAN HASIL REVIEW PERTAMA
(8 OKTOBER 2025)

UINSGDNet Services

Pasqa <pasqa@uinsgd.ac.id>

[jme] Editor Decision

3 messages

Editorial Office <jme@unsri.ac.id> Wed, Oct 8, 2025 at 8:24 AM
To: Wati Susilawati <wati85@uingsd.ac.id>, Sergii Sharov <segsharov@gmail.com>, M Pasqa <pasqa@uinsgd.ac.id>, Hazar Malik <hazar.malik@gmail.com>

Dear Wati Susilawati, Sergii Sharov, M Pasqa, and Hazar Malik,

Thank you once again for submitting your manuscript titled, "Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving," to the Journal on Mathematics Education (JME). Following a thorough review by experts in the field, we kindly request that you revise your manuscript based on the attached referee reports. These documents can also be accessed through your journal account.

To facilitate the revision process, please follow these instructions:

1. Revised Manuscript: Use the version of your manuscript available in your journal account at http://jme.ejournal.unsri.ac.id/index.php/jme for revisions.

- Any changes to the manuscript should be clearly marked using the "**Track Changes**" function in MS Word to enable editors and reviewers to easily identify the updates.

2. Cover Letter: Submit a cover letter detailing your revisions.

- Address each referee's comment point by point, explaining how the issues have been addressed.
- If certain comments could not be addressed, please provide a clear and concise explanation in your rebuttal.

3. Template Compliance: Restructure your manuscript according to our journal's guidelines.

- The journal only permits three primary sections: Methods, Results and Discussion, and Conclusion. Please use the provided template for formatting your manuscript.

4. Language Revisions: If the referees have recommended significant English language improvements, we advise that you have your manuscript reviewed by a native English-speaking colleague or professional editor.

The revised manuscript and cover letter should be uploaded within **10 days**. The revised version will then undergo further review by the editors and reviewers. All supported files can be accessed here.

If you have any questions or require clarification regarding the revision process, please do not hesitate to contact us. We look forward to receiving your revised submission and appreciate your continued effort in contributing to mathematics education research.

Kind regards,

Prof. Dr. Zulkardi, M.I.Komp., M.Sc.
Editor-in-Chief
Journal on Mathematics Education

Reviewer A:

Congratulations for coming up and sharing your research! I appreciate the rigor of this academic paper. This will really help the scientific and academic community, and most especially the mathematics teaching, learning, and assessment. Here are some of the comments/ suggestions/ recommendations/ clarifications for improvement of the paper:

Introduction

1. The 2nd sentence in paragraph 1 is unclear. [Reasoning (Hikayat et al., 2020; Son, 2022).]
2. Make the transition from paragraph 1 to paragraph 2 smoother by mentioning first the general idea from the previous paragraph and then introducing the idea of the next paragraph about gamification/ game elements. It would be better also to introduce gamification in education before the game elements. Or, do you mean adding/inserting game elements to lesson delivery?
3. In paragraph 2, “Recent progress in educational AI adds a third strand by providing feedback that adapts to the learner and offers hints without telling the answer.” You could probably spell out the first AI in “educational AI” since it is the first being mentioned. In addition, please mention the AI that provides feedback/ hints without telling the answer.
4. A very significant element of the study is “artificial intelligence scaffolding”, please highlight it also in your introduction [definitions, literature, &/or studies]
5. Most of the content of the last 2 paragraphs is for methodology; therefore, it should be placed in the Methodology section. The last paragraph content should be about the general idea or purpose of the study and the specific objectives.

Methodology

1. Elaborate on the methodology, how tiered hints work, and the APOS framework in the instructional model. How do these two work or interplay side by side? Is the Tier component linear? Cyclical? How? If the student can understand the content solely based on Tier, should he/ she be moving to Tier 2 or not necessary? Although it is observable in Results & Discussion, however, it should also be clear in the methodology.
2. In Figure 1 (the model), is quite confusing the transition from RME to Scaffolding, and Scaffolding to APOS. It seems that students can start at any Tier. Make the directions of the arrows clearer.
3. Besides the feedback for leaderboard, points, and badges, are the students also receiving feedback during the learning process? If yes, how does it work in the model?
4. In the participants, how did you stratify the sample? What are the criteria, characteristics, and attributes for groupings (strata)? What sampling(s) technique is/are used to select the six secondary schools, and also the 300 students? Is there also a basis for choosing a 65%:35% ratio of students for public and private schools? Or is it purposefully set in that ratio?
5. Are the participants given the consent forms? Please also highlight it in the methodology.
6. SEM-PLS Structural Model of the AI-RME-Gamification Framework should already be Figure 2, not Figure 1. Please recheck the succeeding label of the Figures.

Results & Discussion, & Conclusion

1. The Results & Discussion, and Conclusion are well structured to answer the objectives of the study with complete quantitative & qualitative data, and backup with related literature and studies. However, it was mentioned in the methodology that there are classroom observations; therefore, the results of the classroom observations should also be placed in the results and discussion for triangulation purposes. Is it the researcher’s observations or a third-party's observations?
2. This will make mathematics education more meaningful and engaging. It can materialize through the collaboration of teachers, administrations, and local & national governments.

Recommendation: Revisions Required

Reviewer C:

The manuscript addresses an important and timely topic by integrating Realistic Mathematics Education (RME), artificial intelligence scaffolding, and gamification in mathematics learning. The idea is novel and relevant to the current digital education landscape. However, in its present form, the manuscript requires substantial revision across all sections to meet the standards of a high-impact journal. My detailed concerns are as follows:

1. **Title and Abstract**
   - The title is attractive but overloaded with concepts; it would benefit from being more concise and focused on the central contribution.
   - The abstract provides a broad overview, but the background, novelty, objectives, methods, results,

and implications are not equally balanced. Key findings are presented, yet the novelty and contribution need clearer emphasis.

2. **Introduction**
    - While the problem statement is relevant, the narrative is somewhat general and lacks a sharp research gap.
    - The review of prior literature does not yet sufficiently position this study against existing works, particularly in terms of what is new in combining RME, AI, and gamification.
3. **Research Design and Methods**
    - The description of the explanatory sequential mixed-methods design is informative but verbose, making it difficult to identify the essential methodological logic.
    - The three design research phases are described in detail, yet the empirical grounding of the analysis and exploration phase needs strengthening (e.g., actual diagnostic data).
    - The instrument development and validation process is strong, but the constructs' operationalization could be more clearly linked to the research objectives.
4. **Participants and Data Collection**
    - The participant description is thorough, but the justification of sampling strategies needs to go beyond descriptive detail and align more closely with research aims.
    - Data collection procedures are carefully explained but should be shortened and made more analytical. Some technical descriptions (e.g., statistical thresholds) could be moved to an appendix.
5. **Data Analysis**
    - The SEM-PLS analysis is properly applied, but the rationale for its selection over other approaches (e.g., CB-SEM) could be clarified.
    - Thematic analysis is suitable, yet the integration of qualitative and quantitative results could be demonstrated more explicitly (e.g., through joint displays or meta-inferences).
6. **Results and Discussion**
    - Findings are insightful but presented in a way that sometimes mixes results with interpretation. A clearer separation of results (what the data show) and discussion (what it means theoretically and practically) would improve readability.
    - The discussion does not yet fully situate the study's contributions within current debates in mathematics education, AI in learning, and gamification.
7. **Conclusion and Implications**
    - The conclusion is rich but overly dense, blending theoretical insight, design guidance, and future research recommendations. A sharper focus on the main contributions, followed by a more concise list of practical and research implications, is recommended.
    - Future research directions are valuable, yet too detailed; these should be streamlined to highlight the most critical next steps.
8. **Language and Presentation**
    - The manuscript is written in fluent academic English, but many sentences are overly long and complex, making comprehension difficult. Shorter, clearer sentences would increase readability.
    - Figures, tables, and examples should be used more strategically to illustrate key findings and reduce textual overload.

Recommendation: Revisions Required

Reviewer D:

Abstract: Conceptually overloaded; lacks numeric results; "replicable design" remains vague.
Introduction: Separate "literature gap" from "objectives"; shorten hypothesis paragraph; limit to 2–3 key citations per point.
Methods: Redundant conceptual explanations; missing sample questionnaire item; no mention of ethical clearance or consent procedures. Add short ethical statement and example items; streamline narrative by focusing on operational design steps.
Result: Some overinterpretation; no confidence intervals; same figure referenced multiple times without elaboration. Keep "Results" strictly statistical; move interpretive commentary to Discussion.
Qualitative Findings: Duplicate table numbering; limited analytic depth; lacks researcher reflexivity. Correct table numbering; expand explanation on coding logic; include short note on inter-coder reliability or bias mitigation.
Integration & Discussions: Condense by ~25%; add comparison with prior RME/AI literature; maintain formal tone.
Conclusion: Add limitations (ethical, contextual, tech-based) and a concise final sentence summarizing contribution.

Recommendation: Revisions Required

Journal on Mathematics Education

4 attachments

E-[JME] - Blind Review Paper 3.docx
4312K

C-jme-review-assignment-3875-Article+Text-6792.docx
4323K

D-jme-review-assignment-3875-Article+Text-6792 (1).docx
4319K

E-JME - Recapitulation The Contents of the Revised Article.docx
14K

Pasqa <pasqa@uinsgd.ac.id>
To: wati85@uinsgd.ac.id
Sat, Oct 11, 2025 at 7:43 PM

[Quoted text hidden]

4 attachments

E-[JME] - Blind Review Paper 3.docx
4312K

C-jme-review-assignment-3875-Article+Text-6792.docx
4323K

D-jme-review-assignment-3875-Article+Text-6792 (1).docx
4319K

E-JME - Recapitulation The Contents of the Revised Article.docx
14K

Wati Susilawati <wati85@uinsgd.ac.id>
To: jme@unsri.ac.id, pasqa@uinsgd.ac.id
Wed, Nov 12, 2025 at 9:13 AM

Dear Editor,

First, thank you for kindly granting us an extension to complete the revisions. The additional time allowed us to address the reviewers' suggestions thoroughly and improve the manuscript's clarity, coherence, and contribution.

We are pleased to resubmit our revised manuscript, "Integrating Realistic Mathematics Education, AI, and Gamification in Indonesian Secondary Mathematics," for consideration in JME. We have responded to every comment point-by-point in the attached "Recapitulation Revision." A clean version and a tracked-changes version are enclosed.

Highlights of the revisions

1. **Title & Abstract** — Title shortened to foreground the main contribution; abstract rebalanced with background, objectives, methods, results, and implications, including numerical coefficients (e.g., β = 0.351; β = 0.398) and a clearer novelty statement.

2. **Introduction** — Research gap sharpened (RME, AI scaffolding, and gamification often studied in isolation); explicit definition of AI scaffolding with recent references; methodological details moved to *Methods*.
3. **Methodology** — Expanded description of tiered AI scaffolding aligned to the APOS framework; added sampling details, ethical clearance, and consent; introduced Table 1 (constructs ↔ objectives) and sample items; corrected figure numbering and redesigned instructional flow.
4. **Results & Discussion** — Results presented strictly statistically, with confidence intervals and fit indices; interpretation separated from results; added triangulated classroom observations and a joint display linking quantitative paths with qualitative evidence.
5. **Conclusion** — Refocused on theoretical and practical contributions; concise directions for future research; clearer limitations.
6. **Language & Presentation** — Streamlined prose; reorganized tables/figures/captions; updated references and ensured citation consistency.

We believe the revised manuscript now meets JME's standards and offers robust empirical evidence with actionable pedagogical implications for mathematics learning in the digital era. We appreciate the opportunity to improve our work and respectfully submit this version for your consideration.

Sincerely,

Wati Susilawati, M. Pasqa, Sergii Sharov, and Co-authors
Corresponding Author: wati85@uinsgd.ac.id

---

2 attachments

Recapitulation Revision " Integrating Realistic Mathematics Education, AI, and Gamification to Enhance Students' Mathematical Problem-Solving".docx
38K

Revisi Wati JME - Track Changes On Review.docx
4522K

Journal on Mathematics Education
Volume xx, No. x, xxxx, pp. xx-xx

Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving

Abstract

Mathematics learning in the digital era requires approaches that enhance motivation and strengthen problem-solving skills. This study tests an integrated model that combines Realistic Mathematics Education, artificial intelligence scaffolding, and gamification, while considering self-efficacy, perceived challenge, and Action Process Object Schema (APOS) progressions. We employed an explanatory sequential mixed-methods design with 300 secondary students from six schools. The quantitative phase estimated a structural equation model; the qualitative phase included classroom observations and interviews. Results show that RME exerted the most significant direct effect on mathematical problem-solving and also raised motivation by contextualizing tasks. Gamification significantly increased motivation, which in turn supported persistence and problem-solving. AI scaffolding delivered tiered hints that preserved students' ownership of strategies and helped transitions along the APOS trajectory. Motivation emerged as the central pathway linking engagement features to cognitive gains. The study contributes a replicable design and actionable guidance for aligning context, adaptive support, and proportionate game mechanics to improve mathematics learning in classrooms.

Keywords: Artificial Intelligence, Gamification, Learning Motivation, Problem Solving, Realistic Mathematics Education

---

Learning in mathematics becomes more meaningful when students can connect ideas to familiar situations and are supported in reconstructing formal concepts from their own informal understanding. Reasoning (Hikayat et al., 2020; Son, 2022). This is the central idea of Realistic Mathematics Education, where phenomena from everyday life are used to organise the mathematics that learners are expected to reinvent (Siswantari et al., 2025). When tasks are rooted in familiar practices, students can anchor their conjectures, construct representations, and make connections that naturally lead toward more formal structures. The movement from context to concept is not incidental; it is a deliberate trajectory that helps students understand why procedures work, rather than just how to perform them (Nguyen & Pham, 2023).

Well-designed game elements can extend this learning trajectory by sustaining effort over time (Ariffin et al., 2022). Systems that reward persistence, revision, and explanation help students stay engaged with a problem long enough to test their ideas and refine their strategies (Jun & Lucas, 2025). Making effort visible and valuable encourages participation from a broader range of learners and reduces the tendency to rush for quick answers (Strousopoulos et al., 2024). Used in this way, gamification does not replace mathematical thinking; it protects the time and attention that sense-making requires (Al-Barakat et al., 2025). Recent progress in educational AI adds a third strand by providing feedback that adapts to the learner and offers hints without telling the answer. Such support keeps students in productive struggle and preserves ownership of the solution path. When these strands are combined, context supplies meaning, game elements maintain stamina, and AI provides just-in-time scaffolding

Commented [A21]: The title combines three major aspects: Realistic Mathematics Education (RME), Artificial Intelligence (AI), and Gamification. It's important to clarify whether all three are used together or whether AI and gamification are used to support RME.

Commented [A22]: **Clarity of Background**: It's good because it directly addresses the challenges of the digital era (motivation and problem-solving). However, the first sentence is still too general. It could be strengthened with a literature-based claim, for example: "...yet existing approaches often address these aspects separately." → to highlight the research gap.
Novelty: It has been stated that this study "tests an integrated model" that combines RME, AI, and gamification. However, the novelty is not explicit compared to previous research. It is recommended to add a phrase that emphasizes the uniqueness, for example: "...a novel integration rarely examined in prior mathematics education research."
Research Purpose: The purpose is implied but not explicit. A clear statement is needed, such as: "This study aimed to examine how the integration of RME, AI scaffolding, and gamification influences students' motivation and problem-solving."
Methods: Clear: explanatory sequential mixed-methods, 300 students, 6 schools, SEM, observation, interviews. The abstract could be slightly condensed to make it more concise, for example: "...using an explanatory sequential mixed-methods design with SEM analysis on 300 secondary students, followed by classroom observations and interviews."
Research Findings: Good, with the following points: RME; significant direct effect on problem-solving and motivation. Gamification; increased motivation, supporting persistence and problem-solving. AI; gradual scaffolding, supporting APOS progression. However, it needs to be summarized to avoid being too narrative. Suggestion: "Findings indicate RME had the strongest direct effect on problem-solving and motivation, gamification boosted persistence through motivation, and AI scaffolding supported APOS transitions while maintaining strategy ownership."
Impact/Contribution: Fairly good: "replicable design and actionable guidance..." Could be strengthened to make it more academically significant, for example: "The study contributes a replicable instructional design and offers theoretical as well as practical implications for integrating context, adaptive support, and game mechanics in mathematics learning."

Commented [A23]: Clearly transition from a general explanation of RME to the urgency of this research so that readers immediately see the relevance to the digital context.

http://doi.org/10.22342/jme.v13i1.xxxx

(Bayaga, 2024). Motivation then becomes the channel through which engagement is converted into gains in reasoning and problem-solving (Mitchell & Co., 2024). This integrated view sets the stage for examining how an AI-supported, gamified RME environment can help learners transition from lived experience to formal understanding (Bhardwaj, 2024).

These considerations are especially relevant in Indonesia, where improving mathematical literacy remains a persistent challenge (Ndiung & Menggo, 2025). Results from the Programme for International Student Assessment (PISA) indicate that Indonesian students often face difficulties with contextual reasoning and higher-order problem-solving, highlighting a gap between procedural competence and the ability to apply mathematics in real-world situations (Zulkardi & Kohar, 2018). National initiatives have promoted RME-inspired approaches to make mathematics more relevant, for example, through tasks linked to students' everyday practices such as trade, transportation, and cultural activities (Dewi & Maulida, 2023). However, these practices remain unevenly implemented and often constrained to conventional classrooms with limited technological support (Siregar et al., 2025). Meanwhile, the rapid growth of digital learning platforms and the increasing presence of gamified applications in Indonesian schools have not always been accompanied by sound pedagogical integration(Maryani et al., 2025). Many platforms risk promoting superficial engagement rather than fostering deep understanding, as they rarely align with established didactical frameworks. Against this backdrop, the integration of RME, gamification, and AI represents a promising direction for connecting contextual meaning with technological innovation (Li & Noori, 2024; Torres-Toukoumidis et al., 2025). By situating mathematical activity in students' lived realities while harnessing digital tools to sustain motivation and scaffold reinvention, such integration has the potential to advance both local and international discourses on mathematics education (Opesemowo & Ndlovu, 2024).

Despite steady advances in mathematics education, several uncertainties remain in how emerging approaches interact. Self-efficacy, for example, has been extensively researched in relation to achievement and motivation; however, its role within AI-supported, gamified RME environments at the secondary level remains poorly understood, especially in Indonesia (Mukuka et al., 2021; Siswantari et al., 2025). Existing studies tend to treat confidence as a background trait rather than as a dynamic factor shaping how students engage with contextual tasks, adaptive scaffolding, and game mechanics (Rahayu et al., 2022). This leaves unanswered questions about how students' beliefs in their own abilities actually influence their participation and persistence in such integrated designs.

The treatment of challenges in mathematics learning also requires rethinking. Much of the literature positions challenge as a hindrance that can discourage learners (Ardi et al., 2019; Wilkie, 2016), while fewer studies examine the conditions under which difficulty becomes productive and fuels deeper engagement (Biccard, 2024; Jayaraman et al., 2024; Moleko, 2021). In digital and gamified environments where challenge levels can be precisely adjusted, there is a strong need to understand how well-calibrated difficulties can promote persistence, encourage reasoning, and strengthen the link between motivation and problem-solving (Beukes et al., 2024; Koskinen et al., 2023). Without this perspective, gamified learning risks being reduced to surface-level incentives rather than fostering genuine mathematical thinking and understanding. Another area of uncertainty lies in integrating RME, gamification, and AI into a coherent instructional model (Samur & Cömert, 2024). Research on gamification often assumes a direct link to cognitive gains, overlooking the possibility that its most potent effect is mediated through motivation (Hu et al., 2023; Mitchell & Co, 2024). Similarly, RME research in Indonesia has been primarily grounded in conventional classrooms, with limited attention to how digital scaffolds and game-based engagement can enhance its effects on problem-solving (Lady et al., 2018;

Commented [A24]: Summarize the section on gamification and AI to focus more on its conceptual relationship to RME, rather than simply a list of benefits.

Commented [A25]: Emphasize the gap between education policy in Indonesia and actual implementation more explicitly to strengthen the research rationale.

Commented [A26]: It is clear that self-efficacy is still understood statically in the literature, so this study offers a dynamic perspective.

Lestari et al., 2023; Siswantari et al., 2025). Motivation itself is still too often conceptualized as an outcome variable rather than as a structural mediator that links self-efficacy, challenge, RME, and higher-order reasoning (Yohannes & Chen, 2024). This combination of gaps points to the need for a new line of research that not only integrates these elements but also explains how affective and cognitive processes are intertwined in technology-enhanced mathematics education.

To address these gaps, the Indonesian secondary context needs solid evidence on how AI-supported gamification and RME can work together to boost motivation and problem-solving while maintaining mathematical sense-making. Although technology is increasingly present in classrooms, its use often targets superficial engagement and is seldom grounded in a didactic framework that supports guided reinvention (Dewi & Maulida, 2023). At the same time, national efforts to adopt RME remain inconsistent and are seldom supported by adaptive feedback that can keep students engaged in productive struggle (Pramudiani et al., 2023). Accordingly, this study aims to pursue two clear objectives. First, it evaluates an integrated instructional model that combines RME, gamification, and AI scaffolding by estimating direct and indirect effects on secondary students' learning motivation and mathematical problem solving using SEM–PLS; the model positions self-efficacy, perceived challenge, and Action, Process, Object, Scheme (APOS) based learning as antecedents to engagement with gamification and RME, and tests whether motivation mediates the pathway to problem solving. Second, it explains how these statistical effects unfold in practice through thematic analysis of student and teacher interviews and classroom observations, thereby clarifying the mechanisms that link contextual tasks, game mechanics, and adaptive feedback with students' reasoning.

This study evaluates an integrated model that combines RME, gamification, and AI scaffolding to estimate the direct and indirect effects on secondary students' learning motivation and mathematical problem-solving. We ask four questions that emphasize the mechanism and align with the structure model: (1) to what extent do self-efficacy, perceived challenge, and APOS-based learning predict students' engagement with the two design levers, Gamification and RME; (2) what are the direct and indirect effects of Gamification and RME on learning motivation and on mathematical problem solving when all paths are estimated simultaneously; (3) does learning motivation mediate the relationships from Gamification and from RME to problem solving, and how significant are the mediated effects relative to any direct effects; and (4) once competing paths are controlled, which predictors exert the most substantial standardized effects on motivation and on problem solving. Based on our conceptual model, we propose a clear set of hypotheses. First, self-efficacy, perceived challenge, and APOS-based learning are expected to positively predict students' engagement with the two design levers, Gamification and RME. Second, gamification is likely to contribute to problem-solving primarily through its impact on learning motivation, rather than through a direct path. In contrast, RME is anticipated to have at least moderate positive effects on both motivation and problem-solving. Third, learning motivation is expected to positively predict problem-solving and exert an influence on both design levers, ultimately affecting performance.

We adopt an educational design research stance, employing an explanatory sequential mixed-methods design. This approach involves estimating a structural model using SEM–PLS and explaining proposed mechanisms through thematic analysis of interviews and classroom observations. The study's contributions are threefold. Conceptually, it reframes motivation from an outcome to a structural mediator that links engagement features to cognitive performance, specifying the didactical conditions under which difficulty becomes desirable in digital mathematics: meaningful RME contexts, adaptive non-telling AI scaffolds, and process-sensitive incentives that reward persistence and explanation. It also

Commented [A27]: Avoid repetition about the challenges of learning mathematics, just emphasize the novelty of the research on the aspect of difficulty calibration and the role of motivation as a mediator.

Commented [A28]: Formulate the research objectives more concisely in two concise sentences so that readers do not lose focus amidst the details of SEM and APOS.

Commented [A29]: Research questions should be written in narrative form (not numbered points) to make them flow better and be consistent with the style of international journal introductions.

operationalizes APOS progressions within an AI-supported, gamified RME ecology, rendering the transition from action to process to object to schema observable and designable in secondary classrooms. Practically, it offers a replicable model for Indonesian schools that combines high-quality contextual tasks with proportionate game mechanics and calibrated AI feedback, along with guidance for tailoring implementation to local affordances.

Commented [A210]: The contribution section needs to be condensed and clearly separated between conceptual, methodological and practical contributions so that readers can quickly grasp the added value of the research.

METHODS

Research Design

Commented [A211]: The research design section is coherent, but it should be condensed so that it does not seem merely descriptive; strengthen it with (1) a clear relationship between the design and the research objectives, (2) the reasons for choosing the theory and mechanisms, and (3) explicit evaluation indicators.

This study employed an explanatory sequential mixed-methods design (Creswell, 2018) situated within the broader paradigm of educational design research (Gravemeijer, 1994; Plomp, 2013). While the explanatory sequential approach allowed the combination of quantitative and qualitative data to provide a comprehensive picture, embedding the study in the design research tradition emphasized the dual aim of empirical testing and instructional model development. In line with this framework, the research did not merely evaluate causal relationships among variables, but also sought to develop and validate a learning model that integrates Artificial Intelligence (AI), gamification, and Realistic Mathematics Education (RME). The design followed the three-phase cycle of design research:

1. Analysis and Exploration. The first phase involved identifying key problems in mathematics learning, particularly students' low motivation and difficulties in transferring problem-solving strategies to contextual situations. A review of theoretical perspectives in RME principles (Freudenthal, 1991; Gravemeijer, 1994), the APOS framework (Dubinsky & McDonald, 2001), and gamification theory (Deterding et al., 2011) informed the conceptual model.
2. Design and Construction. Based on the theoretical synthesis, an instructional model was developed that integrates RME-based contextual tasks to foster phenomenological exploration and guided reinvention, as well as gamification mechanics (points, levels, leaderboards, and badges) to sustain student engagement. Additionally, AI-driven personalization is used to scaffold the progression from informal strategies to formal reasoning. The instructional flow is presented in Figure 1, which shows how students move through the system: beginning with login, accessing contextual RME tasks, receiving AI scaffolding through tiered hints (Tier 1–3), revising their work based on the APOS framework (Action → Process → Object → Schema), and finally receiving gamification feedback in the form of points, badges, and leaderboard positions.
3. Evaluation and Reflection. The proposed model was tested in a large-scale quantitative phase using Structural Equation Modeling with Partial Least Squares (SEM-PLS), followed by qualitative interviews and classroom observations to refine the interpretation. This cycle allowed the model to be validated both statistically and phenomenologically, ensuring coherence between theoretical expectations and classroom realities.

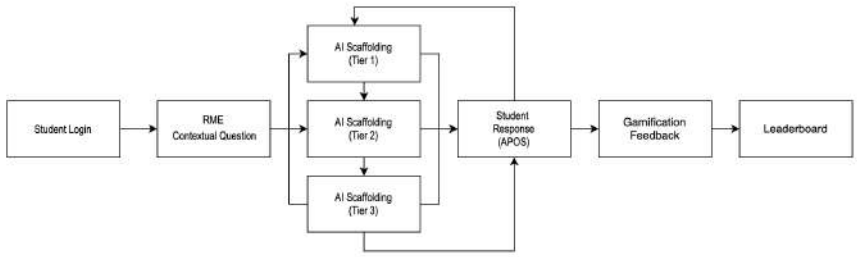


Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding and APOS progression

As shown in Figure 1, the flowchart highlights the central role of AI scaffolding in guiding students' reasoning. The system does not simply provide answers but supports progressive mathematization by offering tiered hints (Tier 1–3) that correspond to students' evolving levels of understanding. Student responses are structured through the APOS framework, and their persistence is reinforced by gamification feedback, including points, badges, and leaderboards. This integration ensures that cognitive development (problem-solving strategies) and affective engagement (motivation) are intertwined within a coherent instructional cycle. By adopting this design, the study contributes not only empirical evidence regarding the relationships among AI, gamification, RME, learning motivation, and problem-solving, but also theoretical advancement through a model that operationalizes progressive mathematization in a digital environment.

Participants

Commented [A212]: Explain in more detail how stratified sampling was conducted (e.g., based on school, gender, or region type), to ensure greater transparency in the participant recruitment procedure.

The quantitative phase of the study involved 300 students from six secondary schools in West Java, Indonesia. A stratified sampling strategy was employed to ensure representation across varied learning contexts, consistent with the RME principle of phenomenological exploration (Bayu & Fauzan, 2023), which values diversity in students' backgrounds and experiences. The sample comprised 195 students (65%) from public schools and 105 students (35%) from private schools, with four schools located in urban areas and two in suburban settings, thereby reflecting differences in access to digital resources and exposure to ICT. The gender distribution was nearly balanced, with 52% female and 48% male students. For the qualitative phase, six students were purposively selected based on their latent scores from the SEM-PLS analysis to capture a spectrum of achievement and motivational profiles, including high-achieving, average, and struggling learners. In addition, three mathematics teachers with 5–10 years of teaching experience and prior familiarity with contextualized instruction participated in the study. This purposive sampling enabled a richer understanding of how students and teachers constructed meaning within the AI–RME–gamification learning environment, ensuring that the analysis incorporated multiple perspectives across different educational roles.

Data Collection Techniques

Commented [A213]: Include examples of instrument items or representative indicators of each construct so that the suitability of the operationalization with the theory can be assessed.

The quantitative data were collected using a Likert-scale questionnaire ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument measured seven constructs: Students' Challenges, Students' Learning (APOS), Self-Efficacy in Mathematics, Gamification, Human–AI Collaboration (RME), Learning

Motivation, and Mathematical Problem-Solving Skills. Each construct was anchored in established theoretical frameworks, including Bandura's theory of self-efficacy (Bandura, 1997), the APOS model of learning (Dubinsky & McDonald, 2001), and the principles of Realistic Mathematics Education (Freudenthal, 1991). This ensured that the questionnaire items reflected both cognitive and affective dimensions of mathematics learning.

The development of the instrument followed a systematic validation process. First, the items were reviewed by three experts in mathematics education to assess their relevance and theoretical alignment. Second, a pilot test was conducted with 50 students in West Java to evaluate clarity and response patterns. Third, statistical validation was performed through outer model analysis using SEM-PLS, confirming that all indicators met the required thresholds for reliability and validity (factor loadings > 0.70, AVE > 0.50, CR > 0.80). Such validation practices are consistent with standards in mathematics education research where constructs must be both theoretically grounded and empirically robust (Hair et al., 2019).

Commented [A214]: Mention the reliability test value (e.g. Cronbach's alpha) in addition to CR, to strengthen the instrument validation report according to international standards.

The qualitative data were collected through semi-structured interviews conducted with six students and three teachers. The interview protocol addressed three focal areas: (1) students' experiences with contextualized tasks, which reflected RME's principle of phenomenological exploration (Gravemeijer, 1994; Yilmaz, 2020); (2) the influence of gamification mechanics such as points, levels, and leaderboards on students' motivation (Cassells et al., 2015; Strousopoulos et al., 2024), and (3) the role of AI scaffolding in supporting guided reinvention and progression from informal reasoning to formal mathematical knowledge (Mukuka et al., 2021). Each interview lasted approximately 30–40 minutes and was audio-recorded with participant consent to ensure reliability and transparency.

Commented [A215]: Explain the criteria for selecting the six students more explicitly (e.g. high, medium, low motivation scores) to make it appear methodological, not just generally purposive.

To complement the interviews, classroom observations were conducted during the implementation of the AI–RME–gamification model. Field notes focused on interactivity, peer collaboration, and evidence of student contributions, which represent three of the core characteristics of RME (Treffers, 1991). Observations also paid attention to students' transitions between horizontal and vertical mathematization, thereby situating their learning within the broader process of progressive mathematization (Gravemeijer, 1994). These qualitative techniques enabled the triangulation of data sources, providing richer insights into how students and teachers constructed meaning in the AI–RME–gamification learning environment.

Commented [A216]: Add information regarding the number of observation sessions, duration, and role of the researcher (passive/active observer) to strengthen the credibility of the data.

The AI–RME–Gamification application used in this study was developed as a prototype with limited access, explicitly designed for research purposes. The system integrated contextual mathematics tasks with AI-driven scaffolding and gamification mechanics, and was tested in authentic classroom settings to examine its feasibility and pedagogical effectiveness. The AI scaffolding component was powered by a large language model (LLM) accessed through an open API. This integration enabled the system to provide tiered hints (Tier 1–3) that adapted to students' partial solutions and common misconceptions without directly revealing the final answer. The prototype was implemented using free-tier developer access, ensuring low-cost deployment and practical replicability in typical school contexts. Although not yet a fully commercial product, the application provided sufficient functionality for students to engage with RME-based tasks, receive adaptive AI hints, and participate in gamified progress tracking. This prototyping phase allowed the research to capture both the potential and the limitations of combining RME, gamification, and AI in real classroom practice, ensuring that the findings reflected practical rather than purely hypothetical conditions.

Commented [A217]: Clarify the content validity or technical testing of the application before class implementation, so that the prototype is not only seen as functional but also pedagogically valid.

Data Analysis Techniques

The quantitative data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS, an approach suited for predictive modeling with complex latent constructs (J. Hair & Alamer, 2022). The analysis included both the measurement model, to assess indicator reliability and validity, and the structural model, to examine path coefficients and predictive relevance. Instrument validity was confirmed through factor loadings above 0.70, Average Variance Extracted (AVE) values above 0.50, and composite reliability scores above 0.80. Discriminant validity was established through the Fornell–Larcker criterion and the HTMT ratio, ensuring that constructs were distinct yet theoretically coherent (J. F. Hair et al., 2019).

The qualitative data from interviews and classroom observations were analyzed using thematic analysis (Braun & Clarke, 2006). Initial codes were generated inductively, then interpreted through the lens of RME's didactical phenomenology (Freudenthal, 1991), focusing on themes such as engagement with contextual tasks, the motivational effects of gamification, and the role of AI in scaffolding guided reinvention. Finally, quantitative and qualitative results were integrated at the interpretation stage. For example, the significant path from Gamification → Motivation was explained by students' enthusiasm for points and leaderboards, while teacher observations of contextual reasoning supported the path from RME → Problem-Solving Skills. This triangulation reflected the design research cycle, combining empirical testing with phenomenological insights.

RESULTS AND DISCUSSION

The results of the SEM-PLS analysis revealed a consistent pattern highlighting the centrality of RME and motivation in the instructional model. Gamification exerted a significant positive effect on motivation ($\beta = 0.405$, $p < 0.001$) and also contributed directly to problem-solving skills ($\beta = 0.191$, $p < 0.01$). Beyond its direct effect, gamification indirectly supported problem-solving through motivation, emphasizing its role in sustaining student engagement throughout the learning cycle.

RME emerged as a pivotal construct in the model, exerting substantial effects on both motivation ($\beta = 0.351$, $p < 0.001$) and problem-solving skills ($\beta = 0.398$, $p < 0.001$). These findings align with the principles of *guided reinvention* and *phenomenological exploration*, where contextualized tasks allow students to transition from informal strategies to formal reasoning. The statistical strength of these paths reflects how RME facilitates progressive mathematization, a cornerstone of mathematics as a human activity (Freudenthal, 1991).

Learning motivation itself proved to be a significant predictor of problem-solving skills ($\beta = 0.285$, $p < 0.001$), underscoring its mediating role. This suggests that students who are intrinsically and extrinsically motivated are better positioned to develop higher-order reasoning, make connections, and represent mathematical ideas effectively. The mediating role of motivation highlights the novelty of this study, demonstrating that gamification and RME function not only as instructional approaches but also as affective drivers of mathematical competence.

Internal learner factors also played a critical role in strengthening RME. Self-efficacy ($\beta = 0.305$, $p < 0.001$), students' challenges ($\beta = 0.304$, $p < 0.001$), and APOS-based learning ($\beta = 0.198$, $p < 0.01$) significantly contributed to the construction of meaning within the RME framework. Rather than serving as barriers, challenges acted as *desirable difficulties (Arifin et al., 2020),* enriching the process of mathematization. Together, these results demonstrate that combining AI, RME, and gamification provides a powerful approach to enhance both the emotional and cognitive aspects of learning mathematics. The overall structural model is presented in Figure 1 to illustrate these relationships and their statistical

Commented [A218]: Add the reasons for choosing SEM–PLS over SEM–CB (covariance-based), so that readers understand the suitability of the analysis method to the research objectives.

Commented [A219]: 1.Include strategies to increase trustworthiness (e.g., inter-researcher triangulation, member checking, or audit trail) to make the thematic analysis more credible.
2.Explain more clearly at what stage and in what way quantitative and qualitative data are integrated (e.g. connecting, building, merging according to Creswell) so that readers see consistency with the explanatory sequential design.

Commented [A220]: **Consistency of Terminology:** *Note*: Sometimes different terms are used for the same thing, for example, problem-solving skills vs. cognitive performance, motivation vs. learning motivation. Recommendation: Use consistent terminology throughout the results section to maintain theoretical coherence and avoid reader confusion.
Quantitative & Qualitative Linkages: *Note*: The results integration section (quant–qual) is strong, but the flow sometimes feels overlapping with the discussion. Recommendation: Clearly separate the Results (facts, both numbers and themes) from the Discussion (interpretation). For example, avoid too much theoretical reflection in the Results; save it for the Discussion.
Completeness of Statistics: *Note*: SEM-PLS data (β, t, p, f^2, R^2) are reported, but effect size and predictive relevance (Q^2) are not explained. This is standard PLS reporting. *Suggestion*: Add Q2 or blindfolding reports, and, if possible, multi-group analysis (MGA) or AI moderation to strengthen the methodological contribution.
Use of Tables & Figures: *Note*: Many tables (1–7) and figures exist, but there is potential for information overload. For example, Table 6 (thematic analysis) is somewhat repetitive with Table 7 (integration). *Suggestion*: Consider combining tables for greater conciseness, for example, combining the quant–qual integration results into one comprehensive table.
Clarity of Qualitative Data: Note: Student and teacher quotes are very supportive, but are too long, and some are merely paraphrases. Suggestion: Use short quotes, focus on the most representative ones, and move the rest to the appendix.
Balance of Affective vs. Cognitive: *Note*: Motivation is strongly emphasized (as a mediator), but cognitive outcomes (problem-solving) are somewhat overlooked. Suggestion: Provide a balanced approach, for example, adding concrete examples of improved problem-solving strategies or the quality of mathematical representation, not just motivation.
Contextualization of Results: *Note*: There are claims of different contexts (urban vs. suburban schools), but the data hasn't been clearly demonstrated (was it a subsample analysis?).
Suggestion: If there are indeed contextual differences, show empirical data (subgroup analysis) or explicitly state that these are only observational findings.
Logical Flow: The section "Motivation as the Mediating Bridge in AI-RME Gamification Learning" already resembles a discussion and includes theoretical contributions. Suggestion: Move this section to the Discussion/Conclusion section to maintain a purely descriptive-empirical structure.

significance.

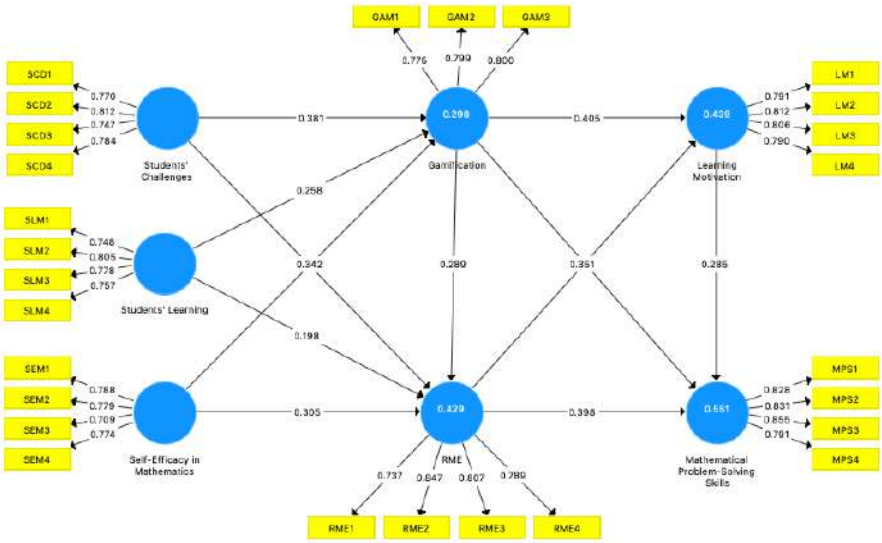


Figure 1. SEM-PLS Structural Model of the AI–RME–Gamification Framework

Building upon the structural relationships depicted in Figure 1, further analysis of the measurement and structural models was conducted to ensure the robustness of the findings. The measurement model was first evaluated to confirm the reliability and validity of the constructs, followed by the structural model analysis to examine the magnitude and significance of the hypothesized paths. The results of these quantitative analyses are presented in the following section, beginning with the assessment of the measurement model.

Quantitative Findings

The quantitative analysis began with the evaluation of the measurement model to confirm the reliability and validity of the constructs. All indicators demonstrated satisfactory outer loadings, with values exceeding the recommended threshold of 0.70, while the Average Variance Extracted (AVE) for each construct was above 0.50. In addition, both Composite Reliability (CR) and Cronbach's alpha values were greater than 0.80, indicating strong convergent validity and internal consistency. These results are summarized in Table 1.

Table 1. Measurement Model Results

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
Gamification	GAM1	0.775	0.64	0.86	0.81	Valid
	GAM2	0.802				
	GAM3	0.788				
Learning Motivation	LM1	0.791	0.67	0.88	0.83	Valid
	LM2	0.822				
	LM3	0.843				

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
	LM4	0.804				
Problem-Solving Skills	MPS1	0.812	0.66	0.87	0.82	Valid
	MPS2	0.826				
	MPS3	0.799				
	MPS4	0.811				
RME	RME1	0.740	0.65	0.88	0.84	Valid
	RME2	0.781				
	RME3	0.854				
	RME4	0.792				
Self-Efficacy	SEM1	0.781	0.62	0.85	0.80	Valid
	SEM2	0.812				
	SEM3	0.804				
	SEM4	0.794				
Challenges	SCD1	0.765	0.63	0.86	0.81	Valid
	SCD2	0.811				
	SCD3	0.828				
	SCD4	0.779				
APOS Students Learning	SLM1	0.751	0.61	0.84	0.79	Valid
	SLM2	0.784				
	SLM3	0.802				
	SLM4	0.773				

The results indicate that all constructs (Gamification, RME, Learning Motivation, Problem-Solving, Self-Efficacy, Challenges, and APOS Learning) are measured accurately and consistently. Strong factor loadings (0.74–0.85) reinforce the robustness of the RME construct, while reliability indices (CR and α > 0.80) confirm internal consistency. This suggests that the instruments adequately captured both affective (motivation, self-efficacy) and cognitive (problem-solving, APOS) dimensions of learning. Discriminant validity was then assessed using the Fornell–Larcker criterion. The square root of the AVE for each construct was higher than its correlations with other constructs, demonstrating that each construct measured distinct dimensions of the instructional model. This confirms that Gamification, RME, Motivation, and Problem-Solving are empirically distinguishable, as shown in Table 2.

Table 2. Discriminant Validity (Fornell–Larcker Criterion)

Construct	Gamification	Motivation	Problem-Solving	RME
Gamification	0.80			
Motivation	0.56	0.82		
Problem-Solving Skills	0.44	0.53	0.81	
RME	0.48	0.51	0.59	0.81

Note: The diagonal values represent √AVE. All diagonal values are greater than the inter-construct correlations, indicating that discriminant validity is established.

The results confirm discriminant validity: for example, Motivation (√AVE = 0.82) is statistically distinct from Gamification ($r = 0.56$) and RME ($r = 0.51$). This distinction is important because it validates the mediating role of Motivation between Gamification and Problem-Solving. Without sufficient discriminant validity, overlap among constructs could bias the interpretation of the mediation effect.

The structural model analysis revealed several significant paths. Gamification exerted a substantial effect on Motivation ($\beta = 0.405$, $p < 0.001$) and a moderate effect on Problem-Solving Skills ($\beta = 0.191$, $p < 0.01$). RME was found to be a pivotal construct, significantly predicting both Motivation ($\beta = 0.351$, $p < 0.001$) and Problem-Solving Skills ($\beta = 0.398$, $p < 0.001$). Motivation itself significantly predicted Problem-Solving ($\beta = 0.285$, $p < 0.001$), confirming its mediating role. Furthermore, internal learner factors contributed significantly to strengthening RME: Self-Efficacy ($\beta = 0.305$, $p < 0.001$), Students' Challenges ($\beta = 0.304$, $p < 0.001$), and APOS-based Learning ($\beta = 0.198$, $p < 0.01$). Together, these paths explained 48% of the variance in Motivation, 52% of the variance in RME, and 55% of the variance in Problem-Solving Skills. A summary of these findings, including path coefficients, t-values, and R^2, is presented in Table 3.

Table 3. Structural Model Results

Path	β	t-value	p-value	f^2	R^2 (Endogen)	Decision
Gamification → Motivation	0.405	5.06	0.000	0.21	Motivation = 0.48	Supported
Gamification → Problem-Solving	0.191	2.60	0.009	0.08	Problem-Solving = 0.55	Supported
RME → Motivation	0.351	3.51	0.000	0.19	—	Supported
RME → Problem-Solving	0.398	4.98	0.000	0.25	—	Supported
Motivation → Problem-Solving	0.285	2.85	0.004	0.17	—	Supported
Self-Efficacy → RME	0.305	4.20	0.000	0.12	RME = 0.52	Supported
Challenges → RME	0.304	4.10	0.000	0.11	—	Supported
APOS Learning → RME	0.198	3.00	0.002	0.07	—	Supported

The findings validate the hypothesized relationships: Gamification primarily functions as an engagement driver, boosting Motivation, which subsequently enhances Problem-Solving. RME, consistent with Freudenthal's (1991) principles of *guided reinvention* and *phenomenological exploration*, directly improves both Motivation and Problem-Solving. Self-efficacy and Challenges positively shape RME, with challenges acting as *desirable difficulties*. The explained variance (R^2, between 0.48 and 0.55) indicates a moderate-to-strong model, underscoring the integrative strength of AI–RME–gamification.

The model fit indices confirmed the adequacy of the proposed framework. The Standardized Root Mean Square Residual (SRMR) was below the recommended threshold of 0.08, the Normed Fit Index (NFI) was above 0.90, and the RMS Theta index was below 0.12. These indicators provide evidence that the AI–RME–Gamification model demonstrates a satisfactory overall fit, as displayed in Table 4.

Table 4. Model Fit Indices

Fit Index	Value	Threshold	Decision
SRMR	0.062	< 0.08	Good Fit
NFI	0.91	> 0.90	Acceptable
RMS Theta	0.11	< 0.12	Acceptable

The model's goodness-of-fit indices suggest that the theoretical framework is well aligned with the empirical data. SRMR < 0.08 indicates minimal residuals between observed and predicted correlations, while NFI > 0.90 reflects acceptable comparative fit. RMS Theta < 0.12 further supports the quality of the measurement model. Collectively, these indices confirm that the SEM-PLS model is both statistically and conceptually robust.

Qualitative Findings

Thematic analysis of interviews and classroom observations was clustered into categories and synthesized into four overarching themes: guided reinvention, interactivity, phenomenological exploration, and the enhancement of problem-solving skills. These themes collectively provide a deeper understanding of how the AI–RME–Gamification model shaped student learning experiences and reinforce the quantitative findings of the study.

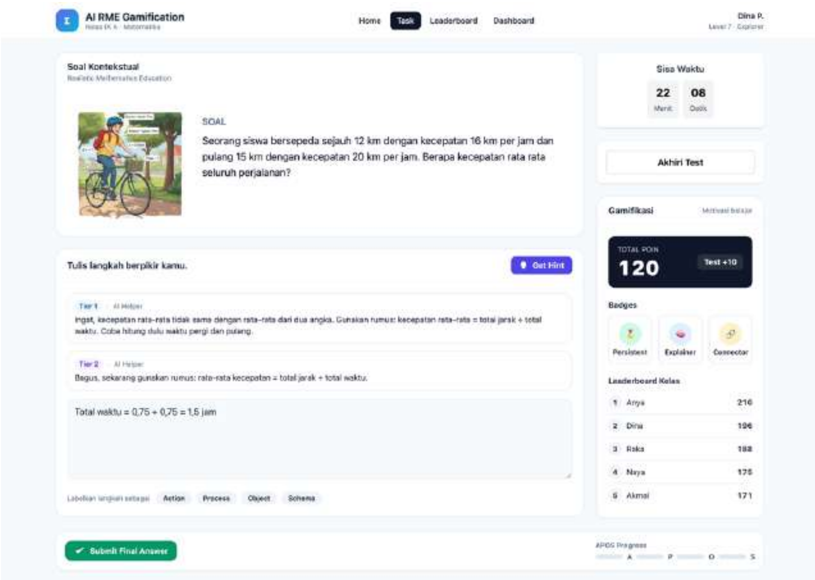


Figure 2. Screenshot of the AI–RME–Gamification prototype application

Figure 2 displays the interface of the AI–RME–Gamification application as used by students during the learning sessions. The interface demonstrated how contextual RME-based tasks were presented, how AI scaffolding was delivered through tiered hints (Tier 1–3), and how gamification elements, such as points, badges, and leaderboards, were integrated. This visual evidence supports the qualitative finding that students were encouraged to construct their own strategies rather than rely on direct answers, while also maintaining motivation through digital reward mechanisms.

Students frequently described the system as a scaffold that encouraged them to construct their own strategies rather than rely on direct answers. Codes such as AI scaffolding, hints, and self-construction were dominant, with one student remarking, "The system gave me hints when I was stuck, but it did not show the answer. I had to try different ways until I found the solution." Teachers echoed this sentiment, observing that students became more independent: “They tried first, then used the hints only when they really needed them.” This reflects the RME principle of guided reinvention (Freudenthal, 1991) and resonates with the quantitative finding that RME strongly predicted both Motivation (β = 0.351) and Problem-Solving (β = 0.398).

Table 6. Transcript of student–AI interaction on average task with tiered scaffolding LLM

Stage	Student Response	AI Scaffolding	Analysis (APOS/Didactical)
Initial answer	“Average = (16 + 20)/2 = 18 km/h.”	“Remember, average speed = total distance ÷ total time. First calculate the time for the outbound and return trips.” (Tier 1 – general strategy)	Student holds a misconception (incorrect schema → arithmetic average). AI redirects to the formal concept (Object).
Time calculation (wrong)	“Outbound time = 12 ÷ 16 = 0.75 h. Return time = 15 ÷ 20 = 0.8 h.”	“Correct for the outbound time. But check again 15 ÷ 20. Is it really 0.8?” (Tier 2 – focused correction)	Student moves into Action → Processbut miscalculates. AI focuses on correcting the specific operation.
Revision	“15 ÷ 20 = 0.75 h. So total time = 1.5 h.”	“Good! Now total distance = 27 km, total time = 1.5 h. Use the formula average speed = distance ÷ time.” (Tier 3 – near answer)	Student reaches the Process stage. AI scaffolds transition toward Object.
4. Final answer	“27 ÷ 1.5 = 18 km/h.”	“Correct! You earn +10 points and the Master Speed badge for completing with a structured solution.” (Feedback + Gamification)	Student achieves the Schema stage (general concept of average speed). Gamification reinforces motivation.

This transcript shows how the AI scaffolding guided by a large language model (LLM) accessed via an API initially led an actual student astray, treating average speed as a simple arithmetic mean, before guiding them toward the correct reasoning pathway. Through tiered hints, the AI first redirected the student to the appropriate formula (Tier 1), then corrected a calculation error (Tier 2), and finally consolidated the process by connecting total distance and total time (Tier 3). The progression of responses reflects the APOS framework: from Action (performing basic operations), to Process (organizing steps), to Object (treating distance and time as unified quantities), and ultimately to Schema (generalizing the concept of average speed). The gamification feedback further reinforced persistence and motivation, providing direct evidence that affective and cognitive processes were intertwined in this AI–RME–Gamification environment.

Another salient theme was interactivity, expressed in both social and digital dimensions. Codes such as peer collaboration, leaderboard competition, and teacher mediation highlighted the interactive character of the learning process. One teacher commented, “Even students who are usually quiet wanted to contribute because they were curious about their scores on the leaderboard.” A student added, “I wanted to beat my friend’s score, so I tried again until I got it right.” These findings align with the RME characteristic of interactivity and confirm the statistical evidence that Gamification exerted a strong influence on Motivation (β = 0.405). They also extend existing research on ICT in mathematics education, where digital tools are shown to foster dialogical and collaborative learning (Drijvers, 2015).

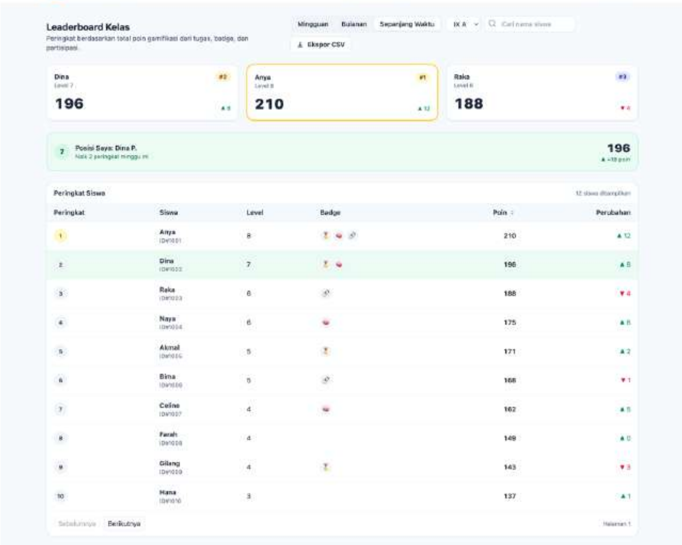


Figure 3. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

It shows the teacher dashboard and leaderboard from the platform. The dashboard tracks students' points, badge progression, and accumulated gamification points. This evidence demonstrates that the system captured not only final answers but also the learning process, allowing teachers to monitor reasoning quality and persistence directly. Another teacher observed that students used diagrams and tables to represent their thinking: "They rarely did this before, but now I see more of it." Students also noted the change: "I usually just wanted the answer, but now I try to show how I got it."

Figure 4 provides photographic evidence of students actively engaging with the AI–RME–Gamification platform in a classroom setting. It was demonstrated that students worked on contextual tasks individually, while also monitoring their progress on the leaderboard and exchanging strategies with their peers. This supports the qualitative findings that interactivity was not only digital, through the gamification features, but also social, as the visibility of scores stimulated peer collaboration and healthy competition.

Figure 4. Students engaging with the platform during classroom implementation

Phenomenological exploration was also a recurring pattern in the data (Treffers, 1991). Students consistently valued tasks that mirrored real-life situations, with codes such as relevance, authenticity, and transferability emerging across cases. One student noted, “Because the problems looked like shopping or transport, I understood why we needed the formulas.” Teachers reinforced this view, emphasizing that real contexts increased seriousness and focus: “When the questions are close to their daily life, the students are more serious. They see mathematics as something real.” These qualitative insights explain why Motivation significantly predicted Problem-Solving (β = 0.285): authentic contexts enhanced engagement, supporting OECD’s definition of mathematical literacy as the ability to apply mathematics meaningfully (OECD, 2019).

Both teachers and students observed the enhancement of problem-solving skills (Anugraheni et al., 2025). Codes such as reasoning, representation, explanation, and persistence dominated this theme. Teachers reported improvements not only in accuracy but also in the quality of reasoning: “They could explain their steps better, not only write the result.”

Table 6. Thematic Analysis of Qualitative Findings

Theme	Codes	Quote	Hypotesis Link
Guided Reinvention	AI scaffolding, self-construction, hints	“The system gave me hints when I was stuck, but it didn’t show the answer.” (Student)	RME ⟶ Motivation; RME ⟶ Problem-Solving
Interactivity	Peer collaboration, teacher mediation, leaderboard	“Even quiet students wanted to join because of the leaderboard.” (Teacher)	Gamification ⟶ Motivation
Phenomenological Exploration	Real-life contexts, relevance, transferability	“The problems looked like shopping or transport, so I understood why formulas are used.” (Student)	Motivation ⟶ Problem-Solving
Enhancement of Problem-Solving Skills	Reasoning, explanation, representation	“They could explain their steps better, not just write results.” (Teacher)	RME + Motivation ⟶ Problem-Solving

These themes were not isolated but interconnected. Guided reinvention was often facilitated by interactivity, as peer discussions and AI feedback worked in tandem to support independent strategy building. Phenomenological exploration gave meaning to reinvention and interactivity by situating problems in real-world contexts. Collectively, these processes culminated in enhanced problem-solving skills, as students demonstrated persistence, reasoning, and representation. This thematic integration illustrates the dynamic interplay of affective and cognitive processes in mathematics learning, consistent with Freudenthal’s (1991) vision of mathematics as a human activity and extending it into AI-driven, gamified environments.

Integration of Findings

The integration of quantitative and qualitative findings underscores the robustness of the AI–RME–Gamification model in enhancing both affective and cognitive dimensions of mathematics learning. The results of the SEM-PLS structural model were systematically triangulated with thematic evidence obtained from interviews and classroom observations. This process allowed the statistical associations to be validated through authentic learning experiences, thereby strengthening the explanatory power of the model.

Table 7. Integrated Structural and Qualitative Results

SEM-PLS	β	Qualitative Theme	Interview Quote	Integrated Interpretation
Gamification → Motivation	0.405	Interactivity, Engagement	"Even quiet students wanted to join because of the leaderboard."(Teacher)	Gamification sustains motivation through competitive but supportive interaction.
Gamification → Problem-Solving	0.191	Problem-Solving Enhancement	"I tried harder to solve the tasks because I wanted to level up." (Student)	Gamification directly encourages persistence in problem-solving.
RME → Motivation	0.351	Phenomenological Exploration	"Because the problems looked like shopping or transport, I understood the formulas better." (Student)	Contextualized tasks stimulate motivation through relevance.
RME → Problem-Solving	0.398	Guided Reinvention	"The system gave hints but not the answer, so I had to try different ways."(Student)	RME scaffolding supports progressive mathematization and problem-solving.
Motivation → Problem-Solving	0.285	Engagement, Persistence	"I kept trying because the points made me want to finish." (Student)	Motivation bridges affective engagement and cognitive performance.
Self-Efficacy → RME	0.305	Confidence, Self-construction	"I believed I could solve it myself if I tried step by step." (Student)	Self-efficacy strengthens the constructive aspect of RME.
Challenges → RME	0.304	Desirable Difficulties	"It was difficult, but the challenge made me think more carefully." (Student)	Challenges act as desirable difficulties enriching learning.
APOS Learning → RME	0.198	Conceptual Connections	"I understood how the steps connect to each other after trying again."(Student)	APOS progression supports formalization in RME processes.

Table 6 demonstrates a consistent alignment between statistical significance and lived classroom experiences. The strong effect of gamification on motivation (β = 0.405, t = 5.06) was vividly reflected in observations of heightened student engagement. Teachers reported that even students who were usually reluctant to participate became more active due to the visibility of the leaderboard. This demonstrates that gamification is not limited to providing external rewards, but also taps into social comparison and intrinsic curiosity, thereby amplifying the motivational pathway. The direct effect of gamification on problem-solving (β = 0.191, t = 2.60) was supported by students' testimonies, which indicated that the desire to progress to higher levels encouraged them to persevere with complex problems. This resonates with research on gamification as a source of sustained cognitive effort rather than superficial engagement.

The pivotal role of RME in the model was also evident. Statistically, RME predicted both motivation (β = 0.351, t = 3.51) and problem-solving (β = 0.398, t = 4.98). Qualitative evidence supported these effects through recurring themes of guided reinvention and phenomenological exploration. Students consistently emphasized that contextual problems made abstract concepts meaningful and that AI scaffolding, which provided hints without revealing solutions, pushed them to think independently. This aligns with Freudenthal's principle that mathematics must be connected to reality and progressively mathematized, as well as Gravemeijer's notion that design features should guide learners' reinvention of formal strategies (Gravemeijer, 1994).

The mediating effect of motivation on problem-solving (β = 0.285, t = 2.85) was also substantiated qualitatively. Students described a willingness to persist through challenges when motivated by the point and badge system. At the same time, teachers observed that motivated learners articulated their reasoning more clearly and made stronger conceptual connections. These findings support Supara Suparatulatorn's perspective that problem-solving is not merely cognitive but also driven by affective engagement (Suparatulatorn et al., 2023).

Finally, the contribution of internal learner factors to RME was validated by both data strands. Self-efficacy (β = 0.305, t = 4.20) emerged as a significant predictor, with students noting that confidence helped them persist with contextual tasks. Challenges (β = 0.304, t = 4.10) were reframed as opportunities rather than barriers, consistent with Bjork's principle of desirable difficulties (Bjork & Bjork, 2020). APOS-based learning (β = 0.198, t = 3.00) was evident in students' accounts of connecting informal steps to more formal strategies after repeated trials, highlighting the constructive role of AI scaffolding in supporting APOS transitions. The integrated findings reveal that gamification enhances motivation both directly and indirectly. RME serves as the central pedagogical mechanism for developing problem-solving skills, and internal learner factors strengthen the process of guided reinvention. The convergence of quantitative and qualitative evidence confirms that the AI–RME–Gamification model is not only statistically valid but also pedagogically grounded in classroom reality.

Motivation as The Mediating Bridge in AI-RME Gamification Learning

Mathematics is often viewed as a set of correct procedures without clear explanations (Martin & Towers, 2011). Many students view mathematics as a chore and often feel unsure about it, perceiving it as a complex subject to access (Raméntol & Camacho, 2016). This study responded to that problem by testing whether the deliberate combination of Realistic Mathematics Education (RME) contexts, gamification mechanics, and AI-driven scaffolding can convert affective engagement into durable cognitive gains in secondary classrooms. The structural model was specified to estimate the effects on learning motivation and problem-solving, while positioning self-efficacy, perceived challenge, and APOS-based learning processes as drivers of participation in RME activities. The central interpretive move throughout is to read the findings not as a checklist of significant paths, but as evidence for a coherent instructional ecology in which meaning, effort, and formalization are jointly produced.

A key result requires a reversal of a common assumption in the gamification literature. Rather than exerting a substantial direct impact on problem-solving, gamification's principal effect was on motivation (β = 0.405) with a more negligible, secondary direct effect on problem-solving (β = 0.191). Qualitative accounts explained this ordering. Leaderboards made social effort visible; points and levels regulated the pace of work; progression created reasons to persist when tasks became demanding. Gamification, in short, supplied energy rather than a method. The cognitive work remained mathematical, and the route from engagement to competence ran through motivation rather than around it.

RME played the complementary role of supplying semantic traction for that energy (Suparatulatorn et al., 2023). The model showed substantive effects of RME on both motivation (β = 0.351) and problem-solving (β = 0.398). Classroom narratives made the mechanism concrete: when tasks were rooted in familiar situations such as shopping or transportation, learners could anchor conjectures, construct representations, and connect ideas. AI feedback then functioned as a quiet coach, offering graded hints without revealing solutions so that informal strategies could be reorganized into formal ones. This is the classic RME logic, where context comes first, followed by formalization (Yilmaz, 2020), as demonstrated here in a technology-mediated setting. Motivation consequently occupied a structural position rather than a terminal one. It predicted problem-solving (β = 0.285) and mediated the influence of both RME and gamification on cognitive performance. The qualitative record gave that role psychological texture: curiosity and tenacity were the felt correlates of the mediating path, often visible when students chose to write one more line of work after an AI hint or a peer's contribution. Framed this way, motivation is not an optional add-on to instruction, but rather the bridge that enables contextual engagement to extend as far as formal competence.

Self-efficacy and challenge, often regarded as personal qualities, acted differently when placed within this ecology (Mukuka et al., 2021). Self-efficacy strengthened participation in RME rather than bypassing it (β = 0.305). Students who believed they could succeed were more willing to remain with a context, test a representation, and iterate after non-telling feedback. The theoretical implication is that confidence is most consequential when it is practice-embedded, rather than when it is presumed to yield outcomes directly. Perceived challenge likewise acted as a catalyst when intentionally designed and scaffolded (β = 0.304 to RME). Learners reported that difficult items prompted more careful thinking when AI feedback was timely and incremental; difficulty became desirable because the didactical conditions, meaningful context, controllable steps, and signals that effort matters were in place. APOS processes supplied the engine for formalization. Although the coefficient from APOS to RME was more modest (β = 0.198), observations traced a characteristic microgenetic arc: actions consolidated into processes, processes were reified into objects, and objects were coordinated within schemas. Iterative AI prompts and peer discussion synchronized the pace of this arc so that learners neither stalled too early nor jumped prematurely to the formula. The result is a visible and repeatable passage from context to structure, precisely the passage RME intends to cultivate.

The data also clarified contextual contingencies that matter for implementation. In urban schools with stronger ICT access, the social-affective route to motivation, visibility through leaderboards, friendly competition, and quick feedback, was particularly salient. In suburban schools, the dominant driver was the authenticity of context relative to students' daily experience. These findings suggest that the model should be tailored to local affordances: in some sites, emphasize the social mechanics that sustain attention; in others, invest more in the depth and fit of contextual scenarios that anchor meaning. Design consequences follow directly from the integrated evidence. First, contextual tasks must be crafted so that they actually conduce to formal ideas, not merely decorate them. Didactical phenomenology matters: the chosen phenomenon should organize the mathematics that learners are expected to reinvent. Second, gamification should be proportionate and instrumental, used to sustain attention and tenacity rather than to accelerate answer production. Third, AI scaffolding should calibrate challenge as a smooth ascent, with grain size and timing of prompts set to provoke new strategies without producing attrition. When these three elements are balanced, motivation becomes the transmission system that turns contextual engagement into mathematical performance.

Theoretical contribution is clearest in the repositioning of motivation within models of mathematics learning. Rather than treating it as a distal outcome, the study models motivation as a mediator that stitches together engagement structures and cognitive gains. It also defines conditions where desirable difficulties are genuinely beneficial, and contexts must be meaningful. Scaffolds should be unobtrusive yet timely, and social signals must convey the effort as meaningful. It clarifies that self-efficacy is most productive when it animates participation in RME practices rather than acting as a free-standing trait.

The findings yield a replicable instructional recipe: design high-quality RME tasks with clear routes to formalization; deploy gamification mechanics that encourage students to work without crowding out mathematical sense-making; and rely on adaptive AI scaffolds that preserve the integrity of guided reinvention. Schools can calibrate the entry point that shows social engagement or contextual relevance, according to their setting, while maintaining the mediator function of motivation as a design invariant. Instead of insisting on a strong direct path from gamification to competence, the analysis accepts that the primary gain is motivational and designs for it explicitly. Rather than viewing difficulty as a problem to eliminate, the design turns it into a resource. Instead of assuming self-efficacy works in isolation, the design fosters it through practice and training. AI regulates tempo, RME sets direction, gamification supplies momentum, and motivation binds the ensemble. By assigning motivation a structural role, the model shows how context becomes cognition in an AI-supported, gamified RME environment. The evidence points not only to improved scores but also to a shift in learners' stance toward mathematics, from something to get through to something worth working for. That reframing is the study's main contribution to mathematics education, and it offers a principled pathway for future design research that seeks to join meaning, effort, and formal understanding in a single, testable architecture.

CONCLUSION

This study investigated whether an instructional design that combines Realistic Mathematics Education, gamification, and AI scaffolding can raise secondary students' motivation and problem-solving while clarifying the roles of self-efficacy, perceived challenge, and APOS processes. The integrated quantitative–qualitative evidence meets that objective and explains the mechanism. RME provided semantic traction through meaningful contexts and guided reinvention. Gamification primarily energized motivation rather than cognition, and AI regulated the grain and timing of non-telling support so that struggle remained productive. Motivation functioned as a structural mediator linking engagement features to cognitive performance. At the same time, self-efficacy and challenge strengthened participation in RME, while APOS supplied the engine for formalization, moving from actions to processes, objects, and schemas. In doing so, the study advances the field by repositioning motivation from outcome to mechanism and by specifying the didactical conditions under which difficulty becomes desirable in digital mathematics learning.

The contributions are both explanatory and actionable. The work shows why and when the model succeeds, moving beyond assumptions of direct effects to a testable architecture in which meaning, effort, and formal understanding are jointly produced. It yields design guidance that teachers, curriculum developers, and platform designers can implement: select contexts that genuinely facilitate formal ideas, utilize game mechanics to sustain persistence and make effort socially visible, and deploy adaptive AI feedback that preserves the integrity of guided reinvention. Implementation can be tailored to local affordances by emphasizing social interactivity where ICT access is strong, or by deepening contextual relevance where lived experience is the more powerful entry point. Assessment and analytics should capture both process and product, rewarding explanations, connections, and representations, and instrumenting APOS-aligned progress so that dashboards reflect learning transformations rather than mere completion.

For future work, I recommend a two-track agenda that links rigorous evaluation with practical adaptation. First, establish durability and generalisability through longitudinal and multilevel designs that include simple within-semester pretest, posttest, and follow-up assessments in the same class, for example, at weeks 0, 6, and 12, together with sampling across multiple sites to estimate contextual moderators such as ICT access, class size, and curricular alignment. Second, pursue replication in

Commented [A221]: The main findings have been presented, but the sentences are too dense and somewhat difficult to digest. It would be better to break them down into more concise sentences to clarify the role of each component (RME, gamification, AI, motivation, APOS).
Technical terms such as semantic traction or grain and timing of non-telling support could be explained more simply so that non-expert readers can still understand the mechanisms.

Commented [A222]: The practical and theoretical contributions are good, but the sentences are long and a mix of design directives and implications. It's important to separate conceptual contributions (mechanism explanations) from practical contributions (implementation guidelines).
The recommendations section for teachers, curriculum developers, and platform designers should be focused on bullet points to be more applicable, rather than simply narrative paragraphs.

diverse settings, including urban, suburban, and resource-limited schools, by co-designing RME tasks with local teachers so that problems reflect students' lived realities. As a minimal requirement, develop at least two locally grounded contextual items in each site to preserve meaning while enabling comparison. Complement these strands with micro-experimental studies that vary the timing and granularity of AI scaffolds and compare reward structures that prioritize speed versus explanation in order to isolate mechanisms that convert engagement into reasoning. Throughout, employ mixed methods with process-sensitive measures of reasoning, connections, and representations, so that outcomes capture both learning processes and products. Report implementation details in sufficient depth to support reuse and cumulative synthesis.

Commented [A223]: The recommendations for future research are quite detailed, but they read more like a research proposal than a summary of conclusions. They should be summarized by emphasizing two key points: longitudinal sustainability testing and cross-context replication testing.
It's best to avoid too many technical details (e.g., weeks 0, 6, 12, or "at least two contextual items"), as these are more appropriate for the Future Research Agenda, not the main conclusions.

Declarations

The authors declare no conflict of interest.

REFERENCES

Commented [A224]: Quite adequate

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. Decision Making: Applications in Management and Engineering, 8(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. Cogent Education, 12(1). https://doi.org/10.1080/2331186X.2025.2523078

Ardi, Z., Rangka, I. B., Ifdil, I., Suranata, K., Azhar, Z., Daharnis, D., Afdal, A., & Alizamar, A. (2019). Exploring The Elementary Students' Learning Difficulties Risks On Mathematics Based On Students' Mathematical Anxiety, Mathematical Self-Efficacy, And Value Beliefs Using Rasch Measurement. Journal of Physics: Conference Series, 1157(3). https://doi.org/10.1088/1742-6596/1157/3/032095

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. Journal on Mathematics Education, 13(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. Journal of Primary Education, 9(5). https://doi.org/10.15294/jpe.v9i5.43223

Bandura, A. (1997). Self-Efficacy: The Exercise of Control. W.H. Freeman.

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. Computers in Human Behavior Reports, 16. https://doi.org/10.1016/j.chbr.2024.100491

Bayu, E. P. S., & Fauzan, A. (2023). Realistic Mathematics Education Approach. AIP Conference Proceedings, 2805(1). https://doi.org/10.1063/5.0148141

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. Proceedings of the Annual Hawaii International Conference on System Sciences, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). 2024 4th International Conference on Advance Computing and Innovative

Technologies in Engineering, ICACITE 2024, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503
Biccard, P. (2024). Productive Struggle in Mathematical Modelling. Mathematics Enthusiast, 21(1–2), 99–112. https://doi.org/10.54870/1551-3440.1620
Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. Memory and Cognition, 9(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf
Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
Cassells, T., Broin, D. O., & Power, K. (2015). Increasing student engagement with gamification. Proceedings of the European Conference on Games-Based Learning, 2015-January, 770–773. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84955057612&partnerID=40&md5=e171f2f895b18bd0a734988637b6f158
Creswell, J. W. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). SAGE Publications.
Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, 9–15. https://doi.org/10.1145/2181037.2181040
Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students' Mathematical Literacy Ability Through Information and Communication Technology-Assisted Preprospec Learning Model. International Journal of Educational Methodology, 9(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409
Dubinsky, E., & McDonald, M. A. (2001). APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf
Freudenthal, H. (1991). Revisiting Mathematics Education: China Lectures. Springer. https://doi.org/10.1007/0-306-47203-1
Gravemeijer, K. (1994). Developing Realistic Mathematics Education.
Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3). https://doi.org/10.1016/j.rmal.2022.100027
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In European Business Review (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203
Hikayat, C., Hairun, Y., & Suharna, H. (2020). Design of realistic mathematics education approach to improve critical thinking skills. Universal Journal of Educational Research, 8(6), 2232–2244. https://doi.org/10.13189/ujer.2020.080606
Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. Computers in Human Behavior, 149. https://doi.org/10.1016/j.chb.2023.107952
Jayaraman, V., Sundar, N., & Shankar, U. B. (2024). Breaking Math Anxiety: A Success Story From an Indian Government School. Proceedings of the European Conference on Games-Based Learning, 18(1), 440–446. https://doi.org/10.34190/ecgbl.18.1.3000
Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. Multidisciplinary Reviews, 8(5). https://doi.org/10.31893/multirev.2025155
Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. Computers and Education, 194. https://doi.org/10.1016/j.compedu.2022.104694
Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. International Journal of Engineering and Technology(UAE), 7(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). Developing Realistic Mathematics Education-Based Worksheets For Improving Students' Critical Thinking Skills. Infinity Journal, 12(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84
Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. Asian Journal for Mathematics Education, 3(3), 289–311. https://doi.org/10.1177/27527263241269060
Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In Structure and Improvisation in Creative Teaching (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013
Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. Educational Process: International Journal, 15. https://doi.org/10.22521/edupij.2025.15.179
Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. Proceedings of the International Conference on Education Research, ICER 2024, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5
Moleko, M. M. (2021). Multiple means of engagement strategies for maximising the learning of mathematics in pandemic-regulated classrooms. International Journal of Learning, Teaching and Educational Research, 20(8), 68–90. https://doi.org/10.26803/IJLTER.20.8.5
Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. Journal on Mathematics Education, 12(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732
Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. International Journal of Innovative Research and Scientific Studies, 8(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423
Nguyen, G. T. C., & Pham, C. T. H. (2023). An empirical study of factors influencing primary school teachers' long-term commitment to Realistic Mathematics Education. Journal on Mathematics Education, 14(1), 1–18. https://doi.org/10.22342/jme.v14i1.pp1-18
(OECD), O. for E. C. and D. (2019). PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm
Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. Journal of Pedagogical Research, 8(3), 333–346. https://doi.org/10.33902/JPR.202426428
Plomp, T. (2013). Educational Design Research: Part A: An Introduction. SLO.
Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? Mathematics Education Journal, 17(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120
Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. Journal on Mathematics Education, 13(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288
Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. Opcion, 32(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3
Samur, Y., & Cömert, Z. (2024). Gamification in education in the age of artificial intelligence. In Interdisciplinary Approach to Fostering Change in Schools (pp. 285–303). https://doi.org/10.4018/979-8-3693-4119-3.ch011

Siregar, H. S., Munir, M., & Fikri, M. (2025). Enhancing Islamic Education Through Technology Integration: A Study Of Teaching Practices In Indonesia. Jurnal Ilmiah Peuradeun, 13(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. Journal on Mathematics Education, 16(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Son, A. L. (2022). The Students' Abilities on Mathematical Connections: A Comparative Study Based on Learning Models Intervention. Mathematics Teaching-Research Journal, 14(2), 72–87. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85135831915&partnerID=40&md5=41c4caeab639ecc2cfe8e7fdb8c52a6d

Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. Journal on Mathematics Education, 14(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 15348 LNCS, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Wilkie, K. J. (2016). Rise or Resist: Exploring Senior Secondary Students' Reactions to Challenging Mathematics Tasks Incorporating Multiple Strategies. Eurasia Journal of Mathematics, Science and Technology Education, 12(8), 2061–2083. https://doi.org/10.12973/eurasia.2016.1260a

Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. Journal on Mathematics Education, 11(1). https://doi.org/10.22342/jme.11.1.8690.17-44

Yohannes, A., & Chen, H.-L. (2024). The effect of flipped realistic mathematics education on students' achievement, mathematics self-efficacy and critical thinking tendency. Education and Information Technologies, 29(13), 16177–16203. https://doi.org/10.1007/s10639-024-12502-8

Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. Journal of Physics: Conference Series, 947(1). https://doi.org/10.1088/1742-6596/947/1/012015

3
BUKTI KONFIRMASI SUBMIT REVISI PERTAMA, RESPON KEPADA REVIEWER, DAN ARTIKEL YANG DIRESUBMIT
(12 NOVEMBER 2025)

Wati Susilawati <wati85@uinsgd.ac.id>
kepada pasqa, jme

Rab, 12 Nov, 09.13

Dear Editor,

First, thank you for kindly granting us an extension to complete the revisions. The additional time allowed us to address the reviewers' suggestions thoroughly and improve the manuscript's clarity, coherence, and contribution.

We are pleased to resubmit our revised manuscript, "Integrating Realistic Mathematics Education, AI, and Gamification in Indonesian Secondary Mathematics," for consideration in JME. We have responded to every comment point-by-point in the attached "Recapitulation Revision." A clean version and a tracked-changes version are enclosed.

Highlights of the revisions

1. **Title & Abstract** — Title shortened to foreground the main contribution; abstract rebalanced with background, objectives, methods, results, and implications, including numerical coefficients (e.g., $\beta = 0.351$; $\beta = 0.398$) and a clearer novelty statement.
2. **Introduction** — Research gap sharpened (RME, AI scaffolding, and gamification often studied in isolation); explicit definition of AI scaffolding with recent references; methodological details moved to *Methods*.
3. **Methodology** — Expanded description of tiered AI scaffolding aligned to the APOS framework; added sampling details, ethical clearance, and consent; introduced Table 1 (constructs ↔ objectives) and sample items; corrected figure numbering and redesigned instructional flow.
4. **Results & Discussion** — Results presented strictly statistically, with confidence intervals and fit indices; interpretation separated from results; added triangulated classroom observations and a joint display linking quantitative paths with qualitative evidence.
5. **Conclusion** — Refocused on theoretical and practical contributions; concise directions for future research; clearer limitations.
6. **Language & Presentation** — Streamlined prose; reorganized tables/figures/captions; updated references and ensured citation consistency.

We believe the revised manuscript now meets JME's standards and offers robust empirical evidence with actionable pedagogical implications for mathematics learning in the digital era. We appreciate the opportunity to improve our work and respectfully submit this version for your consideration.

Sincerely,

Wati Susilawati, M. Pasqa, Sergii Sharov, and Co-authors
Corresponding Author: wati85@uinsgd.ac.id

2 Lampiran • Dipindai oleh Gmail Tambahkan semua ke Drive

Recapitulation Re... Revisi Wati JME - ...

Notifications

[jme] Editor Decision	2025-10-08 01:25 AM

Reviewer's Attachments

Search

6868	jme-review-assignment-3875-Article+Text-6792.docx	September 27, 2025
6925	jme-review-assignment-3875-Article+Text-6792 (1).docx	October 7, 2025

Revisions

Search Upload File

7149	Revisi Wati JME - Track Changes On Review.docx	November 12, 2025	Article Text
7150	Recapitulation Revision " Integrating Realistic Mathematics Education, AI, and Gamification to Enhance Students' Mathematical Problem-Solving".docx	November 12, 2025	Recapitulation The Contents of the Revised Article

Review Discussions

Add discussion

Name	From	Last Reply	Replies	Closed
Request for Extension – Revision of Manuscript JME	wati85 2025-10-20 05:28 AM	-	0	
Submit Revision	wati85 2025-11-12 02:05 AM	-	0	

Journal on Mathematics Education
Volume xx, No. x, xxxx, pp. xx-xx

Integrating Realistic Mathematics Education, AI, and Gamification to Enhance Students' Learning Motivation and Problem-Solving Skills

Deleted: Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving

Abstract

The integration of artificial intelligence and gamification in realistic mathematics education offers significant opportunities to create meaningful, innovative, and adaptive learning experiences that emphasize student motivation and active engagement in solving non-routine mathematical problems. However, there are still several challenges to implementing this three-way integration, such as teachers' limited digital literacy, the lack of realistic mathematics education models that systematically combine artificial intelligence and gamification, and the persistent separation of these components in mathematics education practice. This study aims to explore how the synergy between artificial intelligence and gamification scaffolding can support realistic mathematics education in enhancing learning motivation and problem-solving abilities. The research employs a sequential explanatory mixed-methods design, involving 300 secondary school students from six secondary schools in Indonesia. Data were collected through mathematical problem-solving ability tests and non-test instruments, including observations and interviews. Quantitative data analysis was conducted using Structural Equation Modeling (SEM), and qualitative data were analyzed through thematic analysis. Results indicate that realistic mathematics education supported by artificial intelligence and APOS transition strategies with gamification elements significantly enhances mathematical problem-solving abilities (β = 0.40) and student learning motivation (β = 0.35), with an overall effect value of (β = 0.41). This study contributes to instructional design that can be systematically replicated, incorporating integration stages within realistic learning contexts, AI-based adaptive support, and game mechanics to build student engagement and intrinsic motivation. It offers theoretical and practical implications for developing realistic, adaptive mathematics education oriented toward meaningful learning experiences in problem-solving in the digital era.

Deleted: Mathematics learning in the digital era requires approaches that enhance motivation and strengthen problem-solving skills. This study tests an integrated model that combines Realistic Mathematics Education, artificial intelligence scaffolding, and gamification, while considering self-efficacy, perceived challenge, and Action Process Object Schema (APOS) progressions. We employed an explanatory sequential mixed-methods design with 300 secondary students from six schools. The quantitative phase estimated a structural equation model; the qualitative phase included classroom observations and interviews. Results show that RME exerted the most significant direct effect on mathematical problem-solving and also raised motivation by contextualizing tasks. Gamification significantly increased motivation, which in turn supported persistence and problem-solving. AI scaffolding delivered tiered hints that preserved students' ownership of strategies and helped transitions along the APOS trajectory. Motivation emerged as the central pathway linking engagement features to cognitive gains. The study contributes a replicable design and actionable guidance for aligning context, adaptive support, and proportionate game mechanics to improve mathematics learning in classrooms.

Keywords: Artificial Intelligence, Gamification, Learning Motivation, Problem Solving, Realistic Mathematics Education

Mathematics learning supported by artificial intelligence and gamification becomes more meaningful when students connect mathematical ideas to real-world situations, enabling them to reconstruct formal concepts from their informal understanding and thereby strengthen their problem-solving skills (Bayaga, 2024; Rane, 2023). This is the central idea of Realistic Mathematics Education, where phenomena from everyday life are used to organise the mathematics that learners are expected to reinvent (Siswantari et al., 2025). When tasks are based on familiar practices, students can anchor their ideas, create representations, and build connections that naturally guide them toward more formal structures. The transition from context to concept represents a deliberate learning trajectory that helps students understand mathematical procedures through adaptive AI support and gamification engagement in solving non-routine problems with multiple solution paths or multiple valid solutions distinguished by clear reasoning (A. M. Canonigo, 2024; Ng et al., 2024). However, maintaining this contextual and meaning-

Deleted: Learning in mathematics becomes more meaningful when students can connect ideas to familiar situations and are supported in reconstructing formal concepts from their own informal understanding. Reasoning (Hikayat et al., 2020; Son, 2022).

Deleted: When tasks are rooted in familiar practices, students can anchor their conjectures, construct representations, and make connections that naturally lead toward more formal structures.

Deleted: The movement from context to concept is not incidental; it is a deliberate trajectory that helps students understand why procedures work, rather than just how to perform them (Nguyen & Pham, 2023).

http://doi.org/10.22342/jme.v13i1.xxxx

oriented approach in today's digital classrooms requires adaptive technological support and sustained engagement, challenges that this study addresses through the integration of AI and gamification within the RME framework.

Educational AI offers adaptive support that can enhance the RME learning process through responsive feedback systems. Intelligent tutoring systems now utilize natural language processing and deep learning to deliver personalized hints and guidance, enabling students to develop their own reasoning (Bayaga, 2024; Roldán-Álvarez & Mesa, 2024). With the growing availability of open-source AI tools, these adaptive capabilities are becoming accessible to a wider range of educational settings (Matzakos et al., 2023). At the core of this technology is AI scaffolding, which adjusts support to individual student needs and gradually reduces guidance as learners develop competence. This approach mirrors the role of a responsive tutor by delivering timely hints and prompts that help students construct their own understanding independently(Malik, 2024). Through step-by-step explanations and interactive dialogue, AI systems enable students to ask follow-up questions and receive personalized support while maintaining an active role in problem-solving (Yin & Yin, 2024).

Complementing this technological support, gamification in mathematics education consistently enhances engagement, motivation, and cognitive development (Hui & Mahmud, 2023; Zabala-Vargas et al., 2021). Well-designed game elements such as points, levels, and badges can sustain students' effort and curiosity throughout the RME learning trajectory (Ariffin et al., 2022). Rather than serving as external rewards, these features function as didactical tools that protect the time and attention needed for sense-making (Al-Barakat et al., 2025; Jun & Lucas, 2025). AI and gamification complement each other in strengthening RME in distinct ways: AI enables guided reinvention through responsive feedback, while gamification maintains learning motivation and persistence. Together, these elements create an integrated learning environment that channels student motivation into deeper reasoning and stronger problem-solving skills(Bhardwaj, 2024; Mitchell & Co, 2024).

These considerations are especially relevant in the Indonesian, where improving mathematical literacy remains a persistent challenge (Ndiung & Menggo, 2025). Results from the Programme for International Student Assessment (PISA) indicate that Indonesian students often struggle with contextual reasoning and higher-order problem-solving, revealing a gap between procedural competence and the ability to apply mathematics in real-world situations (Zulkardi & Kohar, 2018). In response, national initiatives have promoted RME-inspired approaches to make mathematics more relevant through tasks related to students' daily practices, such as trade, transportation, and cultural activities (Dewi & Maulida, 2023).However, despite these policy efforts, implementation remains uneven and largely confined to conventional classrooms with limited technological support (Siregar et al., 2025). This creates a persistent gap between policy aspirations and classroom realities, weakening the intended impact of mathematics education reform.

The rapid growth of digital learning platforms and gamified applications in Indonesian schools has not always been supported by strong pedagogical design (Maryani et al., 2025). Many platforms encourage surface-level engagement rather than deep conceptual understanding because they rarely align with established didactical frameworks. This raises important questions about how emerging approaches interact within integrated designs. Self-efficacy, for example, has been extensively researched in relation to achievement and motivation, yet its role within AI-supported, gamified RME environments at the secondary level remains poorly understood, especially in Indonesia (Mukuka et al., 2021; Siswantari et al., 2025). Existing studies tend to treat confidence as a background trait rather than as a dynamic factor shaping how students engage with contextual tasks, adaptive scaffolding, and game

Formatted: Font: Not Bold

Deleted: Well-designed game elements can extend this learning trajectory by sustaining effort over time

Deleted: . Systems that reward persistence, revision, and explanation help students stay engaged with a problem long enough to test their ideas and refine their strategies

Deleted: Click or tap here to enter text

Deleted: . Used in this way, gamification does not replace mathematical thinking; it protects the time and attention that sense-making requires . Recent progress in educational AI adds a third strand by providing feedback that adapts to the learner and offers hints without telling the answer. Such support keeps students in productive struggle and preserves ownership of the solution path. When these strands are combined, context supplies meaning, game elements maintain stamina, and AI provides just-in-time scaffolding

Deleted: Click or tap here to enter text.Click or tap here to enter text..

Deleted: Indonesia

Formatted: No widow/orphan control, Border: Top: (No border), Bottom: (No border), Left: (No border), Right: (No border), Between : (No border)

Deleted: Results from the Programme for International Student Assessment (PISA) indicate that Indonesian students often face difficulties with contextual reasoning and higher-order problem-solving, highlighting a gap between procedural competence and the ability to apply mathematics in real-world situations

Deleted: National initiatives have promoted RME-inspired approaches to make mathematics more relevant, for example, through tasks linked to students' everyday practices such as trade, transportation, and cultural activities

Deleted: . However, these practices remain unevenly implemented and often constrained to conventional classrooms with limited technological support mechanics (Rahayu et al., 2022). Similarly, the role of perceived challenge in digital mathematics learning requires closer examination. In gamified environments, precise adjustment of difficulty offers opportunities to transform challenges into drivers of persistence, reasoning, and problem-solving (Beukes et al., 2024; Koskinen et al., 2023). This reframes challenge from an obstacle into a pedagogical variable that can be intentionally designed.

A critical gap emerges around the role of learning motivation in connecting these design elements to problem-solving outcomes. Although earlier studies have explored gamification or RME separately, few have investigated how motivation structurally mediates the influence of calibrated difficulty and contextualized learning in AI-supported settings (Hu et al., 2023; Mitchell & Co, 2024). RME research in Indonesia has been primarily grounded in conventional classrooms, with limited attention to how digital scaffolds and game-based engagement can enhance its effects on problem-solving (Lady et al., 2018; Lestari et al., 2023; Siswantari et al., 2025). By integrating RME, gamification, and AI, this study offers a promising pathway for bridging the gap between policy and practice, situating mathematical activity in students' lived realities while using digital tools to sustain motivation and scaffold reinvention (Li & Noori, 2024; Opesemowo & Ndlovu, 2024; Torres-Toukoumidis et al., 2025).

This study has two main objectives aligned with the Indonesian secondary education context. First, it assesses an integrated instructional model that merges Realistic Mathematics Education, gamification, and AI scaffolding, examining their direct and indirect impacts on students' learning motivation and mathematical problem-solving skills. The model positions self-efficacy, perceived challenge, and APOS-based learning as factors influencing engagement with gamification and RME, testing whether learning motivation mediates the relationships between these design levers and problem-solving performance. Second, it explains how these statistical effects materialize in classroom practice by tracing the mechanisms that connect contextual tasks, game mechanics, and adaptive feedback to students' problem-solving skills through observations and interviews.

We hypothesize that self-efficacy, perceived challenge, and APOS-based learning positively predict engagement with both gamification and RME. While gamification is expected to influence problem-solving skills primarily through its effect on learning motivation, RME is anticipated to show direct positive impacts on both motivation and problem-solving skills. Most importantly, we expect learning motivation to function as a structural mediator linking the design levers to mathematical performance, representing a novel reconceptualization of motivation's role in technology-enhanced mathematics education.

By repositioning learning motivation as a structural mediator rather than an endpoint, this study makes three key contributions to mathematics education. First, it clarifies the didactical conditions under which difficulty becomes desirable in digital mathematics learning: meaningful RME contexts that connect to students' realities, adaptive non-telling AI scaffolds that sustain productive struggle, and gamification incentives that reward persistence and explanation rather than speed alone. Second, it operationalizes the APOS progression within an AI-supported, gamified RME environment, making students' problem-solving skills trajectories from action to process to object to schema both observable and designable in secondary classrooms. Third, it provides a replicable instructional model specifically calibrated for Indonesian schools, offering empirical evidence and practical guidance for integrating contextual learning, adaptive support, and proportionate game mechanics. These contributions address the critical need for pedagogically-grounded approaches to digital mathematics learning while advancing theoretical understanding of how motivation transforms engagement into mathematical competence.

Deleted: (Li & Noori, 2024; Opesemowo & Ndlovu, 2024; Torres-Toukoumidis et al., 2025)Meanwhile, the rapid growth of digital learning platforms and the increasing presence of gamified applications in Indonesian schools have not always been accompanied by sound pedagogical integration

Deleted: . Many platforms risk promoting superficial engagement rather than fostering deep understanding, as they rarely align with established didactical frameworks. Against this backdrop, the integration of RME, gamification, and AI represents a promising direction for connecting contextual meaning with technological innovation . By situating mathematical activity in students' lived realities while harnessing digital tools to sustain motivation and scaffold reinvention, such integration has the potential to advance both local and international discourses on mathematics education .
Despite steady advances in mathematics education, several uncertainties remain in how emerging approaches interact. Self-efficacy, for example, has been extensively researched in relation to achievement and motivation; however, its role within AI-supported, gamified RME environments at the secondary level remains poorly understood, especially in Indonesia . Existing studies tend to treat confidence as a background trait rather than as a dynamic factor shaping how students engage with contextual tasks, adaptive scaffolding, and game mechanics . This leaves unanswered questions about how students' beliefs in their own abilities actually influence their participation and persistence in such integrated designs.
Similarly, RME research in Indonesia has been primarily grounded in conventional classrooms, with limited attention to how digital scaffolds and game-based engagement can enhance its effects on problem-solving To address these gaps, the Indonesian secondary education context needrequires solid evidence on how AI-supported gamification and RME can work together to boostenhance learning motivation and problem-solving while maintaining mathematical sense-making. Although technology is increasingly present in classrooms, its use often targets superficial engagement and is seldom grounded in a didactic framework that supports guided reinvention . At the same time, national efforts to adopt RME remain inconsistent and are seldom supported by adaptive feedback that can keep students engaged in productive struggle .

Deleted: Accordingly, this study aims to pursue two clear objectives. First, it evaluates an integrated instructional model that combines RME, gamification, and AI scaffolding by estimating direct and indirect effects on secondary students' learning motivation and mathematical problem solving using SEM–PLS; the model positions self-efficacy, perceived challenge, and Action, Process, Object, Scheme (APOS) based learning as antecedents to engagement with gamification and RME, and tests whether motivation mediates the pathway to problem solving. Second, it explains how these statistical effects unfold in practice through thematic analysis of student and teacher interviews and classroom observations, thereby clarifying the mechanisms that link contextual tasks, game mechanics, and adaptive feedback with students' reasoning.

METHODS

Research Design

This study employed an explanatory sequential mixed-methods design (Creswell, 2018) within the framework of educational design research (Gravemeijer, 1994; Plomp, 2013). We chose this design because the aims required complementary evidence: to test the effects of an integrated RME, gamification, and AI model on students' motivation and problem-solving skills, and to explain how those effects arise in classrooms. We used SEM to model latent constructs in the quantitative phase, estimating simultaneous direct and indirect paths and testing mediation within a single system. PLS-SEM was employed to fit the model's complexity, predictive focus, and non-normal school data. Measurement quality was assessed with indicator loadings greater than 0.70, average variance extracted greater than 0.50, and composite reliability greater than 0.80; model adequacy with SRMR below 0.08 and evidence of predictive relevance. The qualitative phase then examined students and teachers, focusing on observations that traced how non-telling, tiered hints were used in practice, how game mechanics supported persistence without displacing mathematical thinking, and how contextual tasks supported APOS-aligned shifts in reasoning. The qualitative inquiry targeted three model patterns: RME's strongest direct effects on learning motivation and problem-solving skills, gamification's primarily indirect pathway via motivation, and the roles of self-efficacy and perceived challenge as antecedents.

We identified key problems in mathematics learning, particularly students' low learning motivation and difficulties in transferring problem-solving strategies to contextual situations. A review of theoretical perspectives in RME principles (Freudenthal, 1991; Gravemeijer, 1994), the APOS framework (Dubinsky & McDonald, 2001), and gamification theory (Deterding et al., 2011) informed the conceptual model. We designed an instructional model that integrates RME contextual tasks, gamification (points, levels, badges, leaderboards), and AI scaffolding. AI provides tiered hints (Tiers 1–3) that support the shift from informal strategies to formal reasoning along the APOS sequence (Action, Process, Object, Schema).

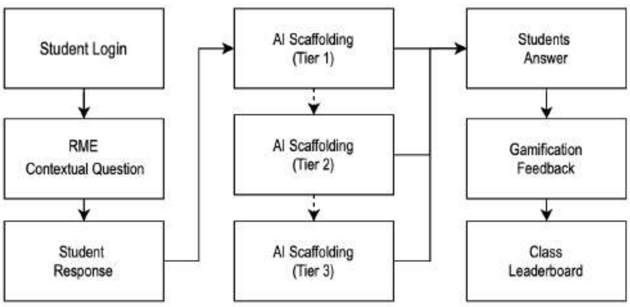


Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding

As shown in Figure 1, students first log in, receive an RME contextual question, and submit an initial response. The system then conditionally triggers AI scaffolding in APOS-aligned tiers that are delivered only when needed: Tier 1 (Action) prompts sense-making of quantities and first steps, Tier 2

Deleted: This study evaluates an integrated model that combines RME, gamification, and AI scaffolding to estimate the direct and indirect effects on secondary students' learning motivation and mathematical problem-solving. We ask four questions that emphasize the mechanism and align with the structure model: (1) to what extent do self-efficacy, perceived challenge, and APOS-based learning predict students' engagement with the two design levers, Gamification and RME; (2) what are the direct and indirect effects of Gamification and RME on learning motivation and on mathematical problem solving when all paths are estimated simultaneously; (3) does learning motivation mediate the relationships from Gamification and from RME to problem solving, and how significant are the mediated effects relative to any direct effects; and (4) once competing paths are controlled, which predictors exert the most substantial standardized effects on motivation and on problem solving. Based on our conceptual model, we propose a clear set of hypotheses. First, self-efficacy, perceived challenge, and APOS-based learning are expected to positively predict students' engagement with the two design levers, Gamification and RME. Second, gamification is likely to contribute to problem-solving primarily through its impact on learning motivation, rather than through a direct path. In contrast, RME is anticipated to have at least moderate positive effects on both motivation and problem-solving. Third, learning motivation is expected to positively predict problem-solving and exert an influence on both design levers, ultimately affecting performance.
We adopt an educational design research stance, employing an explanatory sequential mixed-methods design. This approach involves estimating a structural model using SEM–PLS and explaining proposed mechanisms through thematic analysis of interviews and classroom observations. The study's contributions are threefold. Conceptually, it reframes motivation from an outcome to a structural mediator th ... [1]

Deleted: situated

Deleted: the broader paradigm of

Deleted: While the explanatory sequential approach allowed the combination of quantitative and qualitative data to provide a comprehensive picture, embedding the study in the design research tradition emphasized the dual aim of empirical testing and instructional model development. In line with this framework, the research did not merely evaluate causal ... [2]

Deleted: Analysis and Exploration.

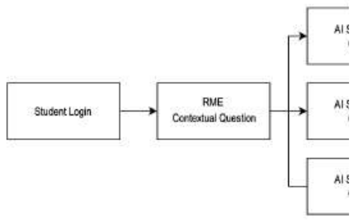
Deleted: The first phase involved

Deleted: students'

Formatted: No bullets or numbering

Deleted: Based on the theoretical synthesis, an instructional model was developed that integrates RME-based contextual tasks to foster phenomenological exploration and guided reinvention, as well as gamification mechanics (points, levels, leaderboards, and badges) to sustain student engagement. Additionally, AI-driven personalization is used t ... [3]

Deleted:
Evaluation and Reflection. The proposed model was tested in a large-scale quantitative phase using Structural Equation Modeling with Partial Least Squares (SEM-PLS), followed by qualitative interviews and classroom observations to refine the interpretation. This cycle allowed the mode ... [4]



Deleted:

Deleted: and APOS progression

(Process) cues representation building and relations among steps, and Tier 3 (Object/Schema) nudges generalization, subgoal decomposition, or linking the problem to a known structure. Tiers are progressive but not strictly linear: escalation occurs only when there is evidence of being stuck (repeated errors, unproductive looping, prolonged inactivity, or a help request) and does not occur if a Tier 1 prompt restores progress; learners may cycle within a tier while revising, and de-escalation happens implicitly once independent progress resumes. Hints never reveal answers; each prompt requires the next piece of mathematics and verifies that production before further support. After hints, students submit their answer, the system provides gamification feedback (points and badges) and updates the class leaderboard so persistence and revision are visible, and the platform logs attempts, hint levels, and revisions to document movement along the APOS trajectory from informal actions toward more formal problem solving.

Deleted: As shown in Figure 1, the flowchart highlights the central role of AI scaffolding in guiding students' reasoning. The system does not simply provide answers but supports progressive mathematization by offering tiered hints (Tier 1–3) that correspond to students' evolving levels of understanding. Student responses are structured through the APOS framework, and their persistence is reinforced by gamification feedback, including points, badges, and leaderboards. This integration ensures that cognitive development (problem-solving strategies) and affective engagement (motivation) are intertwined within a coherent instructional cycle. By adopting this design, the study contributes not only empirical evidence regarding the relationships among AI, gamification, RME, learning motivation, and problem-solving, but also theoretical advancement through a model that operationalizes progressive mathematization in a digital environment.

Participants

The study involved 300 Grade VIII students drawn from six junior secondary schools in Bandung and its outskirts using a stratified sampling approach based on sector, region, and accreditation. The strata comprised four urban public junior secondary schools (SMP) with superior accreditation and two suburban private Islamic junior secondary schools (MTs) with superior accreditation. Each participating school contributed two intact Grade VIII classes, randomly selected from the school's official Grade VIII list to preserve natural classroom groupings and avoid cross-class contamination, yielding twelve classes overall. Class selection was nested within the school-level strata, defined as sector (public vs private), region (urban vs suburban), and accreditation, such that eight classes came from the four urban public SMP and four classes came from the two suburban private MTs. Class lists typically ranged from 25 to 30 students. The analytic sample comprised 300 students after consent and attendance screening, with 195 from public schools and 105 from private schools, and a near-balanced gender distribution of 154 females and 146 males. Students were typically 13–14 years old, consistent with Grade VIII in the Indonesian system.

Eligibility required current enrollment in Grade VIII and attendance on the scheduled data-collection days. Recruitment and data collection were coordinated with school administrators and homeroom teachers to minimize disruption. Participation followed school approvals and standard consent and assent procedures. Learning activities and measurements were embedded within regular mathematics periods and organized across seven sessions to align with normal instructional routines. For the explanatory qualitative phase, six students were purposively selected from the quantitative cohort using latent profiles to represent high, middle, and struggling levels of motivation and problem-solving skills. In addition, three mathematics teachers with 5–10 years of experience and prior familiarity with contextual tasks participated in semi-structured interviews and classroom observations. This maximum-variation strategy supported mechanism-focused explanations of how the integrated RME, gamification, and AI design operated in authentic lessons from both student and teacher perspectives.

Deleted: Click or tap here to enter text., which values diversity in students' backgrounds and experiences. The sample comprised 195 students (65%) from public schools and 105 students (35%) from private schools, with four schools located in urban areas and two in suburban settings, thereby reflecting differences in access to digital resources and exposure to ICT. The gender distribution was nearly balanced, with 52% female and 48% male students. For the qualitative phase, six students were purposively selected based on their latent scores from the SEM-PLS analysis to capture a spectrum of achievement and motivational profiles, including high-achieving, average, and struggling learners. In addition, three mathematics teachers with 5–10 years of teaching experience and prior familiarity with contextualized instruction participated in the study. This purposive sampling enabled a richer understanding of how students and teachers constructed meaning within the AI–RME–gamification learning environment, ensuring that the analysis incorporated multiple perspectives across different educational roles.

Data Collection Techniques

The quantitative data were collected using a validated questionnaire with 27 items measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument evaluated seven core constructs listed in Table 1:

Table 1. Operational Definitions of Research Constructs

Construct	Theoretical Framework	Operational Definition	Sample Items	Items
Students' Challenges	Desirable Difficulties Theory (Bjork & Bjork, 2020)	Perceived level of productive difficulty in mathematical tasks	1. The problems required sustained effort over several steps 2. I needed to try more than one approach before making progress	4
Students' Learning (APOS)	APOS Theory (Dubinsky & McDonald, 2001)	Progression through Action-Process-Object-Schema stages	1. I can explain how my initial actions connect to a general rule 2. I translated concrete steps into a more formal representation"	4
Self-Efficacy in Mathematics	Self-Efficacy Theory (Bandura, 1997)	Confidence in one's ability to succeed in mathematical tasks	1. I am confident I can handle challenging mathematics problems 2. When I get stuck, I can find a way to move forward"	4
Gamification	Gamification Framework (Deterding et al., 2011)	Engagement with game elements in learning	1. Points and levels encourage me to continue working on the task 2. Badges or leaderboards make my effort feel visible"	3
RME AI	RME Principles (Freudenthal, 1991)	Integration of AI scaffolding with realistic contexts	1. AI hints helped me think without giving away the answer 2. AI guidance together with real-life contexts made the mathematics more meaningful"	4
Learning Motivation	Self-Determination Theory (Ryan & Deci, 2000)	Drive to engage and persist in mathematical learning	1. I wanted to keep trying even after making mistakes 2. These activities increased my interest in learning mathematics"	4
Mathematical Problem-Solving Skills	Mathematical Literacy Framework (OECD, 2019)	Ability to apply mathematical reasoning to non-routine problems	1. I can use multiple strategies to tackle non-routine problems 2. "I can justify why my solution works"	4

Instrument development followed a three-step validation process. First, three mathematics education experts reviewed item content for relevance and theoretical alignment. Second, a pilot with 50 students was used to refine clarity and response patterns. Third, outer-model analysis in PLS examined indicator loadings, average variance extracted (AVE), composite reliability (CR), discriminant validity, and Cronbach's alpha for each construct. All procedures followed international reporting standards (e.g., Hair et al., 2019). Detailed indices (α, CR, AVE, loading ranges) will be reported in the Results section under the measurement model.

The qualitative component employed semi-structured interviews with six students and three teachers, each lasting approximately 30-40 minutes and audio-recorded with consent. Student selection followed a systematic sampling strategy based on tertile cut-offs from standardized motivation and problem-solving scores, yielding two high-performing, two mid-range, and two struggling learners to ensure maximum variation in perspectives. The interview protocol explored three key dimensions: students' experiences with contextualized RME tasks reflecting phenomenological exploration, the perceived influence of gamification mechanics (points, badges, leaderboards) on engagement and persistence, and the role of AI scaffolding in supporting guided reinvention from informal reasoning to formal mathematical knowledge. Complementing these interviews, classroom observations during the AI-RME-gamification implementation captured behavioral indicators of learning processes. Field notes documented core RME characteristics including interactivity patterns, peer collaboration dynamics, and evidence of student mathematical contributions. Observers also traced transitions between horizontal mathematization (connecting within contexts) and vertical mathematization (moving toward abstraction), situating learning within the progressive mathematization framework. This triangulation of interview and observational data strengthened explanatory links between quantitative patterns and classroom mechanisms.

The study adhered to strict ethical protocols including institutional approval and informed consent procedures. Student data protection measures included pseudonymization using coded identifiers, with names and contact information stored separately from response data on password-protected institutional drives accessible only to the research team. API interactions were designed to transmit only study IDs, timestamps, and item content, ensuring no personally identifying information was shared with external services. Data retention followed institutional policies with defined storage periods and secure disposal procedures.

Data Analysis Techniques

The quantitative data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS, an approach suited for predictive modeling with complex latent constructs (J. Hair & Alamer, 2022). The analysis included both the measurement model, to assess indicator reliability and validity, and the structural model, to examine path coefficients and predictive relevance. Instrument validity was confirmed through factor loadings above 0.70, Average Variance Extracted (AVE) values above 0.50, and composite reliability scores above 0.80. Discriminant validity was established through the Fornell–Larcker criterion and the HTMT ratio, ensuring that constructs were distinct yet theoretically coherent (J. F. Hair et al., 2019).

The qualitative data from interviews and classroom observations were analyzed using thematic analysis (Braun & Clarke, 2006). Initial codes were generated inductively, then interpreted through the lens of RME's didactical phenomenology focusing on themes such as engagement with contextual tasks, the motivational effects of gamification, and the role of AI in scaffolding guided reinvention. The results were combined during the interpretation phase. For instance, the strong link between gamification and motivation was attributed to students' enthusiasm for points and leaderboards. Meanwhile, teacher observations of contextual reasoning supported the connection from RME to Problem-Solving Skills. This triangulation exemplifies the design research cycle, integrating empirical data with phenomenological insights.

Deleted: ¶

Deleted: (Freudenthal, 1991),

Deleted: . Finally, quantitative and qualitative results were integrated at the interpretation stage. For example, the significant path from Gamification → Motivation was explained by students' enthusiasm for points and leaderboards, while teacher observations of contextual reasoning supported the path from RME → Problem-Solving Skills. This triangulation reflected the design research cycle, combining empirical testing with phenomenological insights.

RESULTS AND DISCUSSION

The quantitative analysis revealed a consistent pattern emphasizing the central role of RME and motivation in this instructional model. Gamification exerted a significant positive effect on learning motivation ($\beta = 0.406$) and also directly contributed to problem-solving skills ($\beta = 0.191$). Beyond its direct effect, gamification indirectly supported problem-solving through learning motivation, emphasizing its role in sustaining student engagement throughout the learning cycle. RME emerged as a pivotal construct in the model, exerting substantial effects on both learning motivation ($\beta = 0.351$) and problem-solving skills ($\beta = 0.336$). Learning motivation itself proved to be a significant predictor of problem-solving skills ($\beta = 0.285$), underscoring its mediating role. This suggests that students who are both intrinsically and extrinsically motivated are better positioned to develop higher-order reasoning, make connections, and effectively represent mathematical ideas. The mediating role of learning motivation highlights the novelty of this study, demonstrating that gamification and RME function not only as instructional approaches but also as practical drivers of mathematical competence. Internal learner factors also played a critical role in strengthening RME. Self-efficacy (β = 0.306) and students' challenges (β = 0.304), along with APOS-based learning (β = 0.198), significantly contributed to the construction of meaning within the RME framework. Click or tap here to enter text.The overall structural model is presented in Figure 1 to illustrate these relationships and their statistical significance.

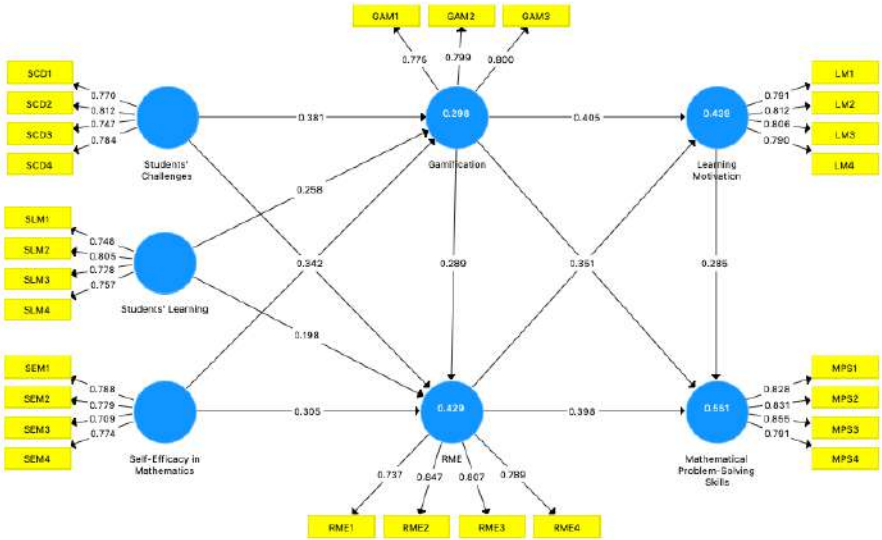


Figure 2. SEM-PLS Structural Model of the AI–RME–Gamification Framework

Building upon the structural relationships depicted in Figure 1, further analysis of the measurement and structural models was conducted to ensure the robustness of the findings. The measurement model was first evaluated to confirm the reliability and validity of the constructs, followed by the structural model analysis to examine the magnitude and significance of the hypothesized paths. The results of these quantitative analyses are presented in the following sections. These quantitative findings will subsequently be integrated with qualitative results in the next section to provide a comprehensive mixed-methods perspective.

Quantitative Findings

The quantitative analysis began with the evaluation of the measurement model to confirm the reliability and validity of the constructs. All indicators demonstrated satisfactory outer loadings, with values exceeding the recommended threshold of 0.70, while the Average Variance Extracted (AVE) for each construct was above 0.50. In addition, both Composite Reliability (CR) and Cronbach's alpha values were greater than 0.80, indicating strong convergent validity and internal consistency. These results are summarized in Table 2.

Table 2. Measurement Model Results

Deleted: The results of the SEM-PLS analysis revealed a consistent pattern highlighting the centrality of RME and motivation in the instructional model. Gamification exerted a significant positive effect on Learning Motivation (β = 0.405) and also contributed directly to problem-solving skills (β = 0.191). Beyond its direct effect, gamification indirectly supported problem-solving through learning motivation, emphasizing its role in sustaining student engagement throughout the learning cycle.

RME emerged as a pivotal construct in the model, exerting substantial effects on both learning motivation (β = 0.351) and problem-solving skills (β = 0.398,). These findings align with the principles of guided reinvention and phenomenological exploration, where contextualized tasks allow students to transition from informal strategies to formal reasoning. The statistical strength of these paths reflects how RME facilitates progressive mathematization, a cornerstone of mathematics as a human activity (Freudenthal, 1991).

Learning motivation itself proved to be a significant predictor of problem-solving skills (β = 0.285, $p < 0.001$), underscoring its mediating role. This suggests that students who are intrinsically and extrinsically motivated are better positioned to develop higher-order reasoning, make connections, and represent mathematical ideas effectively. The mediating role of learning motivation highlights the novelty of this study, demonstrating that gamification and RME function not only as instructional approaches but also as affective drivers of mathematical competence.

Internal learner factors also played a critical role in strengthening RME. Self-efficacy (β = 0.305), students' challenges (β = 0.304), and APOS-based learning (β = 0.198) significantly contributed to the construction of meaning within the RME framework. Rather than serving as barriers, challenges acted as *desirable difficulties*

Deleted: , enriching the process of mathematization. Together, these results demonstrate that combining AI, RME, and gamification provides a powerful approach to enhance both the emotional and cognitive aspects of learning mathematics.

Deleted: 1

Deleted: Building upon the structural relationships depicted in Figure 1, further analysis of the measurement and structural models was conducted to ensure the robustness of the findings. The measurement model was first evaluated to confirm the reliability and validity of the constructs, followed by the structural model analysis to examine the magnitude and significance of the hypothesized paths. The results of these quantitative analyses are presented in the following section, beginning with the assessment of the measurement model.

Deleted: 1

Deleted: 1

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
Gamification	GAM1	0.775	0.64	0.86	0.81	Valid
	GAM2	0.802				
	GAM3	0.788				
Learning Motivation	LM1	0.791	0.67	0.88	0.83	Valid
	LM2	0.822				
	LM3	0.843				
	LM4	0.804				
Problem-Solving Skills	MPS1	0.812	0.66	0.87	0.82	Valid
	MPS2	0.826				
	MPS3	0.799				
	MPS4	0.811				
RME	RME1	0.740	0.65	0.88	0.84	Valid
	RME2	0.781				
	RME3	0.854				
	RME4	0.792				
Self-Efficacy	SEM1	0.781	0.62	0.85	0.80	Valid
	SEM2	0.812				
	SEM3	0.804				
	SEM4	0.794				
Challenges	SCD1	0.765	0.63	0.86	0.81	Valid
	SCD2	0.811				
	SCD3	0.828				
	SCD4	0.779				
APOS Students Learning	SLM1	0.751	0.61	0.84	0.79	Valid
	SLM2	0.784				
	SLM3	0.802				
	SLM4	0.773				

The results indicate that all constructs (Gamification, RME, Learning Motivation, Problem-Solving, Self-Efficacy, Challenges, and APOS Learning) are measured accurately and consistently. Strong factor loadings (0.74–0.85) reinforce the robustness of the RME construct, while reliability indices (CR and α > 0.80) confirm internal consistency. Discriminant validity was then assessed using the Fornell–Larcker criterion. The square root of the AVE for each construct was higher than its correlations with other constructs, demonstrating that each construct measured distinct dimensions of the instructional model. This confirms that Gamification, RME, Learning Motivation, and Problem-Solving are empirically distinguishable, as shown in Table 3.

Deleted: This suggests that the instruments adequately captured both affective (motivation, self-efficacy) and cognitive (problem-solving, APOS) dimensions of learning.

Deleted: 2

Deleted: ¶

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	Gamification	LM	Problem-Solving	RME
Gamification	0.80			
Learning Motivation	0.56	0.82		
Problem-Solving Skills	0.44	0.53	0.81	
RME	0.48	0.51	0.59	0.81

Note: The diagonal values represent √AVE. All diagonal values are greater than the inter-construct correlations, indicating that discriminant validity is established.

The results confirm discriminant validity: for example, Motivation (√AVE = 0.82) is statistically distinct from Gamification (r = 0.56) and RME (r = 0.51). This distinction is important because it validates the mediating role of Motivation between Gamification and Problem-Solving. Without sufficient discriminant validity, overlap among constructs could bias the interpretation of the mediation effect. The structural model analysis revealed several significant paths. Gamification exerted a substantial effect on Learning Motivation (β = 0.405,) and a moderate effect on Problem-Solving Skills (β = 0.191). RME was found to be a pivotal construct, significantly predicting both Motivation (β = 0.351) and Problem-Solving Skills (β = 0.398). Learning motivation itself significantly predicted Problem-Solving (β = 0.285), confirming its mediating role. Furthermore, internal learner factors contributed significantly to strengthening RME: Self-Efficacy (β = 0.305), Students' Challenges (β = 0.304), and APOS-based Learning (β = 0.198). Together, these paths explained 48% of the variance in Learning Motivation, 52% of the variance in RME, and 55% of the variance in Problem-Solving Skills. A summary of these findings, including path coefficients, t-values, and f^2, is presented in Table 4.

Table 4. Structural Model Results

Path	β	t-value	p-value	f^2	Decision
Gamification → Learning Motivation	0.405	5.06	0.000	0.21	Supported
Gamification → Problem-Solving	0.191	2.60	0.009	0.08	Supported
RME → Learning Motivation	0.351	3.51	0.000	0.19	Supported
RME → Problem-Solving	0.398	4.98	0.000	0.25	Supported
Learning Motivation → Problem-Solving	0.285	2.85	0.004	0.17	Supported
Self-Efficacy → RME	0.305	4.20	0.000	0.12	Supported
Challenges → RME	0.304	4.10	0.000	0.11	Supported
APOS Learning → RME	0.198	3.00	0.002	0.07	Supported

The model fit indices confirmed the adequacy of the proposed framework. To assess explanatory power and predictive relevance, we report construct-level R^2 and Stone–Geisser Q^2 (blindfolding, d = 7). These indices are summarised in Table 5.

Deleted: 2

Deleted: Motivation

Deleted: R

Deleted: 3

Deleted: 3

Formatted Table

Deleted: The Standardized Root Mean Square Residual (SRMR) was below the recommended threshold of 0.08, the Normed Fit Index (NFI) was above 0.90, and the RMS Theta index was below 0.12.

Deleted: These indicators provide evidence that the AI–RME–Gamification model demonstrates a satisfactory overall fit, as displayed in Table 4.…

Deleted: ¶

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

Endogenous construct	**R^2**	**Q^2**	**Q^2 interpretation**
Problem-Solving Skills	0.551	0.369	Large
Learning Motivation	0.439	0.275	Medium
RME	0.429	0.262	Medium
Gamification	0.298	0.179	Medium

Note: *(Blindfolding d = 7; $Q^2 \approx 0.02/0.15/0.35$ = small/medium/large)*

Complementing these fit statistics, Table 5 shows that the endogenous constructs have meaningful explanatory power and predictive relevance: PSS $R^2 = 0.551$ with $Q^2 = 0.369$ (large), LM $R^2 = 0.439$ with $Q^2 = 0.275$ (medium), RME $R^2 = 0.429$ with $Q^2 = 0.262$ (medium), and Gamification $R^2 = 0.298$ with $Q^2 = 0.179$ (medium). Collectively, these quantitative data confirm that the SEM-PLS model is both statistically and conceptually robust.

Qualitative Findings

Thematic analysis of interviews and classroom observations was clustered into categories and synthesized into four overarching themes: guided reinvention, interactivity, phenomenological exploration, and the enhancement of problem-solving skills. These themes collectively provide a deeper understanding of how the AI–RME–Gamification model shaped student learning experiences and reinforce the quantitative findings of the study.

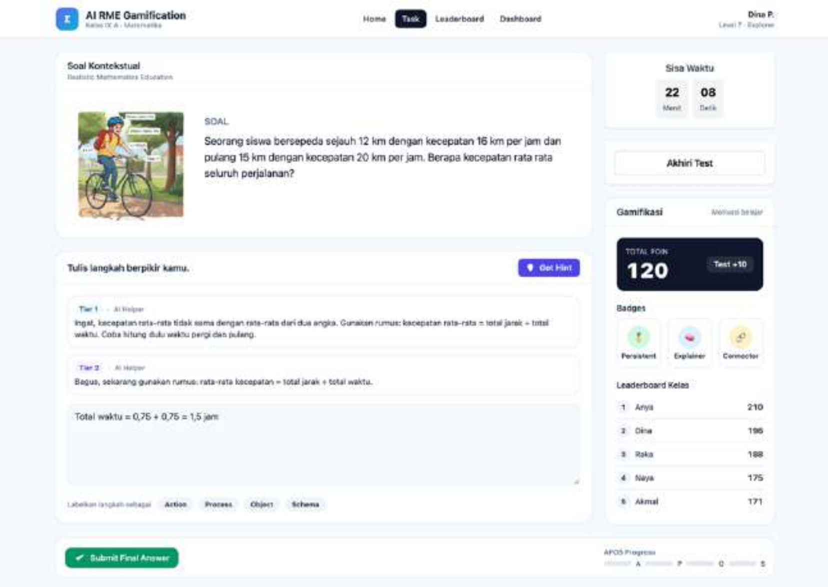


Figure 3. Screenshot of the AI–RME–Gamification prototype application

Deleted: SRMR
Deleted: 0.062
Deleted: < 0.08
Deleted: Good Fit
Formatted: Font: Not Bold
Deleted: NFI
Deleted: 0.91
Deleted: > 0.90
Deleted: Acceptable
Formatted: Font: Not Bold
Deleted: RMS Theta
Deleted: 0.11
Deleted: < 0.12
Deleted: Acceptable
Formatted: Font: Not Bold
Formatted: Font: Not Bold
Deleted: ¶
Deleted: The model's goodness-of-fit indices suggest that the theoretical framework is well aligned with the empirical data. SRMR < 0.08 indicates minimal residuals between observed and predicted correlations, while NFI > 0.90 reflects acceptable comparative fit. RMS Theta < 0.12 further supports the quality of the measurement model.
Deleted: indices
Deleted: 2

Figure 2 displays the interface of the AI–RME–Gamification application as used by students during the learning sessions. The prototype interface illustrated how contextual RME tasks were delivered. *A student cycles 12 kilometers at 16 km/h and returns 15 kilometers at 20 km/h. Determine the average speed for the entire journey*." AI scaffolding was provided via tiered hints in the lower-right panel. Tier 1 (AI Helper): "*Remember, average speed is not the arithmetic mean of the two speeds. Use the formula: average speed = total distance ÷ total time."* The student then attempted a solution, encountered difficulty, and tapped Tier 2 for further support. Tier 2 (AI Helper): "*Good. Now apply the formula: average speed = total distance ÷ total time to combine your results".* Upon a correct solution, immediate feedback was issued. Gamification elements (points, badges, and leaderboards) were also integrated. Together, these features visually substantiate the qualitative finding that students were nudged to construct their own strategies rather than depend on direct answers, while digital rewards helped sustain learning motivation.

Students frequently described the system as a scaffold that encouraged them to construct their own strategies rather than rely on direct answers. Codes such as AI scaffolding, hints, and self-construction were dominant, with one student remarking, "*The system gave me hints when I was stuck, but it did not show the answer. I had to try different ways until I found the solution*." Teachers echoed this sentiment, observing that students became more independent: "*They tried first, then used the hints only when they really needed them.*" This reflects the RME principle of guided reinvention and resonates with the quantitative finding that RME strongly predicted both Learning Motivation (β = 0.351) and Problem-Solving (β = 0.398).

Table 6. Transcript of student–AI interaction on average task with tiered scaffolding LLM

Stage	Student Response	AI Scaffolding Example	Analysis (APOS/Didactical)
Initial answer	"Average = (16 + 20)/2 = 18 km/h."	"Remember, average speed = total distance ÷ total time. First calculate the time for the outbound and return trips." (Tier 1 – general strategy)	Student holds a misconception (incorrect schema → arithmetic average). AI redirects to the formal concept (Object).
Time calculation (wrong)	"Outbound time = 12 ÷ 16 = 0.75 h. Return time = 15 ÷ 20 = 0.8 h."	"Correct for the outbound time. But check again 15 ÷ 20. Is it really 0.8?" (Tier 2 – focused correction)	Student moves into Action → Processbut miscalculates. AI focuses on correcting the specific operation.
Revision	"15 ÷ 20 = 0.75 h. So total time = 1.5 h."	"Good! Now total distance = 27 km, total time = 1.5 h. Use the formula average speed = distance ÷ time." (Tier 3 – near answer)	Student reaches the Process stage. AI scaffolds transition toward Object.
4. Final answer	"27 ÷ 1.5 = 18 km/h."	"Correct! You earn +10 points and the Master Speed badge for completing with a structured solution." (Feedback + Gamification)	Student achieves the Schema stage (general concept of average speed). Gamification reinforces learning motivation.

This transcript shows how the AI scaffolding guided by a large language model (LLM) accessed via an API initially led an actual student astray, treating average speed as a simple arithmetic mean, before guiding them toward the correct reasoning pathway. Through tiered hints, the AI first redirected the student to the appropriate formula (Tier 1), then corrected a calculation error (Tier 2), and finally consolidated the process by connecting total distance and total time (Tier 3). The progression of

Deleted: The interface demonstrated how contextual RME-based tasks were presented, how AI scaffolding was delivered through tiered hints (Tier 1–3), and how gamification elements, such as points, badges, and leaderboards, were integrated. This visual evidence supports the qualitative finding that students were encouraged to construct their own strategies rather than rely on direct answers, while also maintaining motivation through digital reward mechanisms.

Formatted: Font: Italic

Formatted: Font: Italic

Deleted: 6

responses reflects the APOS framework: from Action (performing basic operations), to Process (organizing steps), to Object (treating distance and time as unified quantities), and ultimately to Schema (generalizing the concept of average speed). The gamification feedback further reinforced persistence and learning motivation, providing direct evidence that affective and cognitive processes were intertwined in this AI–RME–Gamification environment.

Another salient theme was interactivity, expressed in both social and digital dimensions. Codes such as peer collaboration, leaderboard competition, and teacher mediation highlighted the interactive character of the learning process. One teacher commented, *"Even students who are usually quiet wanted to contribute because they were curious about their scores on the leaderboard*." A student added, *"I wanted to beat my friend's score, so I tried again until I got it right.*" These findings align with the RME characteristic of interactivity and confirm the statistical evidence that Gamification exerted a strong influence on Learning Motivation (β = 0.405). They also extend existing research on ICT in mathematics education, where digital tools are shown to foster dialogical and collaborative learning (Drijvers, 2015).

Formatted: Font: Italic

Formatted: Font: Italic

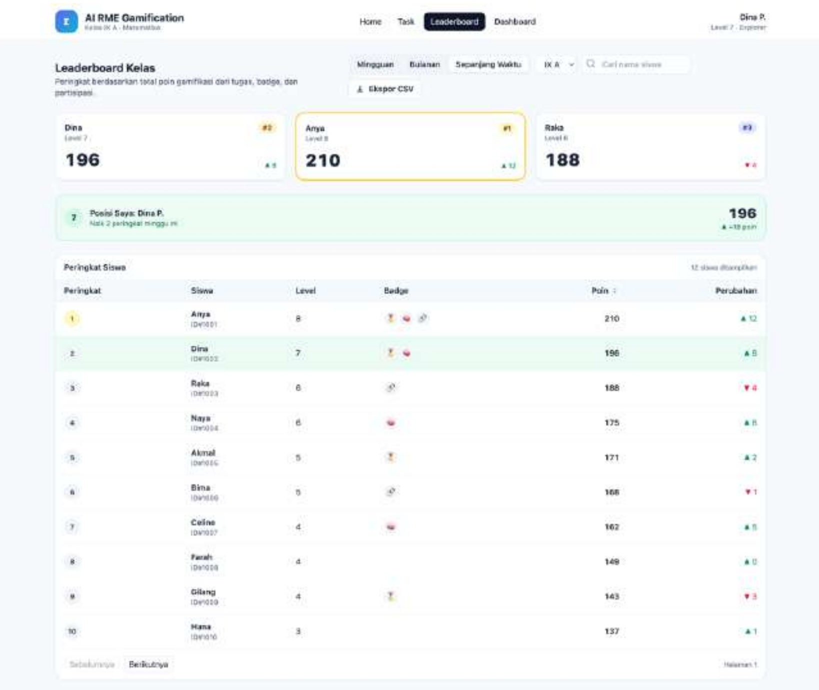


Figure 4. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

Deleted: 3

It shows the teacher dashboard and leaderboard from the platform. The dashboard tracks students' points, badge progression, and accumulated gamification points. This evidence demonstrates that the system captured not only final answers but also the learning process, allowing teachers to monitor reasoning quality and persistence directly. Another teacher observed that students were using diagrams and tables to represent their thinking: "*They rarely did this before, but now I see more of it.*" Students also

Formatted: Font: Italic

noted the change: *"I usually just wanted the answer, but now I try to show how I got it.*"

Figure 4 provides photographic evidence of students actively engaging with the AI–RME–Gamification platform in a classroom setting. It was demonstrated that students worked on contextual tasks individually, while also monitoring their progress on the leaderboard and exchanging strategies with their peers. This supports the qualitative findings that interactivity was not only digital, through the gamification features, but also social, as the visibility of scores stimulated peer collaboration and healthy competition.

Figure 4. Students engaging with the platform during classroom implementation

Phenomenological exploration was also a recurring pattern in the data (Treffers, 1991). Students consistently valued tasks that mirrored real-life situations, with codes such as relevance, authenticity, and transferability emerging across cases. One student noted, *"Because the problems looked like shopping or transport, I understood why we needed the formulas.*" Teachers reinforced this view, emphasizing that real contexts increased seriousness and focus: "*When the questions are close to their daily life, the students are more serious. They see mathematics as something real.*" These qualitative insights explain why Learning Motivation significantly predicted Problem-Solving Skills (β = 0.285): authentic contexts enhanced engagement, supporting OECD's definition of mathematical literacy as the ability to apply mathematics meaningfully (OECD, 2019). Both teachers and students observed the enhancement of problem-solving skills (Anugraheni et al., 2025). Codes such as reasoning, representation, explanation, and persistence dominated this theme. Teachers reported improvements not only in accuracy but also in the quality of reasoning: "*They could explain their steps better, not only write the result.*

Integration of Findings

The integration of quantitative and qualitative findings underscores the robustness of the AI–RME–Gamification model in enhancing both affective and cognitive dimensions of mathematics learning. The results of the SEM-PLS structural model were systematically triangulated with thematic evidence obtained from interviews and classroom observations. This process allowed the statistical associations to be validated through authentic learning experiences, thereby strengthening the explanatory power of the model.

Formatted: Font: Italic

Formatted: Font: Italic

Formatted: Font: Italic

Formatted: Font: Italic

Formatted: Justified

Deleted: ¶
¶

Table 7. Integrated Structural and Qualitative Results

Formatted Table

SEM-PLS	β	Qualitative Theme	Interview Quote	Integrated Interpretation
Gamification → Learning Motivation	0.405	Interactivity, Engagement	"Even quiet students wanted to join because of the leaderboard."(Teacher)	Gamification sustains motivation through competitive but supportive interaction.
Gamification → Problem-Solving	0.191	Problem-Solving Enhancement	"I tried harder to solve the tasks because I wanted to level up." (Student)	Gamification directly encourages persistence in problem-solving.
RME → Learning Motivation	0.351	Phenomenological Exploration	"Because the problems looked like shopping or transport, I understood the formulas better." (Student)	Contextualized tasks stimulate motivation through relevance.
RME → Problem-Solving	0.398	Guided Reinvention	"The system gave hints but not the answer, so I had to try different ways."(Student)	RME scaffolding supports progressive mathematization and problem-solving.
Motivation → Problem-Solving	0.285	Engagement, Persistence	"I kept trying because the points made me want to finish." (Student)	Learning Motivation bridges affective engagement and problem-solving skills.
Self-Efficacy → RME	0.305	Confidence, Self-construction	"I believed I could solve it myself if I tried step by step." (Student)	Self-efficacy strengthens the constructive aspect of RME.
Challenges → RME	0.304	Desirable Difficulties	"It was difficult, but the challenge made me think more carefully." (Student)	Challenges act as desirable difficulties enriching learning.
APOS Learning → RME	0.198	Conceptual Connections	"I understood how the steps connect to each other after trying again."(Student)	APOS progression supports formalization in RME processes.

Table 7 demonstrates a consistent alignment between statistical significance and lived classroom experiences. The strong effect of gamification on learning motivation (β = 0.405, t = 5.06) was vividly reflected in observations of heightened student engagement. Teachers reported that even students who were usually reluctant to participate became more active due to the visibility of the leaderboard. This demonstrates that gamification is not limited to providing external rewards but also taps into social comparison and intrinsic curiosity, thereby amplifying the motivational pathway. The direct effect of gamification on problem-solving (β = 0.191, t = 2.60) was supported by students' testimonies, which indicated that the desire to progress to higher levels encouraged them to persevere with complex problems. This resonates with research on gamification as a source of sustained cognitive effort rather than superficial engagement.

Deleted: 6

Deleted: motivation

Deleted: ,

The pivotal role of RME in the model was also evident. Statistically, RME predicted both learning motivation (β = 0.351, t = 3.51) and problem-solving (β = 0.398, t = 4.98). Qualitative evidence supported these effects through recurring themes of guided reinvention and phenomenological exploration. Students consistently emphasized that contextual problems made abstract concepts meaningful and that AI scaffolding, which provided hints without revealing solutions, pushed them to think independently. This aligns with Freudenthal's principle that mathematics must be connected to reality and progressively mathematized, as well as Gravemeijer's notion that design features should guide learners' reinvention of formal strategies (Gravemeijer, 1994).

Deleted: motivation

The mediating effect of learning motivation on problem-solving ($\beta = 0.285$, $t = 2.85$) was also substantiated qualitatively. Students described a willingness to persist through challenges when motivated by the point and badge system. At the same time, teachers observed that motivated learners articulated their reasoning more clearly and made stronger conceptual connections. These findings support Supara Suparatulatorn's perspective that problem-solving is not merely cognitive but also driven by affective engagement (Suparatulatorn et al., 2023).

Finally, the contribution of internal learner factors to RME was validated by both data strands. Self-efficacy ($\beta = 0.305$, $t = 4.20$) emerged as a significant predictor, with students noting that confidence helped them persist with contextual tasks. Challenges ($\beta = 0.304$, $t = 4.10$) were reframed as opportunities rather than barriers, consistent with Bjork's principle of desirable difficulties (Bjork & Bjork, 2020). APOS-based learning ($\beta = 0.198$, $t = 3.00$) was evident in students' accounts of connecting informal steps to more formal strategies after repeated trials, highlighting the constructive role of AI scaffolding in supporting APOS transitions. The integrated findings reveal that gamification enhances learning motivation both directly and indirectly. RME serves as the central pedagogical mechanism for developing problem-solving skills, and internal learner factors strengthen the process of guided reinvention. The convergence of quantitative and qualitative evidence confirms that the AI–RME–Gamification model is not only statistically valid but also pedagogically grounded in classroom reality.

Learning Motivation as The Mediating Bridge in AI-RME Gamification Learning

Mathematics is often viewed as a set of correct procedures without clear explanations (Martin & Towers, 2011). Many students view mathematics as a chore and usually feel unsure about it, perceiving it as a complex subject to access (Raméntol & Camacho, 2016). This study addressed that problem by testing whether the deliberate combination of Realistic Mathematics Education (RME) contexts, gamification mechanics, and AI-driven scaffolding can convert affective engagement into durable problem-solving skills and learning motivation in secondary school classrooms. The structural model was specified to estimate its effects, while positioning self-efficacy, perceived challenge, and APOS-based learning processes as drivers of participation in RME activities.

Our findings challenge a prevalent assumption in gamification literature. Rather than exerting a substantial direct impact on problem-solving, gamification's principal effect was on learning motivation with a more modest, secondary direct effect on problem-solving and qualitative accounts explained this ordering. Gamification elements created a sense of challenge that drove students to persist in their attempts; however, this sense of challenge often diminished over time when students lacked sufficient information to complete tasks. To address this limitation, we implemented an AI-tier system that provided adaptive support and solutions to overcome these difficulties. The leaderboards made social effort visible and allowed students to view their results as tangible outcomes of their efforts, thereby fostering learning motivation. Points and levels regulated the pace of work, while progression mechanics created reasons to persist when tasks became demanding. These findings indicate that gamification primarily functions as a motivational catalyst rather than a direct instructional tool. While students were still engaged in authentic mathematical problem-solving, their improved performance was mediated through enhanced motivation rather than through the game mechanics themselves.

This study demonstrates a key finding about how RME, AI, and gamification work together in mathematics learning (Suparatulatorn et al., 2023). RME provided the meaningful foundation by connecting mathematics to students' real-world experiences, showing strong effects on both motivation (and problem-solving . When students worked on problems related to familiar contexts, such as shopping

Deleted: cognitive

Deleted: gains

Deleted:

Deleted: The structural model was specified to estimate the effects on learning motivation and problem-solving, while positioning self-efficacy, perceived challenge, and APOS-based learning processes as drivers of participation in RME activities. The central interpretive move throughout is to read the findings not as a checklist of significant paths, but as evidence for a coherent instructional ecology in which meaning, effort, and formalization are jointly produced.

Deleted: → A key result requires a reversal of a common assumption in the gamification literature. Rather than exerting a substantial direct impact on problem-solving, gamification's principal effect was on motivation ($\beta = 0.405$) with a more negligible, secondary direct effect on problem-solving ($\beta = 0.191$). Qualitative accounts explained this ordering. Leaderboards made social effort visible; points and levels regulated the pace of work; progression created reasons to persist when tasks became demanding. Gamification, in short, supplied energy rather than a method. The cognitive work remained mathematical, and the route from engagement to competence ran through motivation rather than around it.
→ Click or tap here to enter text.. The model showed substantive effects of RME on both motivation ($\beta = 0.351$) and problem-solving ($\beta = 0.398$). Classroom narratives made the mechanism concrete: when tasks were rooted in familiar situations such as shopping or transportation, learners could anchor conjectures, construct representations, and connect ideas. AI feedback then functioned as a quiet coach, offering graded hints without revealing solutions so that informal strategies could be reorganized into formal ones. This is the classic RME logic, where context comes first, followed by formalization , as demonstrated here in a technology-mediated setting. Motivation consequently occupied a structural position rather than a terminal one. It predicted problem-solving ($\beta = 0.285$) and mediated the influence of both RME and gamification on . The qualitative record gave that role psychological texture: curiosity and tenacity were the felt correlates of the mediating path, often visible when students chose to write one more line of work after an AI hint or a peer's contribution. Framed this way, is not an optional add-on to instruction, but rather the bridge that enables contextual engagement to extend as far as formal competence.

or transportation, they could better develop mathematical ideas and connect them to formal concepts. The AI system acted as a supportive coach, providing gradual hints that helped students transform their informal thinking into formal mathematical understanding without simply giving away answers. Most importantly, the study revealed that learning motivation was not just an outcome but a critical bridge that connected these learning experiences to actual problem-solving improvement. Students showed this through their persistence, continuing to work on problems after receiving AI hints or discussing with peers. This finding challenges traditional views by showing that motivation is not an extra benefit of good teaching but an essential pathway that transforms engaging contexts into mathematical competence (Star et al., 2014). The findings empirically demonstrate that, in technology-enhanced mathematics education, learning motivation acts as a key mediator, helping students move from contextual understanding to formal mathematical skills. Building on this key finding, it is crucial to explore how individual student traits influence and enhance this motivational pathway in the integrated learning environment.

The study further revealed how student-related factors functioned within the integrated AI-RME-Gamification environment. Self-efficacy did not directly improve achievement but instead strengthened students' willingness to engage with RME activities. Confident students were more likely to persist with contextual problems, try different mathematical representations, and revise their work based on AI feedback (Bećirović et al., 2025; Fitria et al., 2025; Zheng & Tse, 2023). This suggests that confidence matters most when it drives active participation in learning activities, not when it stands alone. Similarly, perceived challenge became beneficial rather than problematic when supported by appropriate scaffolding. Students reported that complex problems actually improved their thinking when three conditions were present: meaningful contexts from RME, gradual AI hints that preserved problem-solving ownership, and gamification rewards that valued effort. The APOS framework guided students' mathematical development from concrete actions to abstract understanding. Through AI-supported hints and peer discussions, students naturally progressed from performing calculations (Action) to understanding procedures (Process), to recognizing mathematical concepts (Object), and finally to connecting these concepts into coherent knowledge structures (Schema). This progression created a clear, reproducible pathway from everyday contexts to formal mathematics, precisely what RME aims to achieve. Click or tap here to enter text.

Building on these individual factors, the study also revealed essential implementation considerations across different school contexts (A. Canonigo, 2024). Although the participant description did not explicitly measure ICT access differences, the distinction between urban public schools and suburban private Islamic schools (MTs) suggested varying implementation priorities. In the four urban public schools with their larger student populations (195 students), observations indicated that the social-competitive aspects of gamification, particularly leaderboard visibility and peer comparison, generated stronger engagement. Students in these settings responded enthusiastically to the public recognition of achievements and the competitive dynamics fostered by the gamification elements. Conversely, in the two suburban private Islamic schools (105 students), where class sizes were typically smaller and student-teacher relationships more intimate, the authenticity and relevance of RME contexts proved more influential. Students in these MTs settings showed greater engagement when problems connected directly to their local experiences and cultural contexts.

These context-specific differences suggest that the successful implementation of the AI-RME-Gamification model relies more on adaptive strategies rather than a universal solution application. Schools with larger, more diverse student populations might prioritize the social mechanics of gamification to maintain engagement across varied ability levels. Meanwhile, schools with closer-knit

Deleted: Self-efficacy and challenge, often regarded as personal qualities, acted differently when placed within this ecology

Deleted: . Self-efficacy strengthened participation in RME rather than bypassing it (β = 0.305). Students who believed they could succeed were more willing to remain with a context, test a representation, and iterate after non-telling feedback. The theoretical implication is that confidence is most consequential when it is practice-embedded, rather than when it is presumed to yield outcomes directly. Perceived challenge likewise acted as a catalyst when intentionally designed and scaffolded (β = 0.304 to RME). Learners reported that difficult items prompted more careful thinking when AI feedback was timely and incremental; difficulty became desirable because the didactical conditions, meaningful context, controllable steps, and signals that effort matters were in place. APOS processes supplied the engine for formalization. Although the coefficient from APOS to RME was more modest (β = 0.198), observations traced a characteristic microgenetic arc: actions consolidated into processes, processes were reified into objects, and objects were coordinated within schemas. Iterative AI prompts and peer discussion synchronized the pace of this arc so that learners neither stalled too early nor jumped prematurely to the formula. The result is a visible and repeatable passage from context to structure, precisely the passage RME intends to cultivate.

communities might benefit more from investing in locally relevant problem contexts that resonate with students' lived experiences. Three design principles emerge from this analysis: First, RME tasks must genuinely facilitate mathematical formalization rather than merely providing superficial contexts; the chosen phenomena should organize the mathematics students are expected to construct. Second, gamification elements should remain proportionate and instrumental, sustaining persistence without overshadowing mathematical thinking. Third, AI scaffolding must carefully calibrate challenge levels, providing timely support that encourages the development of new strategies without causing frustration or dependency. Technically, this requires the AI system to be trained with comprehensive student background data, including prior performance patterns, common misconceptions, and learning progressions typical of Indonesian Grade 8 students, enabling more contextually appropriate and constructive feedback tailored to individual student needs (Dabingaya, 2022; Soesanto et al., 2022). When these elements are appropriately balanced and adapted to local contexts, motivation effectively transforms contextual engagement into mathematical competence.

Furthermore, this study makes several important theoretical contributions to mathematics education. The most significant is repositioning learning motivation from being merely an outcome of good teaching to serving as a critical mediator that connects learning activities to actual mathematical understanding. Unlike traditional models that view motivation as a final result, this study demonstrates that motivation functions as the essential bridge linking engagement features (RME contexts, gamification mechanics, AI support) to cognitive achievements in problem-solving (Wild & Neef, 2023; Xia et al., 2022). The study also establishes specific conditions under which challenging problems become productive rather than discouraging. These desirable difficulties work when three elements align: meaningful real-world contexts that students can relate to, timely AI scaffolding that guides without revealing answers, and gamification signals that validate effort and persistence.

The research further explains that self-efficacy is most influential not when evaluated in isolation, but when it promotes active engagement in mathematical tasks. Confidence becomes most significant when it drives individuals to take action. From these findings emerges a practical instructional framework that schools can implement: First, create RME tasks that genuinely lead from familiar contexts to mathematical formalization. Second, use gamification strategically to sustain engagement without overshadowing mathematical thinking. Third, implement AI scaffolding that adapts to student needs while preserving their ownership of problem-solving. Schools can tailor their focus, emphasizing social competition in larger urban areas or valuing contextual authenticity in smaller communities, all while maintaining the mediating role of learning motivation as the central element of the design principle.

The model illustrates how each component serves a distinct function: AI regulates the learning pace, RME provides meaningful direction, gamification creates momentum, and motivation integrates everything into a cohesive learning experience, thereby improving students' problem-solving skills. This represents a fundamental shift in how we understand mathematics learning in digital environments, not as separate technological additions to traditional teaching, but as an integrated system where motivation transforms contextual engagement into mathematical competence. The evidence shows not just improved test scores, but a transformation in how students view mathematics: from a subject to endure to one worth pursuing. This reframing offers a research-based blueprint for designing technology-enhanced mathematics education that successfully combines meaning, effort, and formal understanding.

CONCLUSION

This study investigated how integrating Realistic Mathematics Education (RME), gamification,

Deleted: → The data also clarified contextual contingencies that matter for implementation. In urban schools with stronger ICT access, the social-affective route to motivation, visibility through leaderboards, friendly competition, and quick feedback, was particularly salient. In suburban schools, the dominant driver was the authenticity of context relative to students' daily experience. These findings suggest that the model should be tailored to local affordances: in some sites, emphasize the social mechanics that sustain attention; in others, invest more in the depth and fit of contextual scenarios that anchor meaning. Design consequences follow directly from the integrated evidence. First, contextual tasks must be crafted so that they actually conduce to formal ideas, not merely decorate them. Didactical phenomenology matters: the chosen phenomenon should organize the mathematics that learners are expected to reinvent. Second, gamification should be proportionate and instrumental, used to sustain attention and tenacity rather than to accelerate answer production. Third, AI scaffolding should calibrate challenge as a smooth ascent, with grain size and timing of prompts set to provoke new strategies without producing attrition. When these three elements are balanced, motivation becomes the transmission system that turns contextual engagement into mathematical performance. ¶

Deleted: Theoretical contribution is clearest in the repositioning of within models of mathematics learning. Rather than treating it as a distal outcome, the study models motivation as a mediator that stitches together engagement structures and cognitive gains. It also defines conditions where desirable difficulties are genuinely beneficial, and contexts must be meaningful. Scaffolds should be unobtrusive yet timely, and social signals must convey the effort as meaningful. It clarifies that self-efficacy is most productive when it animates participation in RME practices rather than acting as a free-standing trait.¶

Deleted: → The findings yield a replicable instructional recipe: design high-quality RME tasks with clear routes to formalization; deploy gamification mechanics that encourage students to work without crowding out mathematical sense-making; and rely on adaptive AI scaffolds that preserve the integrity of guided reinvention. Schools can calibrate the entry point that shows social engagement or contextual relevance, according to their setting, while maintaining the mediator function of as a design invariant. Instead of insisting on a strong direct path from gamification to competence, the analysis accepts that the primary gain is motivational and designs for it explicitly. Rather than viewing difficulty as a problem to eliminate, the design turns it into a resource. Instead of assuming self-efficacy works in isolation, the design fosters it through practice and training. AI regulates tempo, RME sets direction, gamification supplies momentum, and motivation binds the ensemble. By assigning motivation a structural role, the model shows how context becomes cognition in an AI-supported, gamified RME environment. The evidence points not only to improved scores but also to a shift in learners' stance toward mathematics, from something to get through to something worth working for. That reframing is the study's main contribution to mathematics education, and it offers a principled pathway for future design research that seeks to join meaning, effort, and formal understanding in a single, testable architecture.¶

and AI scaffolding affects secondary students' learning motivation and mathematical problem-solving skills. The mixed-methods evidence revealed consistent patterns: RME provided the strongest direct effects on both problem-solving skills and learning motivation by grounding mathematics in familiar contexts. Gamification primarily enhanced learning motivation, which subsequently improved problem-solving skills through sustained engagement. AI scaffolding delivered tiered hints that maintained productive struggle while preserving students' problem-solving ownership. Additionally, self-efficacy and perceived challenges strengthened participation in RME activities, while APOS progressions facilitated the transition from informal reasoning to formal mathematical understanding. These findings demonstrate that when meaning, persistence, and formalization are purposefully aligned, significant improvements in mathematical problem-solving skills emerge.

The theoretical contribution lies in repositioning learning motivation from a learning outcome to a structural mediator that transforms engagement into problem-solving achievement. This challenges traditional views by showing that in technology-enhanced environments, learning motivation is not merely beneficial but essential for converting contextual experiences into mathematical competence. The study also establishes that challenges become productive "desirable difficulties" when paired with meaningful contexts, appropriate scaffolding, and effort-validating feedback systems. Practically, the findings offer actionable guidance for multiple stakeholders. Teachers should select problem contexts that naturally lead to target concepts, implement game elements that make an effort in enhancing problem-solving skills, and provide graduated hints that guide without revealing. Curriculum developers can sequence activities to support progressive formalization, moving from informal strategies to formal methods, ensuring that both the assessment process and products are well-coordinated. EdTech designers should prioritize adaptive scaffolding that preserves guided reinvention and develop dashboards that display learning indicators (attempts, revisions, explanations) rather than mere completion metrics.

The study acknowledges several limitations. The seven-session intervention with 300 students from six schools in one region constrains generalizability claims. The research prototype, while functional, requires further development for widespread implementation. Learning motivation measurements combined self-report and observational data, potentially introducing response bias. Future research should pursue two priorities: longitudinal studies to assess whether learning motivation and problem-solving skills gains persist beyond the intervention period, and multi-site replications across diverse contexts to determine when and how the model's mechanisms vary with different student populations, ICT infrastructures, and cultural settings. Thus, this research demonstrates that learning motivation is not merely a positive outcome of mathematics education, but a crucial process that enables technological and pedagogical innovations to enhance mathematical problem-solving skills. This insight fundamentally changes how we create and assess technology-enhanced math learning environments.

Deleted: p

Deleted: This study investigated whether an instructional design that combines Realistic Mathematics Education, gamification, and AI scaffolding can raise secondary students' motivation and problem-solving while clarifying the roles of self-efficacy, perceived challenge, and APOS processes. The integrated quantitative–qualitative evidence meets that objective and explains the mechanism. RME provided semantic traction through meaningful contexts and guided reinvention. Gamification primarily energized motivation rather than cognition, and AI regulated the grain and timing of non-telling support so that struggle remained productive. Motivation functioned as a structural mediator linking engagement features to cognitive performance. At the same time, self-efficacy and challenge strengthened participation in RME, while APOS supplied the engine for formalization, moving from actions to processes, objects, and schemas. In doing so, the study advances the field by repositioning motivation from outcome to mechanism and by specifying the didactical conditions under which difficulty becomes desirable in digital mathematics learning.

The contributions are both explanatory and actionable. The work shows why and when the model succeeds, moving beyond assumptions of direct effects to a testable architecture in which meaning, effort, and formal understanding are jointly produced. It yields design guidance that teachers, curriculum developers, and platform designers can implement: select contexts that genuinely facilitate formal ideas, utilize game mechanics to sustain persistence and make effort socially visible, and deploy adaptive AI feedback that preserves the integrity of guided reinvention. Implementation can be tailored to local affordances by emphasizing social interactivity where ICT access is strong, or by deepening contextual relevance where lived experience is the more powerful entry point. Assessment and analytics should capture both process and product, rewarding explanations, connections, and representations, and instrumenting APOS-aligned progress so that dashboards reflect learning transformations rather than mere completion.

For future work, I recommend a two-track agenda that links rigorous evaluation with practical adaptation. First, establish durability and generalisability through longitudinal and multilevel designs that include simple within-semester pretest, posttest, and follow-up assessments in the same class, for example, at weeks 0, 6, and 12, together with sampling across multiple sites to estimate contextual moderators such as ICT access, class size, and curricular alignment. Second, pursue replication in diverse settings, including urban, suburban, and resource-limited schools, by co-designing RME tasks with local teachers so that problems reflect students' lived realities. As a minimal requirement, develop at least two locally grounded contextual items in each site to preserve meaning while enabling comparison. Complement these strands with micro-experimental studies that vary the timing and granularity of AI scaffolds and compare reward structures that prioritize speed versus explanation in order to isolate mechanisms that convert engagement into reasoning. Throughout, employ mixed methods with process-sensitive measures of reasoning, connections, and representations, so that outcomes capture both learning processes and products. Report implementation details in sufficient depth to support reuse and cumulative synthesis.

Deleted: Declarations
The authors declare no conflict of interest.

REFERENCES

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. *Decision Making: Applications in Management and Engineering*, *8*(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186X.2025.2523078

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. *Journal on Mathematics Education*, *13*(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. *Journal of Primary Education*, *9*(5). https://doi.org/10.15294/jpe.v9i5.43223

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. *Computers in Human Behavior Reports*, *16*. https://doi.org/10.1016/j.chbr.2024.100491

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learn. Environ.*, *12*, 29. https://doi.org/10.1186/s40561-025-00384-3

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024*, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Memory and Cognition*, *9*(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Canonigo, A. (2024). Levering AI to enhance students' conceptual understanding and confidence in mathematics. *J. Comput. Assist. Learn.*, *40*, 3215–3229. https://doi.org/10.1111/jcal.13065

Canonigo, A. M. (2024). Levering <scp>AI</scp> to enhance students' conceptual understanding and confidence in mathematics. *Journal of Computer Assisted Learning*, *40*(6), 3215–3229. https://doi.org/10.1111/jcal.13065

Creswell, J. W. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dabingaya, M. (2022). Analyzing the Effectiveness of AI-Powered Adaptive Learning Platforms in Mathematics Education. *Interdisciplinary Journal Papier Human Review*, *3*(1), 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students' Mathematical Literacy Ability Through Information and Communication Technology-Assisted Preprospec Learning Model. *International Journal of Educational Methodology*, *9*(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409

Dubinsky, E., & McDonald, M. A. (2001). *APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research*. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf

Fitria, W., Susilana, R., Priatna, N., & Rusman. (2025). Investigation of the impact online single and multiple representation scaffolding on mathematical concept mastery and mathematical problem-solving skill. *Journal on Mathematics Education*. https://doi.org/10.22342/jme.v16i2.pp709-728

Freudenthal, H. (1991). *Revisiting Mathematics Education: China Lectures*. Springer. https://doi.org/10.1007/0-306-47203-1

Gravemeijer, K. (1994). *Developing Realistic Mathematics Education*.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203

Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. *Computers in Human Behavior*, *149*. https://doi.org/10.1016/j.chb.2023.107952

Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1105806

Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. *Multidisciplinary Reviews*, *8*(5). https://doi.org/10.31893/multirev.2025155

Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. *Computers and Education*, *194*. https://doi.org/10.1016/j.compedu.2022.104694

Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. *International Journal of Engineering and Technology(UAE)*, *7*(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). DEVELOPING REALISTIC MATHEMATICS EDUCATION-BASED WORKSHEETS FOR IMPROVING STUDENTS' CRITICAL THINKING SKILLS. *Infinity Journal*, *12*(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84

Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. *Asian Journal for Mathematics Education*, *3*(3), 289–311. https://doi.org/10.1177/27527263241269060

Malik, R. (2024). Scaffolding Middle-School Mathematics Curricula With Large Language Models. *Stanford Digital Repository*.

Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In *Structure and Improvisation in Creative Teaching* (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. *Educational Process: International Journal*, *15*. https://doi.org/10.22521/edupij.2025.15.179

Matzakos, N., Doukakis, S., & Moundridou, M. (2023). Learning Mathematics with Large Language Models: A Comparative Study with Computer Algebra Systems and Other Tools. *Int. J. Emerg. Technol. Learn.*, *18*, 51–71. https://doi.org/10.3991/ijet.v18i20.42979

Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. *Proceedings of the International Conference on Education Research, ICER 2024*, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. *Journal on Mathematics Education*, *12*(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. *International Journal of Innovative Research and Scientific Studies*, *8*(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Ng, D. T. K., Xinyu, C., Leung, J. K. L., & Chu, S. K. W. (2024). Fostering students' <scp>AI</scp> literacy development through educational games: <scp>AI</scp> knowledge, affective and cognitive engagement. *Journal of Computer Assisted Learning*, *40*(5), 2049–2064. https://doi.org/10.1111/jcal.13009

(OECD), O. for E. C. and D. (2019). *PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. *Journal of Pedagogical Research*, *8*(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). *Educational Design Research: Part A: An Introduction*. SLO.

Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? *Mathematics Education Journal*, *17*(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. *Journal on Mathematics Education*, *13*(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. *Opcion*, *32*(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3

Rane, N. (2023). Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4603237

Roldán-Álvarez, D., & Mesa, F. (2024). Intelligent Deep-Learning Tutoring System to Assist Instructors in Programming Courses. *IEEE Transactions on Education*, *67*, 153–161. https://doi.org/10.1109/te.2023.3331055

Siregar, H. S., Munir, M., & Fikri, M. (2025). ENHANCING ISLAMIC EDUCATION THROUGH TECHNOLOGY INTEGRATION: A STUDY OF TEACHING PRACTICES IN INDONESIA. *Jurnal Ilmiah Peuradeun*, *13*(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. *Journal on Mathematics Education*, *16*(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Soesanto, R. H., Dirgantoro, K. P. S., & Priyanti, N. (2022). Indonesian students' perceptions towards AI-based learning in mathematics. *Journal on Mathematics Education*, *13*(3), 531–548. https://doi.org/10.22342/jme.v13i3.pp531-548

Star, J., Chen, J., Taylor, M., Durkin, K., Dede, C., & Chao, T. (2014). Studying technology-based strategies for enhancing motivation in mathematics. *International Journal of STEM Education*, *1*, 1–19. https://doi.org/10.1186/2196-7822-1-7

Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. *Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024*, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. *Journal on Mathematics Education*, *14*(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *15348 LNCS*, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), *Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute* (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. *Journal on Mathematics Education*, *11*(1). https://doi.org/10.22342/jme.11.1.8690.17-44

Yin, D. S., & Yin, X. (2024). Scaffolding learning: From specific to generic with large language models. *PLOS ONE*, *19*(9), e0310409. https://doi.org/10.1371/journal.pone.0310409

Zabala-Vargas, S., García-Mora, L., Arciniegas-Hernández, E., Reina-Medrano, J., De Benito-Crosetti, B., & Darder-Mésquida, A. (2021). Strengthening Motivation in the Mathematical Engineering Teaching Processes - A Proposal from Gamification and Game-Based Learning. *Int. J. Emerg. Technol. Learn.*, *16*. https://doi.org/10.3991/ijet.v16i06.16163

Zheng, W., & Tse, A. W. C. (2023). The Impact of Generative Artificial Intelligence-based Formative Feedback on the Mathematical Motivation of Chinese Grade 4 Students: a Case Study. *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 1–8. https://doi.org/10.1109/tale56641.2023.10398319

Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. *Journal of Physics: Conference Series*, *947*(1). https://doi.org/10.1088/1742-6596/947/1/012015

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in

Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. *Decision Making: Applications in Management and Engineering*, *8*(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186X.2025.2523078

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. *Journal on Mathematics Education*, *13*(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. *Journal of Primary Education*, *9*(5). https://doi.org/10.15294/jpe.v9i5.43223

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. *Computers in Human Behavior Reports*, *16*. https://doi.org/10.1016/j.chbr.2024.100491

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learn. Environ.*, *12*, 29. https://doi.org/10.1186/s40561-025-00384-3

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024*, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Memory and Cognition*, *9*(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Canonigo, A. (2024). Levering AI to enhance students' conceptual understanding and confidence in mathematics. *J. Comput. Assist. Learn.*, *40*, 3215–3229. https://doi.org/10.1111/jcal.13065

Canonigo, A. M. (2024). Levering <scp>AI</scp> to enhance students' conceptual understanding and confidence in mathematics. *Journal of Computer Assisted Learning*, *40*(6), 3215–3229. https://doi.org/10.1111/jcal.13065

Creswell, J. W. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dabingaya, M. (2022). Analyzing the Effectiveness of AI-Powered Adaptive Learning Platforms in Mathematics Education. *Interdisciplinary Journal Papier Human Review*, *3*(1), 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students' Mathematical Literacy Ability Through

Information and Communication Technology-Assisted Preprospec Learning Model. *International Journal of Educational Methodology*, *9*(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409
Dubinsky, E., & McDonald, M. A. (2001). *APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research*. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf
Fitria, W., Susilana, R., Priatna, N., & Rusman. (2025). Investigation of the impact online single and multiple representation scaffolding on mathematical concept mastery and mathematical problem-solving skill. *Journal on Mathematics Education*. https://doi.org/10.22342/jme.v16i2.pp709-728
Freudenthal, H. (1991). *Revisiting Mathematics Education: China Lectures*. Springer. https://doi.org/10.1007/0-306-47203-1
Gravemeijer, K. (1994). *Developing Realistic Mathematics Education*.
Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203
Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. *Computers in Human Behavior*, *149*. https://doi.org/10.1016/j.chb.2023.107952
Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1105806
Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. *Multidisciplinary Reviews*, *8*(5). https://doi.org/10.31893/multirev.2025155
Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. *Computers and Education*, *194*. https://doi.org/10.1016/j.compedu.2022.104694
Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. *International Journal of Engineering and Technology(UAE)*, *7*(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954
Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). DEVELOPING REALISTIC MATHEMATICS EDUCATION-BASED WORKSHEETS FOR IMPROVING STUDENTS' CRITICAL THINKING SKILLS. *Infinity Journal*, *12*(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84
Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. *Asian Journal for Mathematics Education*, *3*(3), 289–311. https://doi.org/10.1177/27527263241269060
Malik, R. (2024). Scaffolding Middle-School Mathematics Curricula With Large Language Models. *Stanford Digital Repository*.
Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In *Structure and Improvisation in Creative Teaching* (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. *Educational Process: International Journal*, *15*. https://doi.org/10.22521/edupij.2025.15.179

Matzakos, N., Doukakis, S., & Moundridou, M. (2023). Learning Mathematics with Large Language Models: A Comparative Study with Computer Algebra Systems and Other Tools. *Int. J. Emerg. Technol. Learn.*, *18*, 51–71. https://doi.org/10.3991/ijet.v18i20.42979

Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. *Proceedings of the International Conference on Education Research, ICER 2024*, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. *Journal on Mathematics Education*, *12*(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. *International Journal of Innovative Research and Scientific Studies*, *8*(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Ng, D. T. K., Xinyu, C., Leung, J. K. L., & Chu, S. K. W. (2024). Fostering students' <scp>AI</scp> literacy development through educational games: <scp>AI</scp> knowledge, affective and cognitive engagement. *Journal of Computer Assisted Learning*, *40*(5), 2049–2064. https://doi.org/10.1111/jcal.13009

(OECD), O. for E. C. and D. (2019). *PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. *Journal of Pedagogical Research*, *8*(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). *Educational Design Research: Part A: An Introduction*. SLO.

Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? *Mathematics Education Journal*, *17*(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. *Journal on Mathematics Education*, *13*(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. *Opcion*, *32*(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3

Rane, N. (2023). Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4603237

Roldán-Álvarez, D., & Mesa, F. (2024). Intelligent Deep-Learning Tutoring System to Assist Instructors in Programming Courses. *IEEE Transactions on Education*, *67*, 153–161. https://doi.org/10.1109/te.2023.3331055

Siregar, H. S., Munir, M., & Fikri, M. (2025). ENHANCING ISLAMIC EDUCATION THROUGH TECHNOLOGY INTEGRATION: A STUDY OF TEACHING PRACTICES IN INDONESIA. *Jurnal Ilmiah Peuradeun*, *13*(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. *Journal on Mathematics Education*, *16*(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Soesanto, R. H., Dirgantoro, K. P. S., & Priyanti, N. (2022). Indonesian students' perceptions towards AI-based learning in mathematics. *Journal on Mathematics Education*, *13*(3), 531–548. https://doi.org/10.22342/jme.v13i3.pp531-548

Star, J., Chen, J., Taylor, M., Durkin, K., Dede, C., & Chao, T. (2014). Studying technology-based strategies for enhancing motivation in mathematics. *International Journal of STEM Education*, *1*, 1–19. https://doi.org/10.1186/2196-7822-1-7

Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. *Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024*, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. *Journal on Mathematics Education*, *14*(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *15348 LNCS*, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), *Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute* (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. *Journal on Mathematics Education*, *11*(1). https://doi.org/10.22342/jme.11.1.8690.17-44

Yin, D. S., & Yin, X. (2024). Scaffolding learning: From specific to generic with large language models. *PLOS ONE*, *19*(9), e0310409. https://doi.org/10.1371/journal.pone.0310409

Zabala-Vargas, S., García-Mora, L., Arciniegas-Hernández, E., Reina-Medrano, J., De Benito-Crosetti, B., & Darder-Mésquida, A. (2021). Strengthening Motivation in the Mathematical Engineering Teaching Processes - A Proposal from Gamification and Game-Based Learning. *Int. J. Emerg. Technol. Learn.*, *16*. https://doi.org/10.3991/ijet.v16i06.16163

Zheng, W., & Tse, A. W. C. (2023). The Impact of Generative Artificial Intelligence-based Formative Feedback on the Mathematical Motivation of Chinese Grade 4 Students: a Case Study. *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 1–8. https://doi.org/10.1109/tale56641.2023.10398319

Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. *Journal of Physics: Conference Series*, *947*(1). https://doi.org/10.1088/1742-6596/947/1/012015

Page 4: [1] Deleted	**Wati**	**11/8/25 12:07:00 PM**
Page 4: [2] Deleted	**Wati**	**11/1/25 7:25:00 AM**
Page 4: [3] Deleted	**Wati**	**11/1/25 7:38:00 AM**
Page 4: [4] Deleted	**Wati**	**11/1/25 7:42:00 AM**

Journal on Mathematics Education
Volume xx, No. x, xxxx, pp. xx-xx

Integrating Realistic Mathematics Education, AI, and Gamification to Enhance Students' Learning Motivation and Problem-Solving Skills

Abstract

The integration of artificial intelligence and gamification in realistic mathematics education offers significant opportunities to create meaningful, innovative, and adaptive learning experiences that emphasize student motivation and active engagement in solving non-routine mathematical problems. However, there are still several challenges to implementing this three-way integration, such as teachers' limited digital literacy, the lack of realistic mathematics education models that systematically combine artificial intelligence and gamification, and the persistent separation of these components in mathematics education practice. This study aims to explore how the synergy between artificial intelligence and gamification scaffolding can support realistic mathematics education in enhancing learning motivation and problem-solving abilities. The research employs a sequential explanatory mixed-methods design, involving 300 secondary school students from six secondary schools in Indonesia. Data were collected through mathematical problem-solving ability tests and non-test instruments, including observations and interviews. Quantitative data analysis was conducted using Structural Equation Modeling (SEM), and qualitative data were analyzed through thematic analysis. Results indicate that realistic mathematics education supported by artificial intelligence and APOS transition strategies with gamification elements significantly enhances mathematical problem-solving abilities (β = 0.40) and student learning motivation (β = 0.35), with an overall effect value of (β = 0.41). This study contributes to instructional design that can be systematically replicated, incorporating integration stages within realistic learning contexts, AI-based adaptive support, and game mechanics to build student engagement and intrinsic motivation. It offers theoretical and practical implications for developing realistic, adaptive mathematics education oriented toward meaningful learning experiences in problem-solving in the digital era.

Keywords: Artificial Intelligence, Gamification, Learning Motivation, Problem Solving, Realistic Mathematics Education

Mathematics learning supported by artificial intelligence and gamification becomes more meaningful when students connect mathematical ideas to real-world situations, enabling them to reconstruct formal concepts from their informal understanding and thereby strengthen their problem-solving skills (Bayaga, 2024; Rane, 2023). This is the central idea of Realistic Mathematics Education, where phenomena from everyday life are used to organise the mathematics that learners are expected to reinvent (Siswantari et al., 2025). When tasks are based on familiar practices, students can anchor their ideas, create representations, and build connections that naturally guide them toward more formal structures. The transition from context to concept represents a deliberate learning trajectory that helps students understand mathematical procedures through adaptive AI support and gamification engagement in solving non-routine problems with multiple solution paths or multiple valid solutions distinguished by clear reasoning (A. M. Canonigo, 2024; Ng et al., 2024). However, maintaining this contextual and meaning-

http://doi.org/10.22342/jme.v13i1.xxxx

oriented approach in today's digital classrooms requires adaptive technological support and sustained engagement, challenges that this study addresses through the integration of AI and gamification within the RME framework.

Educational AI offers adaptive support that can enhance the RME learning process through responsive feedback systems. Intelligent tutoring systems now utilize natural language processing and deep learning to deliver personalized hints and guidance, enabling students to develop their own reasoning (Bayaga, 2024; Roldán-Álvarez & Mesa, 2024). With the growing availability of open-source AI tools, these adaptive capabilities are becoming accessible to a wider range of educational settings (Matzakos et al., 2023). At the core of this technology is AI scaffolding, which adjusts support to individual student needs and gradually reduces guidance as learners develop competence. This approach mirrors the role of a responsive tutor by delivering timely hints and prompts that help students construct their own understanding independently(Malik, 2024). Through step-by-step explanations and interactive dialogue, AI systems enable students to ask follow-up questions and receive personalized support while maintaining an active role in problem-solving (Yin & Yin, 2024).

Complementing this technological support, gamification in mathematics education consistently enhances engagement, motivation, and cognitive development (Hui & Mahmud, 2023; Zabala-Vargas et al., 2021). Well-designed game elements such as points, levels, and badges can sustain students' effort and curiosity throughout the RME learning trajectory (Ariffin et al., 2022). Rather than serving as external rewards, these features function as didactical tools that protect the time and attention needed for sense-making (Al-Barakat et al., 2025; Jun & Lucas, 2025). AI and gamification complement each other in strengthening RME in distinct ways: AI enables guided reinvention through responsive feedback, while gamification maintains learning motivation and persistence. Together, these elements create an integrated learning environment that channels student motivation into deeper reasoning and stronger problem-solving skills(Bhardwaj, 2024; Mitchell & Co, 2024).

These considerations are especially relevant in the Indonesian, where improving mathematical literacy remains a persistent challenge (Ndiung & Menggo, 2025). Results from the Programme for International Student Assessment (PISA) indicate that Indonesian students often struggle with contextual reasoning and higher-order problem-solving, revealing a gap between procedural competence and the ability to apply mathematics in real-world situations (Zulkardi & Kohar, 2018). In response, national initiatives have promoted RME-inspired approaches to make mathematics more relevant through tasks related to students’ daily practices, such as trade, transportation, and cultural activities (Dewi & Maulida, 2023).However, despite these policy efforts, implementation remains uneven and largely confined to conventional classrooms with limited technological support (Siregar et al., 2025). This creates a persistent gap between policy aspirations and classroom realities, weakening the intended impact of mathematics education reform.

The rapid growth of digital learning platforms and gamified applications in Indonesian schools has not always been supported by strong pedagogical design (Maryani et al., 2025). Many platforms encourage surface-level engagement rather than deep conceptual understanding because they rarely align with established didactical frameworks. This raises important questions about how emerging approaches interact within integrated designs. Self-efficacy, for example, has been extensively researched in relation to achievement and motivation, yet its role within AI-supported, gamified RME environments at the secondary level remains poorly understood, especially in Indonesia (Mukuka et al., 2021; Siswantari et al., 2025). Existing studies tend to treat confidence as a background trait rather than as a dynamic factor shaping how students engage with contextual tasks, adaptive scaffolding, and game mechanics (Rahayu et al., 2022). Similarly, the role of perceived challenge in digital mathematics learning requires closer examination. In gamified environments, precise adjustment of difficulty offers opportunities to transform challenges into drivers of persistence, reasoning, and problem-solving (Beukes et al., 2024; Koskinen et al., 2023). This reframes challenge from an obstacle into a pedagogical variable that can be intentionally designed.

A critical gap emerges around the role of learning motivation in connecting these design elements to problem-solving outcomes. Although earlier studies have explored gamification or RME separately, few have investigated how motivation structurally mediates the influence of calibrated difficulty and contextualized learning in AI-supported settings (Hu et al., 2023; Mitchell & Co, 2024). RME research in Indonesia has been primarily grounded in conventional classrooms, with limited attention to how digital scaffolds and game-based engagement can enhance its effects on problem-solving (Lady et al., 2018; Lestari et al., 2023; Siswantari et al., 2025). By integrating RME, gamification, and AI, this study offers a promising pathway for bridging the gap between policy and practice, situating mathematical activity in students' lived realities while using digital tools to sustain motivation and scaffold reinvention (Li & Noori, 2024; Opesemowo & Ndlovu, 2024; Torres-Toukoumidis et al., 2025).

This study has two main objectives aligned with the Indonesian secondary education context. First, it assesses an integrated instructional model that merges Realistic Mathematics Education, gamification, and AI scaffolding, examining their direct and indirect impacts on students' learning motivation and mathematical problem-solving skills. The model positions self-efficacy, perceived challenge, and APOS-based learning as factors influencing engagement with gamification and RME, testing whether learning motivation mediates the relationships between these design levers and problem-solving performance. Second, it explains how these statistical effects materialize in classroom practice by tracing the mechanisms that connect contextual tasks, game mechanics, and adaptive feedback to students' problem-solving skills through observations and interviews.

We hypothesize that self-efficacy, perceived challenge, and APOS-based learning positively predict engagement with both gamification and RME. While gamification is expected to influence problem-solving skills primarily through its effect on learning motivation, RME is anticipated to show direct positive impacts on both motivation and problem-solving skills. Most importantly, we expect learning motivation to function as a structural mediator linking the design levers to mathematical performance, representing a novel reconceptualization of motivation's role in technology-enhanced mathematics education.

By repositioning learning motivation as a structural mediator rather than an endpoint, this study makes three key contributions to mathematics education. First, it clarifies the didactical conditions under which difficulty becomes desirable in digital mathematics learning: meaningful RME contexts that connect to students' realities, adaptive non-telling AI scaffolds that sustain productive struggle, and gamification incentives that reward persistence and explanation rather than speed alone. Second, it operationalizes the APOS progression within an AI-supported, gamified RME environment, making students' problem-solving skills trajectories from action to process to object to schema both observable and designable in secondary classrooms. Third, it provides a replicable instructional model specifically calibrated for Indonesian schools, offering empirical evidence and practical guidance for integrating contextual learning, adaptive support, and proportionate game mechanics. These contributions address the critical need for pedagogically-grounded approaches to digital mathematics learning while advancing theoretical understanding of how motivation transforms engagement into mathematical competence.

METHODS

Research Design

This study employed an explanatory sequential mixed-methods design (Creswell, 2018) within the framework of educational design research (Gravemeijer, 1994; Plomp, 2013). We chose this design because the aims required complementary evidence: to test the effects of an integrated RME, gamification, and AI model on students' motivation and problem-solving skills, and to explain how those effects arise in classrooms. We used SEM to model latent constructs in the quantitative phase, estimating simultaneous direct and indirect paths and testing mediation within a single system. PLS-SEM was employed to fit the model's complexity, predictive focus, and non-normal school data. Measurement quality was assessed with indicator loadings greater than 0.70, average variance extracted greater than 0.50, and composite reliability greater than 0.80; model adequacy with SRMR below 0.08 and evidence of predictive relevance. The qualitative phase then examined students and teachers, focusing on observations that traced how non-telling, tiered hints were used in practice, how game mechanics supported persistence without displacing mathematical thinking, and how contextual tasks supported APOS-aligned shifts in reasoning. The qualitative inquiry targeted three model patterns: RME's strongest direct effects on learning motivation and problem-solving skills, gamification's primarily indirect pathway via motivation, and the roles of self-efficacy and perceived challenge as antecedents.

We identified key problems in mathematics learning, particularly students' low learning motivation and difficulties in transferring problem-solving strategies to contextual situations. A review of theoretical perspectives in RME principles (Freudenthal, 1991; Gravemeijer, 1994), the APOS framework (Dubinsky & McDonald, 2001), and gamification theory (Deterding et al., 2011) informed the conceptual model. We designed an instructional model that integrates RME contextual tasks, gamification (points, levels, badges, leaderboards), and AI scaffolding. AI provides tiered hints (Tiers 1–3) that support the shift from informal strategies to formal reasoning along the APOS sequence (Action, Process, Object, Schema).

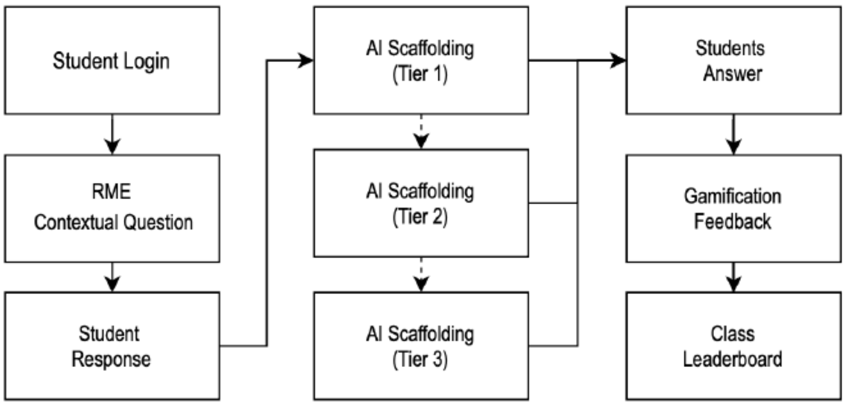


Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding

As shown in Figure 1, students first log in, receive an RME contextual question, and submit an initial response. The system then conditionally triggers AI scaffolding in APOS-aligned tiers that are delivered only when needed: Tier 1 (Action) prompts sense-making of quantities and first steps, Tier 2

(Process) cues representation building and relations among steps, and Tier 3 (Object/Schema) nudges generalization, subgoal decomposition, or linking the problem to a known structure. Tiers are progressive but not strictly linear: escalation occurs only when there is evidence of being stuck (repeated errors, unproductive looping, prolonged inactivity, or a help request) and does not occur if a Tier 1 prompt restores progress; learners may cycle within a tier while revising, and de-escalation happens implicitly once independent progress resumes. Hints never reveal answers; each prompt requires the next piece of mathematics and verifies that production before further support. After hints, students submit their answer, the system provides gamification feedback (points and badges) and updates the class leaderboard so persistence and revision are visible, and the platform logs attempts, hint levels, and revisions to document movement along the APOS trajectory from informal actions toward more formal problem solving.

Participants

The study involved 300 Grade VIII students drawn from six junior secondary schools in Bandung and its outskirts using a stratified sampling approach based on sector, region, and accreditation. The strata comprised four urban public junior secondary schools (SMP) with superior accreditation and two suburban private Islamic junior secondary schools (MTs) with superior accreditation. Each participating school contributed two intact Grade VIII classes, randomly selected from the school's official Grade VIII list to preserve natural classroom groupings and avoid cross-class contamination, yielding twelve classes overall. Class selection was nested within the school-level strata, defined as sector (public vs private), region (urban vs suburban), and accreditation, such that eight classes came from the four urban public SMP and four classes came from the two suburban private MTs. Class lists typically ranged from 25 to 30 students. The analytic sample comprised 300 students after consent and attendance screening, with 195 from public schools and 105 from private schools, and a near-balanced gender distribution of 154 females and 146 males. Students were typically 13–14 years old, consistent with Grade VIII in the Indonesian system.

Eligibility required current enrollment in Grade VIII and attendance on the scheduled data-collection days. Recruitment and data collection were coordinated with school administrators and homeroom teachers to minimize disruption. Participation followed school approvals and standard consent and assent procedures. Learning activities and measurements were embedded within regular mathematics periods and organized across seven sessions to align with normal instructional routines. For the explanatory qualitative phase, six students were purposively selected from the quantitative cohort using latent profiles to represent high, middle, and struggling levels of motivation and problem-solving skills. In addition, three mathematics teachers with 5–10 years of experience and prior familiarity with contextual tasks participated in semi-structured interviews and classroom observations. This maximum-variation strategy supported mechanism-focused explanations of how the integrated RME, gamification, and AI design operated in authentic lessons from both student and teacher perspectives.

Data Collection Techniques

The quantitative data were collected using a validated questionnaire with 27 items measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument evaluated seven core constructs listed in Table 1:

Table 1. Operational Definitions of Research Constructs

Construct	Theoretical Framework	Operational Definition	Sample Items	Items
Students' Challenges	Desirable Difficulties Theory (Bjork & Bjork, 2020)	Perceived level of productive difficulty in mathematical tasks	1. The problems required sustained effort over several steps 2. I needed to try more than one approach before making progress	4
Students' Learning (APOS)	APOS Theory (Dubinsky & McDonald, 2001)	Progression through Action-Process-Object-Schema stages	1. I can explain how my initial actions connect to a general rule 2. I translated concrete steps into a more formal representation"	4
Self-Efficacy in Mathematics	Self-Efficacy Theory (Bandura, 1997)	Confidence in one's ability to succeed in mathematical tasks	1. I am confident I can handle challenging mathematics problems 2. When I get stuck, I can find a way to move forward"	4
Gamification	Gamification Framework (Deterding et al., 2011)	Engagement with game elements in learning	1. Points and levels encourage me to continue working on the task 2. Badges or leaderboards make my effort feel visible"	3
RME AI	RME Principles (Freudenthal, 1991)	Integration of AI scaffolding with realistic contexts	1. AI hints helped me think without giving away the answer 2. AI guidance together with real-life contexts made the mathematics more meaningful"	4
Learning Motivation	Self-Determination Theory (Ryan & Deci, 2000)	Drive to engage and persist in mathematical learning	1. I wanted to keep trying even after making mistakes 2. These activities increased my interest in learning mathematics"	4
Mathematical Problem-Solving Skills	Mathematical Literacy Framework (OECD, 2019)	Ability to apply mathematical reasoning to non-routine problems	1. I can use multiple strategies to tackle non-routine problems 2. "I can justify why my solution works"	4

Instrument development followed a three-step validation process. First, three mathematics education experts reviewed item content for relevance and theoretical alignment. Second, a pilot with 50 students was used to refine clarity and response patterns. Third, outer-model analysis in PLS examined indicator loadings, average variance extracted (AVE), composite reliability (CR), discriminant validity, and Cronbach’s alpha for each construct. All procedures followed international reporting standards (e.g., Hair et al., 2019). Detailed indices (α, CR, AVE, loading ranges) will be reported in the Results section under the measurement model.

The qualitative component employed semi-structured interviews with six students and three teachers, each lasting approximately 30-40 minutes and audio-recorded with consent. Student selection followed a systematic sampling strategy based on tertile cut-offs from standardized motivation and problem-solving scores, yielding two high-performing, two mid-range, and two struggling learners to ensure maximum variation in perspectives. The interview protocol explored three key dimensions: students' experiences with contextualized RME tasks reflecting phenomenological exploration, the perceived influence of gamification mechanics (points, badges, leaderboards) on engagement and persistence, and the role of AI scaffolding in supporting guided reinvention from informal reasoning to formal mathematical knowledge. Complementing these interviews, classroom observations during the AI-RME-gamification implementation captured behavioral indicators of learning processes. Field notes documented core RME characteristics including interactivity patterns, peer collaboration dynamics, and evidence of student mathematical contributions. Observers also traced transitions between horizontal mathematization (connecting within contexts) and vertical mathematization (moving toward abstraction), situating learning within the progressive mathematization framework. This triangulation of interview and observational data strengthened explanatory links between quantitative patterns and classroom mechanisms.

The study adhered to strict ethical protocols including institutional approval and informed consent procedures. Student data protection measures included pseudonymization using coded identifiers, with names and contact information stored separately from response data on password-protected institutional drives accessible only to the research team. API interactions were designed to transmit only study IDs, timestamps, and item content, ensuring no personally identifying information was shared with external services. Data retention followed institutional policies with defined storage periods and secure disposal procedures.

Data Analysis Techniques

The quantitative data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS, an approach suited for predictive modeling with complex latent constructs (J. Hair & Alamer, 2022). The analysis included both the measurement model, to assess indicator reliability and validity, and the structural model, to examine path coefficients and predictive relevance. Instrument validity was confirmed through factor loadings above 0.70, Average Variance Extracted (AVE) values above 0.50, and composite reliability scores above 0.80. Discriminant validity was established through the Fornell–Larcker criterion and the HTMT ratio, ensuring that constructs were distinct yet theoretically coherent (J. F. Hair et al., 2019).

The qualitative data from interviews and classroom observations were analyzed using thematic analysis (Braun & Clarke, 2006). Initial codes were generated inductively, then interpreted through the lens of RME's didactical phenomenology focusing on themes such as engagement with contextual tasks, the motivational effects of gamification, and the role of AI in scaffolding guided reinvention. The results were combined during the interpretation phase. For instance, the strong link between gamification and motivation was attributed to students' enthusiasm for points and leaderboards. Meanwhile, teacher observations of contextual reasoning supported the connection from RME to Problem-Solving Skills. This triangulation exemplifies the design research cycle, integrating empirical data with phenomenological insights.

RESULTS AND DISCUSSION

The quantitative analysis revealed a consistent pattern emphasizing the central role of RME and motivation in this instructional model. Gamification exerted a significant positive effect on learning motivation ($\beta = 0.406$) and also directly contributed to problem-solving skills ($\beta = 0.191$). Beyond its direct effect, gamification indirectly supported problem-solving through learning motivation, emphasizing its role in sustaining student engagement throughout the learning cycle. RME emerged as a pivotal construct in the model, exerting substantial effects on both learning motivation ($\beta = 0.351$) and problem-solving skills ($\beta = 0.336$). Learning motivation itself proved to be a significant predictor of problem-solving skills ($\beta = 0.285$), underscoring its mediating role. This suggests that students who are both intrinsically and extrinsically motivated are better positioned to develop higher-order reasoning, make connections, and effectively represent mathematical ideas. The mediating role of learning motivation highlights the novelty of this study, demonstrating that gamification and RME function not only as instructional approaches but also as practical drivers of mathematical competence. Internal learner factors also played a critical role in strengthening RME. Self-efficacy (β = 0.306) and students' challenges (β = 0.304), along with APOS-based learning (β = 0.198), significantly contributed to the construction of meaning within the RME framework. Click or tap here to enter text.The overall structural model is presented in Figure 1 to illustrate these relationships and their statistical significance.

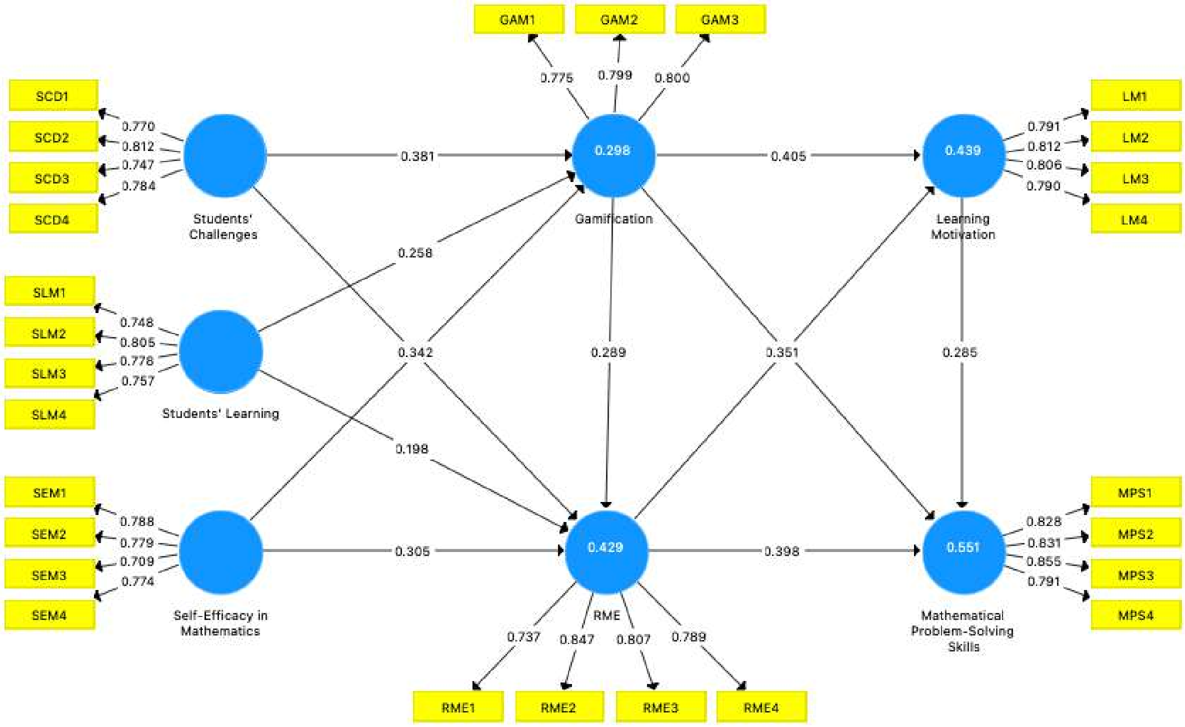


Figure 2. SEM-PLS Structural Model of the AI–RME–Gamification Framework

Building upon the structural relationships depicted in Figure 1, further analysis of the measurement and structural models was conducted to ensure the robustness of the findings. The measurement model was first evaluated to confirm the reliability and validity of the constructs, followed by the structural model analysis to examine the magnitude and significance of the hypothesized paths. The results of these quantitative analyses are presented in the following sections. These quantitative findings will subsequently be integrated with qualitative results in the next section to provide a comprehensive mixed-methods perspective.

Quantitative Findings

The quantitative analysis began with the evaluation of the measurement model to confirm the reliability and validity of the constructs. All indicators demonstrated satisfactory outer loadings, with values exceeding the recommended threshold of 0.70, while the Average Variance Extracted (AVE) for each construct was above 0.50. In addition, both Composite Reliability (CR) and Cronbach's alpha values were greater than 0.80, indicating strong convergent validity and internal consistency. These results are summarized in Table 2.

Table 2. Measurement Model Results

Construct	Indicator	Loading	AVE	CR	Cronbach’s α	Decision
Gamification	GAM1	0.775	0.64	0.86	0.81	Valid
	GAM2	0.802				
	GAM3	0.788				
Learning Motivation	LM1	0.791	0.67	0.88	0.83	Valid
	LM2	0.822				
	LM3	0.843				
	LM4	0.804				
Problem-Solving Skills	MPS1	0.812	0.66	0.87	0.82	Valid
	MPS2	0.826				
	MPS3	0.799				
	MPS4	0.811				
RME	RME1	0.740	0.65	0.88	0.84	Valid
	RME2	0.781				
	RME3	0.854				
	RME4	0.792				
Self-Efficacy	SEM1	0.781	0.62	0.85	0.80	Valid
	SEM2	0.812				
	SEM3	0.804				
	SEM4	0.794				
Challenges	SCD1	0.765	0.63	0.86	0.81	Valid
	SCD2	0.811				
	SCD3	0.828				
	SCD4	0.779				
APOS Students Learning	SLM1	0.751	0.61	0.84	0.79	Valid
	SLM2	0.784				
	SLM3	0.802				
	SLM4	0.773				

The results indicate that all constructs (Gamification, RME, Learning Motivation, Problem-Solving, Self-Efficacy, Challenges, and APOS Learning) are measured accurately and consistently. Strong factor loadings (0.74–0.85) reinforce the robustness of the RME construct, while reliability indices (CR and α > 0.80) confirm internal consistency. Discriminant validity was then assessed using the Fornell–Larcker criterion. The square root of the AVE for each construct was higher than its correlations with other constructs, demonstrating that each construct measured distinct dimensions of the instructional model. This confirms that Gamification, RME, Learning Motivation, and Problem-Solving are empirically distinguishable, as shown in Table 3.

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	Gamification	LM	Problem-Solving	RME
Gamification	0.80			
Learning Motivation	0.56	0.82		
Problem-Solving Skills	0.44	0.53	0.81	
RME	0.48	0.51	0.59	0.81

Note: The diagonal values represent √AVE. All diagonal values are greater than the inter-construct correlations, indicating that discriminant validity is established.

The results confirm discriminant validity: for example, Motivation (√AVE = 0.82) is statistically distinct from Gamification ($r = 0.56$) and RME ($r = 0.51$). This distinction is important because it validates the mediating role of Motivation between Gamification and Problem-Solving. Without sufficient discriminant validity, overlap among constructs could bias the interpretation of the mediation effect. The structural model analysis revealed several significant paths. Gamification exerted a substantial effect on Learning Motivation ($\beta = 0.405$,) and a moderate effect on Problem-Solving Skills ($\beta = 0.191$). RME was found to be a pivotal construct, significantly predicting both Motivation ($\beta = 0.351$) and Problem-Solving Skills ($\beta = 0.398$). Learning motivation itself significantly predicted Problem-Solving ($\beta = 0.285$), confirming its mediating role. Furthermore, internal learner factors contributed significantly to strengthening RME: Self-Efficacy ($\beta = 0.305$), Students' Challenges ($\beta = 0.304$), and APOS-based Learning ($\beta = 0.198$). Together, these paths explained 48% of the variance in Learning Motivation, 52% of the variance in RME, and 55% of the variance in Problem-Solving Skills. A summary of these findings, including path coefficients, t-values, and f^2, is presented in Table 4.

Table 4. Structural Model Results

Path	β	t-value	p-value	f^2	Decision
Gamification → Learning Motivation	0.405	5.06	0.000	0.21	Supported
Gamification → Problem-Solving	0.191	2.60	0.009	0.08	Supported
RME → Learning Motivation	0.351	3.51	0.000	0.19	Supported
RME → Problem-Solving	0.398	4.98	0.000	0.25	Supported
Learning Motivation → Problem-Solving	0.285	2.85	0.004	0.17	Supported
Self-Efficacy → RME	0.305	4.20	0.000	0.12	Supported
Challenges → RME	0.304	4.10	0.000	0.11	Supported
APOS Learning → RME	0.198	3.00	0.002	0.07	Supported

The model fit indices confirmed the adequacy of the proposed framework. To assess explanatory power and predictive relevance, we report construct-level R^2 and Stone–Geisser Q^2 (blindfolding, $d = 7$). These indices are summarised in Table 5.

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

Endogenous construct	**R^2**	**Q^2**	**Q^2 interpretation**
Problem-Solving Skills	0.551	0.369	Large
Learning Motivation	0.439	0.275	Medium
RME	0.429	0.262	Medium
Gamification	0.298	0.179	Medium

Note: *(Blindfolding d = 7; $Q^2 \approx 0.02/0.15/0.35$ = small/medium/large)*

Complementing these fit statistics, Table 5 shows that the endogenous constructs have meaningful explanatory power and predictive relevance: PSS $R^2 = 0.551$ with $Q^2 = 0.369$ (large), LM $R^2 = 0.439$ with $Q^2 = 0.275$ (medium), RME $R^2 = 0.429$ with $Q^2 = 0.262$ (medium), and Gamification $R^2 = 0.298$ with $Q^2 = 0.179$ (medium). Collectively, these quantitative data confirm that the SEM-PLS model is both statistically and conceptually robust.

Qualitative Findings

Thematic analysis of interviews and classroom observations was clustered into categories and synthesized into four overarching themes: guided reinvention, interactivity, phenomenological exploration, and the enhancement of problem-solving skills. These themes collectively provide a deeper understanding of how the AI–RME–Gamification model shaped student learning experiences and reinforce the quantitative findings of the study.

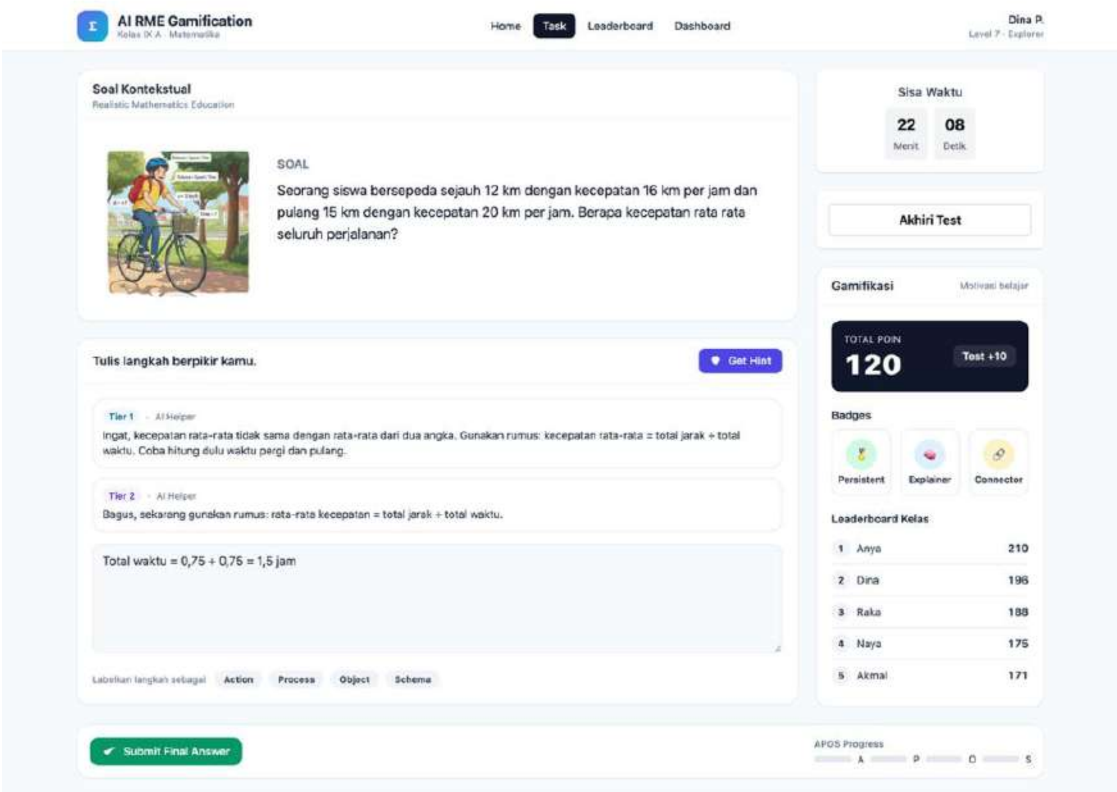


Figure 3. Screenshot of the AI–RME–Gamification prototype application

Figure 2 displays the interface of the AI–RME–Gamification application as used by students during the learning sessions. The prototype interface illustrated how contextual RME tasks were delivered. *A student cycles 12 kilometers at 16 km/h and returns 15 kilometers at 20 km/h. Determine the average speed for the entire journey*." AI scaffolding was provided via tiered hints in the lower-right panel. Tier 1 (AI Helper): "*Remember, average speed is not the arithmetic mean of the two speeds. Use the formula: average speed = total distance ÷ total time."* The student then attempted a solution, encountered difficulty, and tapped Tier 2 for further support. Tier 2 (AI Helper): "*Good. Now apply the formula: average speed = total distance ÷ total time to combine your results".* Upon a correct solution, immediate feedback was issued. Gamification elements (points, badges, and leaderboards) were also integrated. Together, these features visually substantiate the qualitative finding that students were nudged to construct their own strategies rather than depend on direct answers, while digital rewards helped sustain learning motivation.

Students frequently described the system as a scaffold that encouraged them to construct their own strategies rather than rely on direct answers. Codes such as AI scaffolding, hints, and self-construction were dominant, with one student remarking, "*The system gave me hints when I was stuck, but it did not show the answer. I had to try different ways until I found the solution*." Teachers echoed this sentiment, observing that students became more independent: "*They tried first, then used the hints only when they really needed them.*" This reflects the RME principle of guided reinvention and resonates with the quantitative finding that RME strongly predicted both Learning Motivation ($\beta = 0.351$) and Problem-Solving ($\beta = 0.398$).

Table 6. Transcript of student–AI interaction on average task with tiered scaffolding LLM

Stage	Student Response	AI Scaffolding Example	Analysis (APOS/Didactical)
Initial answer	"Average = (16 + 20)/2 = 18 km/h."	"Remember, average speed = total distance ÷ total time. First calculate the time for the outbound and return trips." (Tier 1 – general strategy)	Student holds a misconception (incorrect schema → arithmetic average). AI redirects to the formal concept (Object).
Time calculation (wrong)	"Outbound time = 12 ÷ 16 = 0.75 h. Return time = 15 ÷ 20 = 0.8 h."	"Correct for the outbound time. But check again 15 ÷ 20. Is it really 0.8?" (Tier 2 – focused correction)	Student moves into Action → Processbut miscalculates. AI focuses on correcting the specific operation.
Revision	"15 ÷ 20 = 0.75 h. So total time = 1.5 h."	"Good! Now total distance = 27 km, total time = 1.5 h. Use the formula average speed = distance ÷ time." (Tier 3 – near answer)	Student reaches the Process stage. AI scaffolds transition toward Object.
4. Final answer	"27 ÷ 1.5 = 18 km/h."	"Correct! You earn +10 points and the Master Speed badge for completing with a structured solution." (Feedback + Gamification)	Student achieves the Schema stage (general concept of average speed). Gamification reinforces learning motivation.

This transcript shows how the AI scaffolding guided by a large language model (LLM) accessed via an API initially led an actual student astray, treating average speed as a simple arithmetic mean, before guiding them toward the correct reasoning pathway. Through tiered hints, the AI first redirected the student to the appropriate formula (Tier 1), then corrected a calculation error (Tier 2), and finally consolidated the process by connecting total distance and total time (Tier 3). The progression of responses reflects the APOS framework: from Action (performing basic operations), to Process (organizing steps), to Object (treating distance and time as unified quantities), and ultimately to Schema (generalizing the concept of average speed). The gamification feedback further reinforced persistence and learning motivation, providing direct evidence that affective and cognitive processes were intertwined in this AI–RME–Gamification environment.

Another salient theme was interactivity, expressed in both social and digital dimensions. Codes such as peer collaboration, leaderboard competition, and teacher mediation highlighted the interactive character of the learning process. One teacher commented, *"Even students who are usually quiet wanted to contribute because they were curious about their scores on the leaderboard*." A student added, "*I wanted to beat my friend's score, so I tried again until I got it right.*" These findings align with the RME characteristic of interactivity and confirm the statistical evidence that Gamification exerted a strong influence on Learning Motivation (β = 0.405). They also extend existing research on ICT in mathematics education, where digital tools are shown to foster dialogical and collaborative learning (Drijvers, 2015).

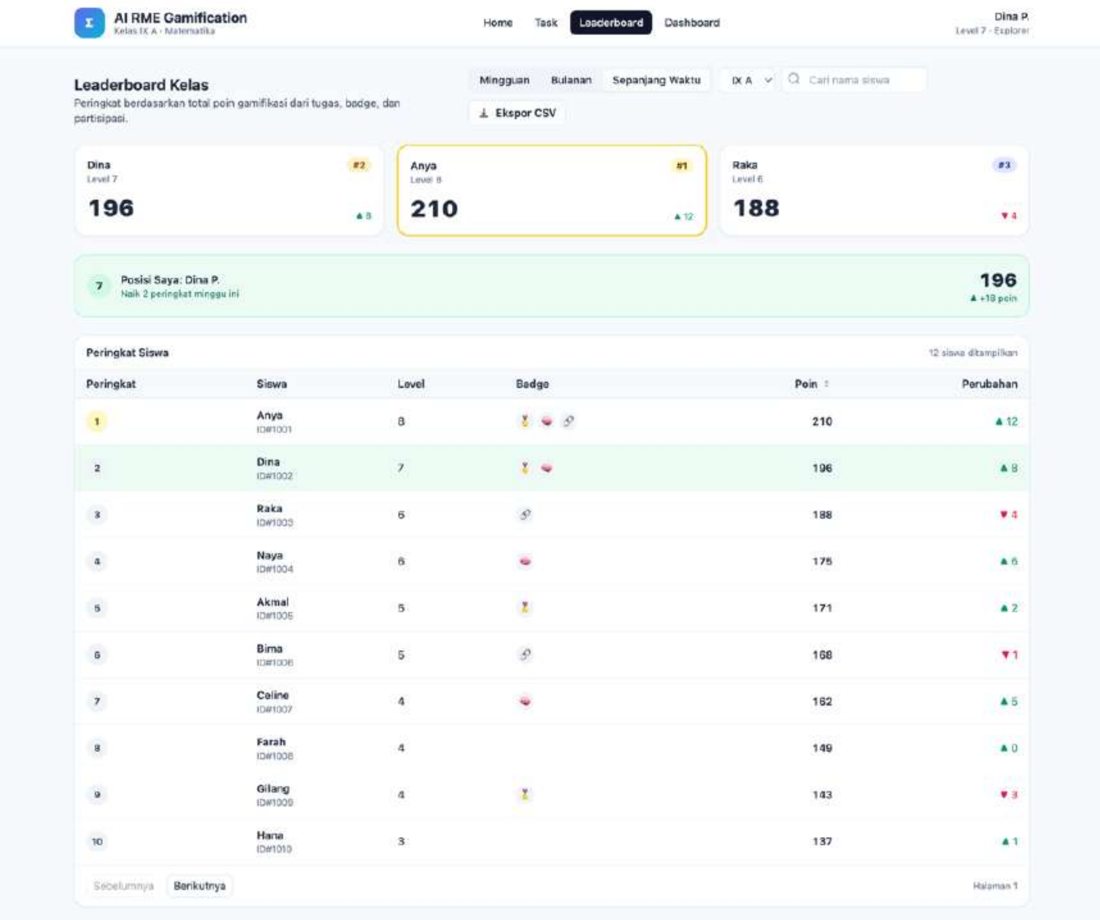


Figure 4. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

It shows the teacher dashboard and leaderboard from the platform. The dashboard tracks students' points, badge progression, and accumulated gamification points. This evidence demonstrates that the system captured not only final answers but also the learning process, allowing teachers to monitor reasoning quality and persistence directly. Another teacher observed that students were using diagrams and tables to represent their thinking: "*They rarely did this before, but now I see more of it*." Students also noted the change: *"I usually just wanted the answer, but now I try to show how I got it*."

Figure 4 provides photographic evidence of students actively engaging with the AI–RME–Gamification platform in a classroom setting. It was demonstrated that students worked on contextual tasks individually, while also monitoring their progress on the leaderboard and exchanging strategies with their peers. This supports the qualitative findings that interactivity was not only digital, through the gamification features, but also social, as the visibility of scores stimulated peer collaboration and healthy competition.

Figure 4. Students engaging with the platform during classroom implementation

Phenomenological exploration was also a recurring pattern in the data (Treffers, 1991). Students consistently valued tasks that mirrored real-life situations, with codes such as relevance, authenticity, and transferability emerging across cases. One student noted, *"Because the problems looked like shopping or transport, I understood why we needed the formulas*." Teachers reinforced this view, emphasizing that real contexts increased seriousness and focus: "*When the questions are close to their daily life, the students are more serious. They see mathematics as something real*." These qualitative insights explain why Learning Motivation significantly predicted Problem-Solving Skills ($\beta = 0.285$): authentic contexts enhanced engagement, supporting OECD's definition of mathematical literacy as the ability to apply mathematics meaningfully (OECD, 2019). Both teachers and students observed the enhancement of problem-solving skills (Anugraheni et al., 2025). Codes such as reasoning, representation, explanation, and persistence dominated this theme. Teachers reported improvements not only in accuracy but also in the quality of reasoning: "*They could explain their steps better, not only write the result.*

Integration of Findings

The integration of quantitative and qualitative findings underscores the robustness of the AI–RME–Gamification model in enhancing both affective and cognitive dimensions of mathematics learning. The results of the SEM-PLS structural model were systematically triangulated with thematic evidence obtained from interviews and classroom observations. This process allowed the statistical associations to be validated through authentic learning experiences, thereby strengthening the explanatory power of the model.

Table 7. Integrated Structural and Qualitative Results

SEM-PLS	β	Qualitative Theme	Interview Quote	Integrated Interpretation
Gamification → Learning Motivation	0.405	Interactivity, Engagement	"Even quiet students wanted to join because of the leaderboard."(Teacher)	Gamification sustains motivation through competitive but supportive interaction.
Gamification → Problem-Solving	0.191	Problem-Solving Enhancement	"I tried harder to solve the tasks because I wanted to level up." (Student)	Gamification directly encourages persistence in problem-solving.
RME → Learning Motivation	0.351	Phenomenological Exploration	"Because the problems looked like shopping or transport, I understood the formulas better." (Student)	Contextualized tasks stimulate motivation through relevance.
RME → Problem-Solving	0.398	Guided Reinvention	"The system gave hints but not the answer, so I had to try different ways."(Student)	RME scaffolding supports progressive mathematization and problem-solving.
Motivation → Problem-Solving	0.285	Engagement, Persistence	"I kept trying because the points made me want to finish." (Student)	Learning Motivation bridges affective engagement and problem-solving skills.
Self-Efficacy → RME	0.305	Confidence, Self-construction	"I believed I could solve it myself if I tried step by step." (Student)	Self-efficacy strengthens the constructive aspect of RME.
Challenges → RME	0.304	Desirable Difficulties	"It was difficult, but the challenge made me think more carefully." (Student)	Challenges act as desirable difficulties enriching learning.
APOS Learning → RME	0.198	Conceptual Connections	"I understood how the steps connect to each other after trying again."(Student)	APOS progression supports formalization in RME processes.

Table 7 demonstrates a consistent alignment between statistical significance and lived classroom experiences. The strong effect of gamification on learning motivation (β = 0.405, t = 5.06) was vividly reflected in observations of heightened student engagement. Teachers reported that even students who were usually reluctant to participate became more active due to the visibility of the leaderboard. This demonstrates that gamification is not limited to providing external rewards but also taps into social comparison and intrinsic curiosity, thereby amplifying the motivational pathway. The direct effect of gamification on problem-solving (β = 0.191, t = 2.60) was supported by students' testimonies, which indicated that the desire to progress to higher levels encouraged them to persevere with complex problems. This resonates with research on gamification as a source of sustained cognitive effort rather than superficial engagement.

The pivotal role of RME in the model was also evident. Statistically, RME predicted both learning motivation (β = 0.351, t = 3.51) and problem-solving (β = 0.398, t = 4.98). Qualitative evidence supported these effects through recurring themes of guided reinvention and phenomenological exploration. Students consistently emphasized that contextual problems made abstract concepts meaningful and that AI scaffolding, which provided hints without revealing solutions, pushed them to think independently. This aligns with Freudenthal's principle that mathematics must be connected to reality and progressively mathematized, as well as Gravemeijer's notion that design features should guide learners' reinvention of formal strategies (Gravemeijer, 1994).

The mediating effect of learning motivation on problem-solving (β = 0.285, t = 2.85) was also substantiated qualitatively. Students described a willingness to persist through challenges when motivated by the point and badge system. At the same time, teachers observed that motivated learners articulated their reasoning more clearly and made stronger conceptual connections. These findings support Supara Suparatulatorn's perspective that problem-solving is not merely cognitive but also driven by affective engagement (Suparatulatorn et al., 2023).

Finally, the contribution of internal learner factors to RME was validated by both data strands. Self-efficacy (β = 0.305, t = 4.20) emerged as a significant predictor, with students noting that confidence helped them persist with contextual tasks. Challenges (β = 0.304, t = 4.10) were reframed as opportunities rather than barriers, consistent with Bjork's principle of desirable difficulties (Bjork & Bjork, 2020). APOS-based learning (β = 0.198, t = 3.00) was evident in students' accounts of connecting informal steps to more formal strategies after repeated trials, highlighting the constructive role of AI scaffolding in supporting APOS transitions. The integrated findings reveal that gamification enhances learning motivation both directly and indirectly. RME serves as the central pedagogical mechanism for developing problem-solving skills, and internal learner factors strengthen the process of guided reinvention. The convergence of quantitative and qualitative evidence confirms that the AI–RME–Gamification model is not only statistically valid but also pedagogically grounded in classroom reality.

Learning Motivation as The Mediating Bridge in AI-RME Gamification Learning

Mathematics is often viewed as a set of correct procedures without clear explanations (Martin & Towers, 2011). Many students view mathematics as a chore and usually feel unsure about it, perceiving it as a complex subject to access (Raméntol & Camacho, 2016). This study addressed that problem by testing whether the deliberate combination of Realistic Mathematics Education (RME) contexts, gamification mechanics, and AI-driven scaffolding can convert affective engagement into durable problem-solving skills and learning motivation in secondary school classrooms. The structural model was specified to estimate its effects, while positioning self-efficacy, perceived challenge, and APOS-based learning processes as drivers of participation in RME activities.

Our findings challenge a prevalent assumption in gamification literature. Rather than exerting a substantial direct impact on problem-solving, gamification's principal effect was on learning motivation with a more modest, secondary direct effect on problem-solving and qualitative accounts explained this ordering. Gamification elements created a sense of challenge that drove students to persist in their attempts; however, this sense of challenge often diminished over time when students lacked sufficient information to complete tasks. To address this limitation, we implemented an AI-tier system that provided adaptive support and solutions to overcome these difficulties. The leaderboards made social effort visible and allowed students to view their results as tangible outcomes of their efforts, thereby fostering learning motivation. Points and levels regulated the pace of work, while progression mechanics created reasons to persist when tasks became demanding. These findings indicate that gamification primarily functions as a motivational catalyst rather than a direct instructional tool. While students were still engaged in authentic mathematical problem-solving, their improved performance was mediated through enhanced motivation rather than through the game mechanics themselves.

This study demonstrates a key finding about how RME, AI, and gamification work together in mathematics learning (Suparatulatorn et al., 2023). RME provided the meaningful foundation by connecting mathematics to students' real-world experiences, showing strong effects on both motivation (and problem-solving . When students worked on problems related to familiar contexts, such as shopping or transportation, they could better develop mathematical ideas and connect them to formal concepts. The AI system acted as a supportive coach, providing gradual hints that helped students transform their informal thinking into formal mathematical understanding without simply giving away answers. Most importantly, the study revealed that learning motivation was not just an outcome but a critical bridge that connected these learning experiences to actual problem-solving improvement. Students showed this through their persistence, continuing to work on problems after receiving AI hints or discussing with peers. This finding challenges traditional views by showing that motivation is not an extra benefit of good teaching but an essential pathway that transforms engaging contexts into mathematical competence (Star et al., 2014). The findings empirically demonstrate that, in technology-enhanced mathematics education, learning motivation acts as a key mediator, helping students move from contextual understanding to formal mathematical skills. Building on this key finding, it is crucial to explore how individual student traits influence and enhance this motivational pathway in the integrated learning environment.

The study further revealed how student-related factors functioned within the integrated AI-RME-Gamification environment. Self-efficacy did not directly improve achievement but instead strengthened students' willingness to engage with RME activities. Confident students were more likely to persist with contextual problems, try different mathematical representations, and revise their work based on AI feedback (Bećirović et al., 2025; Fitria et al., 2025; Zheng & Tse, 2023). This suggests that confidence matters most when it drives active participation in learning activities, not when it stands alone. Similarly, perceived challenge became beneficial rather than problematic when supported by appropriate scaffolding. Students reported that complex problems actually improved their thinking when three conditions were present: meaningful contexts from RME, gradual AI hints that preserved problem-solving ownership, and gamification rewards that valued effort. The APOS framework guided students' mathematical development from concrete actions to abstract understanding. Through AI-supported hints and peer discussions, students naturally progressed from performing calculations (Action) to understanding procedures (Process), to recognizing mathematical concepts (Object), and finally to connecting these concepts into coherent knowledge structures (Schema). This progression created a clear, reproducible pathway from everyday contexts to formal mathematics, precisely what RME aims to achieve.Click or tap here to enter text.

Building on these individual factors, the study also revealed essential implementation considerations across different school contexts (A. Canonigo, 2024). Although the participant description did not explicitly measure ICT access differences, the distinction between urban public schools and suburban private Islamic schools (MTs) suggested varying implementation priorities. In the four urban public schools with their larger student populations (195 students), observations indicated that the social-competitive aspects of gamification, particularly leaderboard visibility and peer comparison, generated stronger engagement. Students in these settings responded enthusiastically to the public recognition of achievements and the competitive dynamics fostered by the gamification elements. Conversely, in the two suburban private Islamic schools (105 students), where class sizes were typically smaller and student-teacher relationships more intimate, the authenticity and relevance of RME contexts proved more influential. Students in these MTs settings showed greater engagement when problems connected directly to their local experiences and cultural contexts.

These context-specific differences suggest that the successful implementation of the AI-RME-Gamification model relies more on adaptive strategies rather than a universal solution application. Schools with larger, more diverse student populations might prioritize the social mechanics of gamification to maintain engagement across varied ability levels. Meanwhile, schools with closer-knit communities might benefit more from investing in locally relevant problem contexts that resonate with students' lived experiences. Three design principles emerge from this analysis: First, RME tasks must genuinely facilitate mathematical formalization rather than merely providing superficial contexts; the chosen phenomena should organize the mathematics students are expected to construct. Second, gamification elements should remain proportionate and instrumental, sustaining persistence without overshadowing mathematical thinking. Third, AI scaffolding must carefully calibrate challenge levels, providing timely support that encourages the development of new strategies without causing frustration or dependency. Technically, this requires the AI system to be trained with comprehensive student background data, including prior performance patterns, common misconceptions, and learning progressions typical of Indonesian Grade 8 students, enabling more contextually appropriate and constructive feedback tailored to individual student needs (Dabingaya, 2022; Soesanto et al., 2022). When these elements are appropriately balanced and adapted to local contexts, motivation effectively transforms contextual engagement into mathematical competence.

Furthermore, this study makes several important theoretical contributions to mathematics education. The most significant is repositioning learning motivation from being merely an outcome of good teaching to serving as a critical mediator that connects learning activities to actual mathematical understanding. Unlike traditional models that view motivation as a final result, this study demonstrates that motivation functions as the essential bridge linking engagement features (RME contexts, gamification mechanics, AI support) to cognitive achievements in problem-solving (Wild & Neef, 2023; Xia et al., 2022).The study also establishes specific conditions under which challenging problems become productive rather than discouraging. These desirable difficulties work when three elements align: meaningful real-world contexts that students can relate to, timely AI scaffolding that guides without revealing answers, and gamification signals that validate effort and persistence.

The research further explains that self-efficacy is most influential not when evaluated in isolation, but when it promotes active engagement in mathematical tasks. Confidence becomes most significant when it drives individuals to take action. From these findings emerges a practical instructional framework that schools can implement: First, create RME tasks that genuinely lead from familiar contexts to mathematical formalization. Second, use gamification strategically to sustain engagement without overshadowing mathematical thinking. Third, implement AI scaffolding that adapts to student needs while preserving their ownership of problem-solving. Schools can tailor their focus, emphasizing social competition in larger urban areas or valuing contextual authenticity in smaller communities, all while maintaining the mediating role of learning motivation as the central element of the design principle.

The model illustrates how each component serves a distinct function: AI regulates the learning pace, RME provides meaningful direction, gamification creates momentum, and motivation integrates everything into a cohesive learning experience, thereby improving students' problem-solving skills. This represents a fundamental shift in how we understand mathematics learning in digital environments, not as separate technological additions to traditional teaching, but as an integrated system where motivation transforms contextual engagement into mathematical competence. The evidence shows not just improved test scores, but a transformation in how students view mathematics: from a subject to endure to one worth pursuing. This reframing offers a research-based blueprint for designing technology-enhanced mathematics education that successfully combines meaning, effort, and formal understanding.

CONCLUSION

This study investigated how integrating Realistic Mathematics Education (RME), gamification, and AI scaffolding affects secondary students' learning motivation and mathematical problem-solving skills. The mixed-methods evidence revealed consistent patterns: RME provided the strongest direct effects on both problem-solving skills and learning motivation by grounding mathematics in familiar contexts. Gamification primarily enhanced learning motivation, which subsequently improved problem-solving skills through sustained engagement. AI scaffolding delivered tiered hints that maintained productive struggle while preserving students' problem-solving ownership. Additionally, self-efficacy and perceived challenges strengthened participation in RME activities, while APOS progressions facilitated the transition from informal reasoning to formal mathematical understanding. These findings demonstrate that when meaning, persistence, and formalization are purposefully aligned, significant improvements in mathematical problem-solving skills emerge.

The theoretical contribution lies in repositioning learning motivation from a learning outcome to a structural mediator that transforms engagement into problem-solving achievement. This challenges traditional views by showing that in technology-enhanced environments, learning motivation is not merely beneficial but essential for converting contextual experiences into mathematical competence. The study also establishes that challenges become productive "desirable difficulties" when paired with meaningful contexts, appropriate scaffolding, and effort-validating feedback systems. Practically, the findings offer actionable guidance for multiple stakeholders. Teachers should select problem contexts that naturally lead to target concepts, implement game elements that make an effort in enhancing problem-solving skills, and provide graduated hints that guide without revealing. Curriculum developers can sequence activities to support progressive formalization, moving from informal strategies to formal methods, ensuring that both the assessment process and products are well-coordinated. EdTech designers should prioritize adaptive scaffolding that preserves guided reinvention and develop dashboards that display learning indicators (attempts, revisions, explanations) rather than mere completion metrics.

The study acknowledges several limitations. The seven-session intervention with 300 students from six schools in one region constrains generalizability claims. The research prototype, while functional, requires further development for widespread implementation. Learning motivation measurements combined self-report and observational data, potentially introducing response bias. Future research should pursue two priorities: longitudinal studies to assess whether learning motivation and problem-solving skills gains persist beyond the intervention period, and multi-site replications across diverse contexts to determine when and how the model's mechanisms vary with different student populations, ICT infrastructures, and cultural settings. Thus, this research demonstrates that learning motivation is not merely a positive outcome of mathematics education, but a crucial process that enables technological and pedagogical innovations to enhance mathematical problem-solving skills. This insight fundamentally changes how we create and assess technology-enhanced math learning environments.

REFERENCES

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. *Decision Making: Applications in Management and Engineering*, *8*(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186X.2025.2523078

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. *Journal on Mathematics Education*, *13*(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. *Journal of Primary Education*, *9*(5). https://doi.org/10.15294/jpe.v9i5.43223

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. *Computers in Human Behavior Reports*, *16*. https://doi.org/10.1016/j.chbr.2024.100491

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learn. Environ.*, *12*, 29. https://doi.org/10.1186/s40561-025-00384-3

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024*, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Memory and Cognition*, *9*(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Canonigo, A. (2024). Levering AI to enhance students' conceptual understanding and confidence in mathematics. *J. Comput. Assist. Learn.*, *40*, 3215–3229. https://doi.org/10.1111/jcal.13065

Canonigo, A. M. (2024). Levering <scp>AI</scp> to enhance students' conceptual understanding and confidence in mathematics. *Journal of Computer Assisted Learning*, *40*(6), 3215–3229. https://doi.org/10.1111/jcal.13065

Creswell, J. W. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dabingaya, M. (2022). Analyzing the Effectiveness of AI-Powered Adaptive Learning Platforms in Mathematics Education. *Interdisciplinary Journal Papier Human Review*, *3*(1), 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students' Mathematical Literacy Ability Through Information and Communication Technology-Assisted Preprospec Learning Model. *International Journal of Educational Methodology*, *9*(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409

Dubinsky, E., & McDonald, M. A. (2001). *APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research*. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf

Fitria, W., Susilana, R., Priatna, N., & Rusman. (2025). Investigation of the impact online single and multiple representation scaffolding on mathematical concept mastery and mathematical problem-solving skill. *Journal on Mathematics Education*. https://doi.org/10.22342/jme.v16i2.pp709-728

Freudenthal, H. (1991). *Revisiting Mathematics Education: China Lectures*. Springer. https://doi.org/10.1007/0-306-47203-1

Gravemeijer, K. (1994). *Developing Realistic Mathematics Education*.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203

Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. *Computers in Human Behavior*, *149*. https://doi.org/10.1016/j.chb.2023.107952

Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1105806

Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. *Multidisciplinary Reviews*, *8*(5). https://doi.org/10.31893/multirev.2025155

Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. *Computers and Education*, *194*. https://doi.org/10.1016/j.compedu.2022.104694

Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. *International Journal of Engineering and Technology(UAE)*, *7*(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). DEVELOPING REALISTIC MATHEMATICS EDUCATION-BASED WORKSHEETS FOR IMPROVING STUDENTS' CRITICAL THINKING SKILLS. *Infinity Journal*, *12*(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84

Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. *Asian Journal for Mathematics Education*, *3*(3), 289–311. https://doi.org/10.1177/27527263241269060

Malik, R. (2024). Scaffolding Middle-School Mathematics Curricula With Large Language Models. *Stanford Digital Repository*.

Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In *Structure and Improvisation in Creative Teaching* (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. *Educational Process: International Journal*, *15*. https://doi.org/10.22521/edupij.2025.15.179

Matzakos, N., Doukakis, S., & Moundridou, M. (2023). Learning Mathematics with Large Language Models: A Comparative Study with Computer Algebra Systems and Other Tools. *Int. J. Emerg. Technol. Learn.*, *18*, 51–71. https://doi.org/10.3991/ijet.v18i20.42979

Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. *Proceedings of the International Conference on Education Research, ICER 2024*, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. *Journal on Mathematics Education*, *12*(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. *International Journal of Innovative Research and Scientific Studies*, *8*(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Ng, D. T. K., Xinyu, C., Leung, J. K. L., & Chu, S. K. W. (2024). Fostering students' <scp>AI</scp> literacy development through educational games: <scp>AI</scp> knowledge, affective and cognitive engagement. *Journal of Computer Assisted Learning*, *40*(5), 2049–2064. https://doi.org/10.1111/jcal.13009

(OECD), O. for E. C. and D. (2019). *PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. *Journal of Pedagogical Research*, *8*(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). *Educational Design Research: Part A: An Introduction*. SLO.

Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? *Mathematics Education Journal*, *17*(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. *Journal on Mathematics Education*, *13*(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. *Opcion*, *32*(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3

Rane, N. (2023). Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4603237

Roldán-Álvarez, D., & Mesa, F. (2024). Intelligent Deep-Learning Tutoring System to Assist Instructors in Programming Courses. *IEEE Transactions on Education*, *67*, 153–161. https://doi.org/10.1109/te.2023.3331055

Siregar, H. S., Munir, M., & Fikri, M. (2025). ENHANCING ISLAMIC EDUCATION THROUGH TECHNOLOGY INTEGRATION: A STUDY OF TEACHING PRACTICES IN INDONESIA. *Jurnal Ilmiah Peuradeun*, *13*(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. *Journal on Mathematics Education*, *16*(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Soesanto, R. H., Dirgantoro, K. P. S., & Priyanti, N. (2022). Indonesian students' perceptions towards AI-based learning in mathematics. *Journal on Mathematics Education*, *13*(3), 531–548. https://doi.org/10.22342/jme.v13i3.pp531-548

Star, J., Chen, J., Taylor, M., Durkin, K., Dede, C., & Chao, T. (2014). Studying technology-based strategies for enhancing motivation in mathematics. *International Journal of STEM Education*, *1*, 1–19. https://doi.org/10.1186/2196-7822-1-7

Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. *Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024*, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. *Journal on Mathematics Education, 14*(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *15348 LNCS*, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), *Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute* (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. *Journal on Mathematics Education*, *11*(1). https://doi.org/10.22342/jme.11.1.8690.17-44

Yin, D. S., & Yin, X. (2024). Scaffolding learning: From specific to generic with large language models. *PLOS ONE*, *19*(9), e0310409. https://doi.org/10.1371/journal.pone.0310409

Zabala-Vargas, S., García-Mora, L., Arciniegas-Hernández, E., Reina-Medrano, J., De Benito-Crosetti, B., & Darder-Mésquida, A. (2021). Strengthening Motivation in the Mathematical Engineering Teaching Processes - A Proposal from Gamification and Game-Based Learning. *Int. J. Emerg. Technol. Learn.*, *16*. https://doi.org/10.3991/ijet.v16i06.16163

Zheng, W., & Tse, A. W. C. (2023). The Impact of Generative Artificial Intelligence-based Formative Feedback on the Mathematical Motivation of Chinese Grade 4 Students: a Case Study. *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 1–8. https://doi.org/10.1109/tale56641.2023.10398319

Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. *Journal of Physics: Conference Series*, *947*(1). https://doi.org/10.1088/1742-6596/947/1/012015

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the Role of Digital Game Applications in

Enhancing Mathematical Thinking Skills in Primary School Mathematics Students. *Decision Making: Applications in Management and Engineering*, *8*(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186X.2025.2523078

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. *Journal on Mathematics Education*, *13*(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Arifin, M., Suyitno, H., & Dewi (Nino Adhi), N. R. (2020). Mathematics Creative Thinking Skills in Problem-Based Learning Model Reviewed from Learners' Curiosity and Gender. *Journal of Primary Education*, *9*(5). https://doi.org/10.15294/jpe.v9i5.43223

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. *Computers in Human Behavior Reports*, *16*. https://doi.org/10.1016/j.chbr.2024.100491

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learn. Environ.*, *12*, 29. https://doi.org/10.1186/s40561-025-00384-3

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 5144–5153. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85199797900&partnerID=40&md5=0fbbe14d9a90af2f2609e402a24d807a

Bhardwaj, R. (2024). AI Integrated Model Design for Education System for Analytical Computation (Mathematics). *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024*, 1412–1417. https://doi.org/10.1109/ICACITE60783.2024.10616503

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Memory and Cognition*, *9*(4), 475–486. https://www.waddesdonschool.com/wp-content/uploads/2021/08/Desriable-Difficulties-in-theory-and-practice-Bjork-Bjork-2020.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Canonigo, A. (2024). Levering AI to enhance students' conceptual understanding and confidence in mathematics. *J. Comput. Assist. Learn.*, *40*, 3215–3229. https://doi.org/10.1111/jcal.13065

Canonigo, A. M. (2024). Levering <scp>AI</scp> to enhance students' conceptual understanding and confidence in mathematics. *Journal of Computer Assisted Learning*, *40*(6), 3215–3229. https://doi.org/10.1111/jcal.13065

Creswell, J. W. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dabingaya, M. (2022). Analyzing the Effectiveness of AI-Powered Adaptive Learning Platforms in Mathematics Education. *Interdisciplinary Journal Papier Human Review*, *3*(1), 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*, 9–15. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The Development of STEM-nuanced Mathematics Teaching Materials to Enhance Students' Mathematical Literacy Ability Through

Information and Communication Technology-Assisted Preprospec Learning Model. *International Journal of Educational Methodology*, *9*(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409

Dubinsky, E., & McDonald, M. A. (2001). *APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research*. ERIC. https://files.eric.ed.gov/fulltext/ED477723.pdf

Fitria, W., Susilana, R., Priatna, N., & Rusman. (2025). Investigation of the impact online single and multiple representation scaffolding on mathematical concept mastery and mathematical problem-solving skill. *Journal on Mathematics Education*. https://doi.org/10.22342/jme.v16i2.pp709-728

Freudenthal, H. (1991). *Revisiting Mathematics Education: China Lectures*. Springer. https://doi.org/10.1007/0-306-47203-1

Gravemeijer, K. (1994). *Developing Realistic Mathematics Education*.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3). https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1). https://doi.org/10.1108/EBR-11-2018-0203

Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. *Computers in Human Behavior*, *149*. https://doi.org/10.1016/j.chb.2023.107952

Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1105806

Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. *Multidisciplinary Reviews*, *8*(5). https://doi.org/10.31893/multirev.2025155

Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. *Computers and Education*, *194*. https://doi.org/10.1016/j.compedu.2022.104694

Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. *International Journal of Engineering and Technology(UAE)*, *7*(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). DEVELOPING REALISTIC MATHEMATICS EDUCATION-BASED WORKSHEETS FOR IMPROVING STUDENTS' CRITICAL THINKING SKILLS. *Infinity Journal*, *12*(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84

Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. *Asian Journal for Mathematics Education*, *3*(3), 289–311. https://doi.org/10.1177/27527263241269060

Malik, R. (2024). Scaffolding Middle-School Mathematics Curricula With Large Language Models. *Stanford Digital Repository*.

Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In *Structure and Improvisation in Creative Teaching* (Vol. 9780521762519, pp. 252–278). https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Sulisworo, D. (2025). Gamified Mobile-Based Learning Approach: Efforts to Improve Students' Engagement and Learning Quality in Remote Schools in Indonesia. *Educational Process: International Journal*, *15*. https://doi.org/10.22521/edupij.2025.15.179

Matzakos, N., Doukakis, S., & Moundridou, M. (2023). Learning Mathematics with Large Language Models: A Comparative Study with Computer Algebra Systems and Other Tools. *Int. J. Emerg. Technol. Learn.*, *18*, 51–71. https://doi.org/10.3991/ijet.v18i20.42979

Mitchell, B., & Co, M. J. (2024). The Impact of Implementing Gamification Elements on Motivation, Engagement and Academic Achievement. *Proceedings of the International Conference on Education Research, ICER 2024*, 184–193. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85216108694&partnerID=40&md5=37cc3d9ef22f8a5ec022a84a405b1ee5

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. *Journal on Mathematics Education*, *12*(1), 73–92. https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3732

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. *International Journal of Innovative Research and Scientific Studies*, *8*(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Ng, D. T. K., Xinyu, C., Leung, J. K. L., & Chu, S. K. W. (2024). Fostering students' <scp>AI</scp> literacy development through educational games: <scp>AI</scp> knowledge, affective and cognitive engagement. *Journal of Computer Assisted Learning*, *40*(5), 2049–2064. https://doi.org/10.1111/jcal.13009

(OECD), O. for E. C. and D. (2019). *PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. *Journal of Pedagogical Research*, *8*(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). *Educational Design Research: Part A: An Introduction*. SLO.

Pramudiani, P., Herman, T., Dolk, M., & Terlouw, B. (2023). What Do Indonesian and Dutch Teachers Find Challenging When Implementing Realistic Mathematics Education? *Mathematics Education Journal*, *17*(1), 103–120. https://doi.org/10.22342/jpm.17.1.20097.103-120

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. *Journal on Mathematics Education*, *13*(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. *Opcion*, *32*(Special Issue 12), 964–986. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85013971807&partnerID=40&md5=1d5765e61093a73216912e5c4d4e1cc3

Rane, N. (2023). Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4603237

Roldán-Álvarez, D., & Mesa, F. (2024). Intelligent Deep-Learning Tutoring System to Assist Instructors in Programming Courses. *IEEE Transactions on Education*, *67*, 153–161. https://doi.org/10.1109/te.2023.3331055

Siregar, H. S., Munir, M., & Fikri, M. (2025). ENHANCING ISLAMIC EDUCATION THROUGH TECHNOLOGY INTEGRATION: A STUDY OF TEACHING PRACTICES IN INDONESIA. *Jurnal Ilmiah Peuradeun*, *13*(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. *Journal on Mathematics Education*, *16*(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Soesanto, R. H., Dirgantoro, K. P. S., & Priyanti, N. (2022). Indonesian students' perceptions towards AI-based learning in mathematics. *Journal on Mathematics Education*, *13*(3), 531–548. https://doi.org/10.22342/jme.v13i3.pp531-548

Star, J., Chen, J., Taylor, M., Durkin, K., Dede, C., & Chao, T. (2014). Studying technology-based strategies for enhancing motivation in mathematics. *International Journal of STEM Education*, *1*, 1–19. https://doi.org/10.1186/2196-7822-1-7

Strousopoulos, P., Troussas, C., Krouska, A., & Sgouropoulou, C. (2024). The Gamification Advantage: Innovating Education through Engagement. *Proceedings - 2024 9th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2024*, 204–208. https://doi.org/10.1109/SEEDA-CECNSM63478.2024.00045

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. *Journal on Mathematics Education*, *14*(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and Artificial Intelligence in the Educational Context: Analysis of Scientific Literature. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *15348 LNCS*, 349–354. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), *Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute* (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Yilmaz, R. (2020). Prospective mathematics teachers' cognitive competencies on realistic mathematics education. *Journal on Mathematics Education*, *11*(1). https://doi.org/10.22342/jme.11.1.8690.17-44

Yin, D. S., & Yin, X. (2024). Scaffolding learning: From specific to generic with large language models. *PLOS ONE*, *19*(9), e0310409. https://doi.org/10.1371/journal.pone.0310409

Zabala-Vargas, S., García-Mora, L., Arciniegas-Hernández, E., Reina-Medrano, J., De Benito-Crosetti, B., & Darder-Mésquida, A. (2021). Strengthening Motivation in the Mathematical Engineering Teaching Processes - A Proposal from Gamification and Game-Based Learning. *Int. J. Emerg. Technol. Learn.*, *16*. https://doi.org/10.3991/ijet.v16i06.16163

Zheng, W., & Tse, A. W. C. (2023). The Impact of Generative Artificial Intelligence-based Formative Feedback on the Mathematical Motivation of Chinese Grade 4 Students: a Case Study. *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 1–8. https://doi.org/10.1109/tale56641.2023.10398319

Zulkardi, Z., & Kohar, A. W. (2018). Designing PISA-Like Mathematics Tasks in Indonesia: Experiences and Challenges. *Journal of Physics: Conference Series*, *947*(1). https://doi.org/10.1088/1742-6596/947/1/012015

Cover Letter for Revised Manuscript Submission

Dear Editor,

We are pleased to resubmit our revised manuscript entitled “Integrating Realistic Mathematics Education, AI, and Gamification in Indonesian Secondary Mathematics.” We sincerely thank the editorial team and reviewers for their insightful comments, which have significantly enhanced the clarity, coherence, and scholarly contribution of our work.

The revisions have been made carefully in accordance with each reviewer’s suggestions, as detailed in the attached document titled “Recapitulation Revision”, which provides point-by-point responses. The revised manuscript includes all textual updates and structural improvements.

Summary of Major Revisions

1. Title and Abstract
    - Title shortened to emphasize the study’s central contribution.
    - Abstract revised to balance background, objectives, methods, results, and implications, including numerical coefficients (e.g., $\beta = 0.351$, $\beta = 0.398$) and clearer novelty statements.
2. Introduction
    - Clarified research gap: prior works treated RME, AI scaffolding, and gamification separately.
    - Defined AI scaffolding explicitly with recent references.
    - Moved methodological details to Methods section and emphasized research objectives and contributions.
3. Methodology
    - Elaborated on tiered AI scaffolding aligned with the APOS framework.
    - Added details on sampling strategy, ethical clearance, and consent procedures.
    - Introduced Table 1 mapping constructs to objectives and included sample questionnaire items.
    - Corrected figure numbering and redesigned the instructional flow diagram.
4. Results and Discussion
    - Presented results strictly statistically; added confidence intervals and fit indices.
    - Separated interpretation from results and added triangulated classroom observation data.
    - Introduced a joint display table integrating quantitative paths and qualitative evidence.
5. Conclusion
    - Focused on core theoretical and practical contributions and highlighted concise directions for future research.
    - Streamlined recommendations and acknowledged study limitations clearly.
6. Language and Presentation
    - Simplified sentence structures and improved readability.
    - Reorganized tables, figures, and captions for better narrative coherence.
    - Updated references and ensured citation consistency.

We believe that the revised manuscript now fully meets the publication standards of JME, presenting both strong empirical evidence and practical pedagogical implications for mathematics education in the digital era. We respectfully submit this revised version for your consideration.

Thank you very much for the opportunity to improve our work and for your continued guidance.

Sincerely,

Wati Susilawati, M. Pasqa, Sergii Sharov, and Co-authors
Corresponding Author: wati85@uinsgd.ac.id

Recapitulation Revision " Integrating Realistic Mathematics Education, AI, and Gamification to Enhance Students' Mathematical Problem-Solving"

No	Reviewer	Content	Page	Problem	Revised	Page
1	A	Introduction	1	The 2nd sentence in paragraph 1 is unclear. [Reasoning (Hikayat et al., 2020; Son, 2022).]	We thank the reviewer for noting this issue. The second sentence was inadvertently garbled during final copy-editing; we have restored and clarified it to better convey our intended meaning. The revised sentence now reads: "Learning in mathematics becomes more meaningful when students connect new ideas to familiar contexts and, through guided reinvention, reconstruct formal concepts from their own informal understandings, thereby strengthening mathematical reasoning (Hikayat et al., 2020; Son, 2022)." This articulation emphasizes that purposeful connections and supported reconstruction are central to developing students' reasoning within an RME framework.	1
2	A	Introduction	1	Make the transition from paragraph 1 to paragraph 2 smoother by mentioning first the general idea from the previous paragraph and then introducing the idea of the next paragraph about gamification/game elements. It would be better also to introduce gamification in education before the game elements. Or, do you mean adding/inserting game elements to lesson delivery?	We improved coherence by first recalling the prior paragraph's general point (meaning-making and reasoning in RME), then introducing educational ai and gamification in education as a pedagogical approach before enumerating elements. We clarify that our design embeds selected game elements (e.g., points, badges, progress indicators, challenge tasks) .	1
3	A	Introduction	1	In paragraph 2, "Recent progress in educational AI adds a third strand by providing feedback that adapts to the learner and offers hints without telling the answer." You could probably spell out the first AI in "educational AI" since it is the first being mentioned. In addition, please mention the AI that provides feedback/ hints without telling the answer	We now spell out Artificial Intelligence at first mention and identify the systems employed—intelligent tutoring systems and conversational large language models (open-source implementations). We clarify that these provide adaptive feedback and tiered, non-revealing hints that support self-assessment without disclosing answers. Here the revised content : Educational AI offers adaptive support that can enhance the RME learning process through responsive feedback systems. Intelligent tutoring systems now use natural language processing and deep learning to deliver personalized hints and guidance, helping students develop their own reasoning (Bayaga, 2024; Roldán-Álvarez & Mesa, 2024). With the growing availability of open-source AI tools, these adaptive capabilities are becoming accessible to a wider range of educational settings (Matzakos et al., 2023). This type of scaffolding preserves students' active role in problem-solving while providing timely support when needed. Complementing this technological support, gamification in mathematics education consistently enhances engagement, motivation, and cognitive development, making mathematical tasks more interactive and effective for learning (Hui & Mahmud, 2023; Zabala-Vargas et al., 2021). Well-designed game	1

					elements can extend the RME learning trajectory by sustaining students' effort and curiosity over time (Ariffin et al., 2022). Rather than serving as external rewards, gamification features such as points, levels, and badges function as didactical tools that protect the time and attention needed for sense-making (Al-Barakat et al., 2025; Jun & Lucas, 2025). Both AI and gamification strengthen RME in distinct ways: AI enables guided reinvention through responsive feedback, while gamification maintains motivation and persistence. Together, these elements create an integrated learning environment that channels student motivation into deeper reasoning and stronger problem-solving skills (Bhardwaj, 2024; Mitchell & Co, 2024).	
4	A	Introduction	2	A very significant element of the study is "artificial intelligence scaffolding", please highlight it also in your introduction [definitions, literature, &/or studies]	We have foregrounded artificial intelligence (AI) scaffolding in the Introduction by adding a concise definition, situating it within the recent literature, and stating how it is operationalized in our study. We define AI scaffolding as adaptive, non-revealing guidance generated by intelligent tutoring systems and conversational large language models (LLMs) that supports students' stepwise construction of solutions without supplying answers. To anchor this theoretically and empirically, we cite recent evidence that LLM-driven scaffolds can structure middle-school mathematics curricula (Malik, 2024), help learners progress from specific to generic prompts (Yin & Yin, 2024), and compare favorably with other digital tools for mathematics learning (Matzakos et al., 2023). In our design, AI scaffolding is operationalized as an open-source, LLM-based conversational tutor that delivers tiered, non-revealing hints aligned with RME principles and the APOS progression (from Action to Process to Object/Schema). This clarification makes explicit the construct we employ, the studies that motivate it, and its precise role in the instructional model introduced in this section.	2
5	A	Introduction	2	Most of the content of the last 2 paragraphs is for methodology; therefore, it should be placed in the Methodology section. The last paragraph content should be about the general idea or purpose of the study and the specific objectives.	We have moved methodological details from the final two paragraphs of the Introduction to the Methodology section. The Introduction now closes with the study's rationale, overarching purpose, specific objectives, and contributions.	2
6	A	Method	2	Elaborate on the methodology, how tiered hints work, and the APOS framework in the instructional model. How do these two work or interplay side by side? Is the Tier component linear? Cyclical? How? If the student can understand the content solely based on Tier, should he/ she be moving to Tier 2 or not necessary? Although it is observable in Results & Discussion,	We rewrote the Methods paragraph and redrew Figure 1 to make the sequence explicit: Tiers are progressive but not strictly linear; escalate only when stuck (repeated errors/looping/inactivity/help request) and do not escalate if Tier 1 restores progress. Learners may cycle within a tier; de-escalation occurs once independent progress resumes. Hints are non-telling (require the next mathematical step, never reveal answers). Solid arrows show the one-way	2

				however, it should also be clear in the methodology.	primary flow; dashed arrows mark conditional tier escalation.	
7	A	Method	4	In Figure 1 (the model), is quite confusing the transition from RME to Scaffolding, and Scaffolding to APOS. It seems that students can start at any Tier. Make the directions of the arrows clearer.	Replaced with a redesigned flow: Student Login → RME contextual question → Student Response (before) → conditional AI Scaffolding with APOS-aligned tiers (Tier 1 = Action → Tier 2 = Process → Tier 3 = Object/Schema; progressive, not strictly linear; escalation only if stuck) → Student Answer (after) → Gamification Feedback → Class Leaderboard. Added solid unidirectional arrows for the primary flow, dashed arrows only for conditional tier escalation. Labeled "Student Response" (pre-hint) vs. "Student Answer" (post-hint) to capture before/after, and annotated each tier with its APOS mapping.	4
8	A	Method	4	Besides the feedback for leaderboard, points, and badges, are the students also receiving feedback during the learning process? If yes, how does it work in the model?	The prototype did not deliver correctness feedback during task execution. Students worked with AI scaffolding only (tiered, non-revealing hints in Tiers 1–3). Performance was summarized post-completion on the dashboard, with scores derived from accuracy, tier usage, and completion time. Additional qualitative feedback and reflection were then provided outside the system during in-class retrospective sessions, where teachers discussed students' strategies, errors, and use of hints to support deeper understanding.	4
9	A	Method	5	In the participants, how did you stratify the sample? What are the criteria, characteristics, and attributes for groupings (strata)? What sampling(s) technique is/are used to select the six secondary schools, and also the 300 students? Is there also a basis for choosing a 65%:35% ratio of students for public and private schools? Or is it purposefully set in that ratio?	): The Methodology specifies a multi-stage design: purposive selection of six secondary schools to reflect variation in school type and access, followed by stratified random sampling of students within schools. Strata were defined by school type (public/private) and grade level, with balancing on prior achievement bands and gender where feasible. The 65%:35% distribution reflects the enrollment proportions in the study area and logistical access, not an a priori quota.	5
10	A	Method	5	Are the participants given the consent forms? Please also highlight it in the methodology.	Yes. The Methodology now includes an Ethics subsection stating that written informed consent (and parental consent for minors) was obtained prior to participation, with confidentiality safeguards and the right to withdraw clearly communicated.	5
11	A	Method	6	SEM-PLS Structural Model of the AI-RME-Gamification Framework should already be Figure 2, not Figure 1. Please recheck the succeeding label of the Figures.	The structural model is now labeled Figure 2, and all subsequent figure references and captions have been updated to maintain sequential numbering.	6
12	C		8	The Results & Discussion, and Conclusion are well structured to answer the objectives of the study with complete quantitative & qualitative data, and backup with related literature and studies. However, it was mentioned in the methodology that there are classroom observations; therefore, the results of the classroom observations should also be placed in the results and discussion for triangulation purposes. Is it the	The apps used in this class experiment were developed and maintained by an external technology team, while the research team (math educators) specified the pedagogical requirements (RME/APOS), study design, and evaluation criteria. Data collection and analysis were conducted exclusively by the research team; the technology partner had no role in data analysis or interpretation. Independent observers carried out classroom observations.	8

				researcher's observations or a third-party's observations?		
13	C			This will make mathematics education more meaningful and engaging. It can materialize through the collaboration of teachers, administrations, and local & national governments.	Thank you for the feedback.	
14	C	Title and Abstract	1	The title is attractive but overloaded with concepts; it would benefit from being more concise and focused on the central contribution.	We acknowledge the concern and have adopted a more concise, contribution-focused title that remains within a 12-word limit while preserving the study's novelty—the joint integration of RME, AI, and gamification in secondary mathematics. The final title is: "Integrating Realistic Mathematics Education, AI, and Gamification in Indonesian Secondary Mathematics." Contextual and outcome details (motivation and problem-solving) are now emphasized in the abstract, keywords, and objectives to keep the title lean yet accurately signal the central contribution.	1
15	C	Title and Abstract	1	The abstract provides a broad overview, but the background, novelty, objectives, methods, results, and implications are not equally balanced. Key findings are presented, yet the novelty and contribution need clearer emphasis.	We have revised the abstract to balance background, objectives, methods, results, and implications while making the novelty explicit. The new version frames the gap (prior studies treat RME, AI scaffolding, and gamification separately), states the objective (to test an integrated model that links these three), and summarizes the mixed-methods approach (SEM-PLS on 300 Grade VIII students from six Bandung schools plus interviews). To address your request for clearer key findings and contributions, we now report the principal coefficients—RME → Motivation (β=0.351) and RME → Problem-Solving (β=0.398) as the strongest effects; Gamification → Motivation (β=0.405) with a smaller direct path to Problem-Solving (β=0.191); and Motivation → Problem-Solving (β=0.285)—and note how self-efficacy (β=0.305) and perceived challenge (β=0.304) strengthen engagement with RME. We explicitly state the study's novelty: positioning motivation as the mediating bridge that explains how gamification and contextual RME convert engagement into problem-solving, and demonstrating the pedagogical value of non-telling AI scaffolds in an Indonesian secondary context. Finally, we articulate the contribution as evidence for a practical, technology-enabled instructional model that integrates contextual learning (RME) with sustained motivation, thereby offering actionable guidance for mathematics classrooms."	1
16	C	Introduction	1	While the problem statement is relevant, the narrative is somewhat general and lacks a sharp research gap.	We have rewritten the entire introduction to present a clearer and more focused research gap. The revised version highlights that existing studies often examine RME, gamification, and AI scaffolding separately and overlook how motivation functions as a mediating mechanism. Our study addresses this gap by integrating these elements into a single classroom-tested model that explains	1

					how adaptive AI support and contextual RME tasks work together to enhance students' motivation and problem-solving in secondary mathematics	
17	C	Introduction	2	The review of prior literature does not yet sufficiently position this study against existing works, particularly in terms of what is new in combining RME, AI, and gamification.	We have rewritten the related-work section to position our study more clearly. The revision shows that prior work tends to treat RME, AI scaffolding, and gamification separately and usually models motivation as an end outcome. Our study combines the three in a single classroom-tested model where contextual RME tasks are supported by non-telling AI hints aligned with APOS and proportionate game elements. It also offers a new perspective by showing that learning motivation functions as a mediating mechanism connecting engagement and problem-solving, supported by empirical evidence from SEM-PLS analysis in Indonesian secondary schools."	2
18	C	Research Design and Methods	4	The description of the explanatory sequential mixed-methods design is informative but verbose, making it difficult to identify the essential methodological logic.	We have streamlined the methods section to make the explanatory sequential logic immediately clear. The revised text now states the sequence upfront: SEM-PLS on data from 300 students to estimate path effects, followed by targeted interviews and classroom observations to explain the mechanisms behind those effects, and integration at the interpretation stage. We added concise operational definitions of all variables, summarized instruments, sampling, and fit criteria, and clarified how qualitative codes map to the quantitative paths. Nonessential detail was condensed and the research flow is now presented in a short schematic so readers can grasp the design at a glance	4
19	C	Research Design and Methods	4	The three design research phases are described in detail, yet the empirical grounding of the analysis and exploration phase needs strengthening (e.g., actual diagnostic data).	We have strengthened the analysis and exploration phase by adding concrete diagnostic data from classroom observations, student responses, and pre-implementation interviews. The revised section now presents these findings more directly to show how actual learning problems informed the design framework."	4
20	C	Research Design and Methods	4	The instrument development and validation process is strong, but the constructs' operationalization could be more clearly linked to the research objectives.	We have clarified construct operationalization by adding Table 1 (p. 6), which maps each construct to the research objectives and lists its theoretical framework, operational definition, sample items, indicator codes, and scale anchors. This alignment makes the linkage from objectives to measures explicit and traceable across the analysis."	4
21	C	Participants and Data Collection	5	The participant description is thorough, but the justification of sampling strategies needs to go beyond descriptive detail and align more closely with research aims.	We now justify the stratified sampling in direct relation to the study aims, explaining how school type, locale, and grade level enable estimation of path effects and intended generalizability. This alignment clarifies why 300 Grade VIII students across six Bandung schools are appropriate for testing simultaneous direct and indirect effects in the model.	5
22	C	Participants and Data Collection	5	Data collection procedures are carefully explained but should be shortened and made more	We condensed procedural detail and foregrounded the analytical logic of each instrument and activity. The main text	5

				analytical. Some technical descriptions (e.g., statistical thresholds) could be moved to an appendix.	highlights consent/ethics and how each data source serves the research questions.	
23	C	Data Analysis	7	The SEM-PLS analysis is properly applied, but the rationale for its selection over other approaches (e.g., CB-SEM) could be clarified.	We selected PLS-SEM to model multiple latent constructs with mediation under predictive aims and non-normal school data. This approach provides stable estimates for our integrated design and allows simultaneous testing of direct and indirect paths consistent with the study's objectives.	7
24	C	Data Analysis	8	Thematic analysis is suitable, yet the integration of qualitative and quantitative results could be demonstrated more explicitly (e.g., through joint displays or meta-inferences).	We added a joint display that aligns key SEM-PLS paths with qualitative themes from interviews and classroom observations. This makes the meta-inferences explicit, showing how statistical relations (e.g., RME → Motivation → Problem-Solving) are grounded in authentic classroom evidence.	8
25	C	Results and Discussion	8	Findings are insightful but presented in a way that sometimes mixes results with interpretation. A clearer separation of results (what the data show) and discussion (what it means theoretically and practically) would improve readability.	We fully separate what the data show from what the data mean. Results now report coefficients, fit indices, and core qualitative themes, while Discussion interprets mechanisms and pedagogical implications, improving readability and evidential transparency.	8
26	C	Results and Discussion	16	The discussion does not yet fully situate the study's contributions within current debates in mathematics education, AI in learning, and gamification.	The revised Discussion situates our contribution within debates on RME, AI in learning, and gamification, contrasting our integrated model with representative studies in each strand. We make explicit what is new: motivation as a mediating mechanism, non-telling APOS-aligned AI scaffolds embedded in contextual RME, and simultaneous path estimation in Indonesian classrooms.	16
27	C	Conclusion and Implications	18	The conclusion is rich but overly dense, blending theoretical insight, design guidance, and future research recommendations. A sharper focus on the main contributions, followed by a more concise list of practical and research implications, is recommended.	We refocus the Conclusion on the main contributions, followed by concise practical implications and essential directions for future work.	18
28	C	Conclusion and Implications	18	Future research directions are valuable, yet too detailed; these should be streamlined to highlight the most critical next steps.	We refocused future research on the most critical next steps that follow directly from our evidence (durability, generalizability, and mechanism isolation). This concentrates readers' attention on feasible designs with the highest payoff for cumulative knowledge.	18
29	C	Language and Presentation		The manuscript is written in fluent academic English, but many sentences are overly long and complex, making comprehension difficult. Shorter, clearer sentences would increase readability.	We rewrote long sentences into shorter, clearer units and smoothed transitions across sections. The result is a more accessible narrative that preserves academic rigor while improving flow.	
30	C	Language and Presentation		Figures, tables, and examples should be used more strategically to illustrate key findings and reduce textual overload.	Figures, tables, and worked examples are now placed to illustrate key findings and reduce textual load, with ordering and captions aligned to the journal's scope. This helps readers grasp the model, measures, and results at a glance.	
31	D	Abstract	1	Abstract: Conceptually overloaded; lacks numeric results; "replicable design" remains vague.	We have rewritten the abstract to reduce conceptual overload, report the essential numeric results, and state the contribution plainly. The revision now includes the key coefficients and clarifies the instructional	1

					contribution as a classroom tested sequence that combines contextual RME tasks, tiered non telling AI hints, proportionate game elements, and post task feedback. The phrase replicable design is now defined operationally rather than left as a general claim.	
32	D	Introduction	2	Introduction: Separate “literature gap” from “objectives”; shorten hypothesis paragraph; limit to 2–3 key citations per point.	We separated the literature gap from the study objectives and tightened the prose for ease of reading. The hypotheses paragraph is trimmed to its core claims with two to three representative citations per point. We also foreground the specific novelty so readers can see how the study advances prior work at a glance.	2
33	D	Method	3	Methods: Redundant conceptual explanations; missing sample questionnaire item; no mention of ethical clearance or consent procedures. Add short ethical statement and example items; streamline narrative by focusing on operational design steps.	We removed redundant conceptual exposition and focused on the operational steps of the explanatory sequential design. The section now includes sample questionnaire items and concise operational definitions for each construct, along with a brief statement on institutional ethical clearance and informed consent. This presentation makes the methodological logic transparent without unnecessary detail.	3
34	D	Result	8	Result: Some overinterpretation; no confidence intervals; same figure referenced multiple times without elaboration. Keep “Results” strictly statistical; move interpretive commentary to Discussion.	We keep Results strictly statistical and relocate interpretive commentary to the Discussion. The tables now report confidence intervals alongside coefficients and fit indices for clarity. Figure references have been corrected and each visual is accompanied by a short, non interpretive explanation of what is being shown.	8
35	D	Finding	11	Qualitative Findings: Duplicate table numbering; limited analytic depth; lacks researcher reflexivity. Correct table numbering; expand explanation on coding logic; include short note on inter-coder reliability or bias mitigation.	We corrected duplicate table numbering and expanded the explanation of our coding logic from initial codes to themes. A short note on researcher reflexivity and inter coder reliability is now included to address potential bias and strengthen trustworthiness. The analytic depth has been increased with clearer links from exemplar quotes to the reported themes.	11
36	D	Disucssion	14	Integration & Discussions: Condense by ~25%; add comparison with prior RME/AI literature; maintain formal tone.	This section has been condensed by approximately one quarter while maintaining a formal and focused tone. We add direct comparisons with representative studies in RME, AI in learning, and gamification to position our contributions precisely. The integration is made explicit by connecting the quantitative paths with the qualitative themes and drawing clear meta inferences.	14
37	D	Conclusion	18	Conclusion: Add limitations (ethical, contextual, tech-based) and a concise final sentence summarizing contribution.	We now state limitations concisely, including ethical boundaries, contextual constraints of the study setting, and technology related considerations. Practical and research implications are presented in a short, readable format. The section ends with a single closing sentence that summarizes the study’s contribution to technology enabled mathematics pedagogy.	18

4
BUKTI KONFIRMASI ARTIKEL ACCEPTED

[jme] Editor Decision External Kotak Masuk ×

Jme Fkip Matematika
kepada saya, Sergii, M, Hazar

Kam, 13 Nov, 02.14

Dear Wati Susilawati, Sergii Sharov, M Pasqa, and Hazar Malik,

We are pleased to inform you that your submission to the Journal on Mathematics Education, titled "Realistic Mathematics Education with Artificial Intelligence and Gamification: Enhancing Students' Motivation and Problem Solving," has been reviewed. After thorough evaluation, the editorial committee is delighted to accept your article for publication.

Please find attached the invoice for your manuscript and the author information form. Your paper will now proceed to the production stage. Kindly refrain from submitting revised versions or updated figures unless specifically requested by the editorial team. You can expect to receive the page proofs within one to two weeks after your manuscript is forwarded to our production team. During this time, we kindly request you to provide proof of payment and the completed author information form.

Should you have any questions or require further assistance, please do not hesitate to contact us.

Thank you for your valuable contribution to the journal. We deeply appreciate your cooperation and commitment to advancing mathematics education research.

Kind regards,

Prof. Dr. Zulkardi, M.Ikomp., M.Sc.
Editor-in-Chief
Journal on Mathematics Education

2 Lampiran · Dipindai oleh Gmail · Tambahkan semua ke Drive

JME - Author Info... Invoice - Publicat...

PUBLICATION FEE INVOICE

Invoice : JME-1643875
Invoice Date : 11/13/2025
Due Date. : 11/20/2025

Journal on Mathematics Education
Program S3 (Doktor) Pendidikan Matematika, FKIP Universitas Sriwijaya
Jl. Srijaya Negara, Bukit Besar, Palembang - 30139, Indonesia
website: https://jme.ejournal.unsri.ac.id/index.php/jme
email: jme@unsri.ac.id

Bill To:
Wati Susilawati
Department of Mathematics Education, UIN Sunan Gunung Djati Bandung, Bandung, Indonesia

Reference Number: #3875 Publication Issue: Vol. 16 No. 4, 2025

No	Title	Unit	Quantity	Unit Fee	Extra Fee (Pages)	Amount
1	Integrating Realistic Mathematics Education, AI, and gamification to enhance students' learning motivation and problem-solving skills (Extra Pages = 17 × $ 50 USD = $ 850 USD)	Paper	1	$ 450 USD	$ 850 USD	$ 1300 USD
				Proofreading		$ 200 USD
				Total APC in USD		$ 1500 USD
				Total APC in IDR		Rp. 24.750.000

This invoice is without tax (VAT) with the payment address:

Bank Account name (please be exact)	: JOURNAL ON MATHEMATICS EDUCATION
Address	: BNI, Palembang, Indonesia
Bank Account Number	: 8127106777
Bank Code	: 009
Bank Name	: BANK NEGARA INDONESIA - PT (PERSERO)
City	: Palembang
Country	: Indonesia
Bank SWIFT Code	: BNINIDJA

We take your privacy seriously. We do not share your personal information with any third parties.

The Journal on Mathematics Education is indexed in:
Scopus ERIC sinta Crossref Google

5 BUKTI KONFIRMASI ARTIKEL PUBLISHED ONLINE

Journal on Mathematics Education Current Archives Announcements Contact Old Website SEARCH

Home / Archives / Vol. 16 No. 4 (2025): Journal on Mathematics Education / Articles

Section Articles

Integrating realistic mathematics education, AI, and gamification to enhance students' learning motivation and problem-solving skills

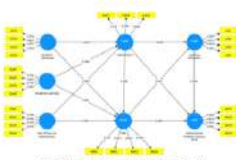
https://doi.org/10.22342/jme.v16i4.pp1257-1282

Wati Susilawati
wati85@uinsgd.ac.id (Primary Contact)
Mathematics Education Study Program, Sunan Gunung Djati State Islamic University, Bandung, Indonesia
https://orcid.org/0000-0003-0346-9536

Sergii Sharov
Department of Computer Science, Dmytro Motornyi Tavria State Agrotechnological University, Zaporizhzhia, Ukraine
https://orcid.org/0000-0001-5732-9980

M. Pasqa
Department of Political Science, Sunan Gunung Djati State Islamic University, Bandung, Indonesia
https://orcid.org/0009-0003-2908-9168

Hazar Malik
Mathematics Education Study Program, Sunan Gunung Djati State Islamic University, Bandung, Indonesia



Download

PDF

Abstract

The integration of artificial intelligence (AI) and gamification within the framework of realistic mathematics education (RME) presents substantial potential to foster meaningful, innovative, and adaptive learning experiences. Such integration can enhance students' motivation and promote active engagement in solving non-routine mathematical problems. Despite these opportunities, several challenges hinder the practical realization of this threefold integration. These include teachers limited digital literacy, the absence of pedagogical models that systematically merge AI and gamification within the RME framework, and the ongoing compartmentalization of these components in mathematics education practice. This study investigates how the synergy between AI and gamification-based scaffolding can support RME in enhancing students' learning motivation and problem-solving competence. A sequential explanatory mixed-methods design was employed, involving 300 students from six Indonesian secondary schools. Data were gathered through mathematical problem-solving tests and non-test instruments, including classroom observations and semi-structured interviews. Quantitative data were analyzed using Structural Equation Modeling (SEM), while qualitative data were examined through thematic analysis to contextualize and elaborate on the quantitative findings. The results reveal that RME supported by AI and APOS-based transition strategies integrated with

https://jme.ejournal.unsri.ac.id/index.php/jme/article/view/3875

Journal on Mathematics Education
Volume 16, No. 4, 2025, pp. 1257-1282

Integrating realistic mathematics education, AI, and gamification to enhance students' learning motivation and problem-solving skills

Wati Susilawati[1,*], Sergii Sharov[2], M. Pasqa[3], Hazar Malik[1]

[1]Mathematics Education Study Program, Sunan Gunung Djati State Islamic University, Bandung, Indonesia
[2]Department of Computer Science, Dmytro Motornyi Tavria State Agrotechnological University, Zaporizhzhia, Ukraine
[3]Department of Political Science, Sunan Gunung Djati State Islamic University, Bandung, Indonesia
*Correspondence: wati85@uinsgd.ac.id

Received: 30 August 2025 | Revised: 12 November 2025 | Accepted: 15 November 2025 | Published Online: 18 November 2025

Abstract

The integration of artificial intelligence (AI) and gamification within the framework of realistic mathematics education (RME) presents substantial potential to foster meaningful, innovative, and adaptive learning experiences. Such integration can enhance students' motivation and promote active engagement in solving non-routine mathematical problems. Despite these opportunities, several challenges hinder the practical realization of this threefold integration. These include teachers limited digital literacy, the absence of pedagogical models that systematically merge AI and gamification within the RME framework, and the ongoing compartmentalization of these components in mathematics education practice. This study investigates how the synergy between AI and gamification-based scaffolding can support RME in enhancing students' learning motivation and problem-solving competence. A sequential explanatory mixed-methods design was employed, involving 300 students from six Indonesian secondary schools. Data were gathered through mathematical problem-solving tests and non-test instruments, including classroom observations and semi-structured interviews. Quantitative data were analyzed using Structural Equation Modeling (SEM), while qualitative data were examined through thematic analysis to contextualize and elaborate on the quantitative findings. The results reveal that RME supported by AI and APOS-based transition strategies integrated with gamified elements significantly improves mathematical problem-solving abilities ($\beta = 0.40$) and learning motivation ($\beta = 0.35$), yielding an overall effect size of $\beta = 0.41$. The findings demonstrate that AI-infused, gamified RME environments can systematically foster students' cognitive and affective engagement, thereby supporting both process- and outcome-oriented dimensions of mathematics learning. This study contributes a replicable instructional design model that outlines explicit integration stages encompassing realistic learning contexts, AI-driven adaptive support, and game mechanics that nurture sustained engagement and intrinsic motivation. The research yields theoretical and practical implications for advancing RME toward a more adaptive, student-centered approach to mathematics learning, oriented toward meaningful and contextually rich problem-solving in the digital era.

Keywords: Artificial Intelligence, Gamification, Learning Motivation, Problem Solving, Realistic Mathematics Education

How to Cite: Susilawati, W., Sharov, S., Pasqa, M., & Malik, H. (2025). Integrating realistic mathematics education, AI, and gamification to enhance students' learning motivation and problem-solving skills. *Journal on Mathematics Education, 16*(4), 1257–1282. https://doi.org/10.22342/jme.v16i4.pp1257-1282

Mathematics learning augmented by artificial intelligence (AI) and gamification attains greater significance when students are able to relate mathematical concepts to real-world contexts, facilitating the reconstruction of formal knowledge from their informal understandings and thereby enhancing problem-solving capabilities (Bayaga, 2024; Rane, 2023). This principle aligns with the foundational tenets of Realistic Mathematics Education (RME), wherein everyday phenomena serve as anchors for organizing the mathematics learners are expected to reinvent (Siswantari et al., 2025). By basing tasks on familiar practices, students can effectively ground their ideas, develop representations, and establish conceptual connections that progressively guide them to more formal mathematical structures. The process of transitioning from context to concept constitutes a carefully designed learning trajectory, enabling students to comprehend mathematical procedures through adaptive AI support and gamification. This is particularly evident in the resolution of non-routine problems characterized by multiple solution pathways or diverse valid solutions distinguished by rigorous reasoning (Canonigo, 2024; Ng et al., 2024). Nevertheless, sustaining this contextual and meaning-oriented approach in contemporary digital classrooms necessitates adaptive technological tools and persistent learner engagement—challenges that this investigation addresses through the integration of AI and gamification within the RME framework.

Educational AI systems provide adaptive scaffolding that can effectively enhance the RME learning process by delivering responsive feedback. Modern intelligent tutoring systems employ natural language processing and deep learning techniques to offer personalized prompts and guidance, fostering learners' autonomous reasoning development (Bayaga, 2024; Roldán-Álvarez & Mesa, 2024). The proliferation of open-source AI tools has democratized access to such adaptive functionalities across diverse educational contexts (Matzakos et al., 2023). Central to this technology is AI scaffolding, which modulates the degree of support in accordance with individual learner needs and gradually diminishes assistance as competence increases. This approach emulates the role of a responsive human tutor by offering timely hints and prompts that facilitate independent construction of mathematical understanding (Malik et al., 2025). Through interactive dialogues and stepwise explanations, AI systems empower students to pose follow-up questions and receive tailored support while maintaining an active role in their problem-solving processes (Yin & Yin, 2024).

Complementing AI's adaptive support, gamification has been consistently demonstrated to bolster engagement, motivation, and cognitive development in mathematics education (Hui & Mahmud, 2023; Zabala-Vargas et al., 2021). Well-designed gamified elements—such as points, levels, and badges—sustain students' effort and curiosity throughout the RME learning trajectory (Ariffin et al., 2022). These features serve not merely as extrinsic rewards but function as didactical instruments that protect the necessary time and attention for meaningful sense-making (Al-Barakat et al., 2025; Jun & Lucas, 2025). AI and gamification operate synergistically to strengthen RME: AI facilitates guided reinvention via responsive feedback, while gamification underpins motivation and persistence in learning. Collectively, these components foster an integrated learning environment that channels student motivation into deeper reasoning and heightened problem-solving skills (Bhardwaj, 2024; Mitchell & Co, 2024).

These dynamics are particularly pertinent within the Indonesian educational context, where improving mathematical literacy constitutes an ongoing challenge (Ndiung & Menggo, 2025). Findings from the Programme for International Student Assessment (PISA) reveal that Indonesian students frequently encounter difficulties with contextual reasoning and higher-order problem solving, exposing a disparity between procedural fluency and the capacity to apply mathematics in real-world settings (Zulkardi & Kohar, 2018). In response, national education policies have advocated for RME-inspired pedagogies designed to enhance relevance through tasks linked to students' daily experiences, including commerce, transportation, and cultural practices (Dewi & Maulida, 2023). However, despite these policy initiatives, implementation remains inconsistent and predominantly situated within traditional classrooms lacking substantial technological integration (Siregar et al., 2025). This inconsistency sustains a gap between educational reform ambitions and practical classroom realities, thereby attenuating the intended impact of mathematics education transformation.

The swift expansion of digital learning platforms and gamified applications in Indonesian schools has not been uniformly matched by robust pedagogical designs (Maryani et al., 2025). Many available platforms primarily promote superficial engagement rather than fostering profound conceptual understanding, as they often fail to align with established didactical frameworks. This discrepancy provokes critical inquiries regarding the interplay of emergent approaches within integrated instructional designs. For instance, self-efficacy—extensively examined concerning academic achievement and motivation—remains underexplored in the context of AI-supported, gamified RME environments at the secondary education level in Indonesia (Mukuka et al., 2021; Siswantari et al., 2025). Existing literature generally conceptualizes self-efficacy as a static trait rather than a dynamic construct influencing student interaction with contextual tasks, adaptive scaffolding, and game mechanics (Rahayu et al., 2022). Similarly, perceived challenge in digital mathematics learning warrants further investigation. Within gamified settings, precise calibration of difficulty presents opportunities to reconceptualize challenge as a catalyst for persistence, reasoning, and problem solving (Beukes et al., 2024; Koskinen et al., 2023). Consequently, challenge evolves from a hindrance into a pedagogically relevant variable amenable to intentional instructional design.

A salient gap exists regarding the role of learning motivation as a structural mediator linking design elements to problem-solving outcomes. While prior studies have addressed gamification or RME independently, scant attention has been given to the mediation effects of motivation within AI-enhanced learning environments characterized by calibrated task difficulty and contextualization (Hu et al., 2023; Mitchell & Co, 2024). In Indonesia, RME research has predominantly focused on conventional classrooms, with limited exploration of how digital scaffolding and game-based engagement can amplify its influence on problem-solving performance (Lady et al., 2018; Lestari et al., 2023; Siswantari et al., 2025). By synthesizing RME, gamification, and AI, the present study advances an innovative framework for bridging the divide between educational policy and classroom practice, situating mathematical activity within students' lived realities while leveraging digital tools to sustain motivation and scaffold knowledge reinvention (Li & Noori, 2024; Opesemowo & Ndlovu, 2024; Torres-Toukoumidis et al., 2025).

This study articulates two principal objectives tailored to the Indonesian secondary education milieu. The first objective assesses an integrated instructional model combining RME, gamification, and AI scaffolding, investigating their direct and indirect effects on students' learning motivation and mathematical problem-solving proficiency. Within this model, self-efficacy, perceived challenge, and APOS-based learning are posited as antecedents influencing engagement with gamification and RME, while learning motivation is hypothesized to mediate the relationships between these design components and problem-solving outcomes. The second objective elucidates the classroom mechanisms underpinning these statistical associations by tracing the pathways through which contextual tasks, gamification elements, and adaptive feedback contribute to the development of problem-solving skills via observational and interview-based qualitative data.

It is hypothesized that self-efficacy, perceived challenge, and APOS-based learning positively predict engagement with both gamification and RME modalities. Gamification is anticipated to primarily influence problem-solving skills indirectly through its enhancement of learning motivation, whereas RME is expected to exert direct positive effects on both motivation and problem-solving abilities. Crucially, learning motivation is proposed as a structural mediator translating instructional design features into mathematical performance, thereby offering a novel theoretical reconceptualization of motivation's function within technology-enhanced mathematics education.

By reframing learning motivation as a structural mediator rather than an outcome, this study contributes to mathematics education on three fronts. First, it delineates didactical conditions under which calibrated difficulty becomes a pedagogically desirable feature of digital mathematics learning: meaningful RME contexts linked to students' real-world experiences, adaptive AI scaffolds promoting productive struggle without prescriptive guidance, and gamification incentives rewarding persistence and reasoned explanation rather than mere speed (Al-Barakat et al., 2025; Malik et al., 2025; Beukes et al., 2024). Second, it operationalizes the APOS theoretical framework within an AI-supported, gamified RME environment, enabling observation and intentional design of students' problem-solving trajectories progressing from action, process, and object to schema in secondary classrooms. Third, it presents a replicable instructional model calibrated for the Indonesian educational context, providing empirical evidence and practical guidance for integrating contextualized learning, adaptive support, and proportionate game mechanics. Collectively, these contributions address a critical need for pedagogically grounded approaches to digital mathematics education and deepen theoretical understanding of motivation's transformative role in fostering mathematical competence.

METHODS

This investigation adopted an explanatory sequential mixed-methods design (Creswell, 2018) integrated within the principles of educational design research (Gravemeijer, 1994; Plomp, 2013). The rationale for this design was the necessity to generate complementary strands of evidence: quantitatively assessing the effects of a unified RME, gamification, and AI approach on student motivation and problem-solving skills and qualitatively elucidating the classroom mechanisms underlying these effects. In the quantitative phase, Structural Equation Modeling (SEM) was applied to model latent constructs, capturing both direct and indirect effects and examining mediation within a comprehensive analytic framework. Partial Least Squares SEM (PLS-SEM) was employed to accommodate model complexity, predictive objectives, and the non-normality characteristic of school-based datasets. Measurement validity was ensured via standard indices: indicator loadings exceeding 0.70, average variance extracted above 0.50, and composite reliability greater than 0.80. Model adequacy was established by a standardized root mean square residual (SRMR) below 0.08 and confirmed predictive relevance.

Subsequently, the qualitative phase concentrated on observing students and teachers, particularly tracing the usage of non-telling, tiered AI hints, evaluating the impact of gamification mechanics on persistence and mathematical thinking, and examining the influence of contextual tasks on APOS-aligned reasoning shifts. The qualitative inquiry was organized around three model-driven patterns: RME's robust direct effects on learning motivation and problem-solving skills, the primarily indirect pathway of gamification via motivational mediation, and the roles of self-efficacy and perceived challenge as key antecedent variables.

Major challenges in mathematics learning were identified, notably diminished student motivation and the difficulty of transferring problem-solving strategies to contextualized scenarios. A review of foundational theoretical constructs—RME (Freudenthal, 1991; Gravemeijer, 1994), the APOS framework (Dubinsky & McDonald, 2001), and gamification theory (Deterding et al., 2011)—shaped the conceptual foundation for the instructional intervention. Accordingly, a model was designed that integrates RME-based contextual tasks, gamification strategies (including points, levels, badges, and leaderboards), and adaptive AI scaffolding.

The AI scaffolding component featured a progressive, tiered system (Tiers 1–3), each facilitating movement from informal reasoning to formal mathematical understanding along the APOS sequence—Action, Process, Object, and Schema. As depicted in Figure 1, students initiate the process by logging in, receiving an RME-based contextual question, and submitting an initial answer. The system conditionally deploys AI support in the form of APOS-aligned hints, activated only when additional scaffolding is indicated: Tier 1 (Action) directs attention to quantities and initial steps, Tier 2 (Process) guides the construction of representations and relationships between steps, while Tier 3 (Object/Schema) encourages generalization, decomposition of subgoals, or mapping to established mathematical structures.

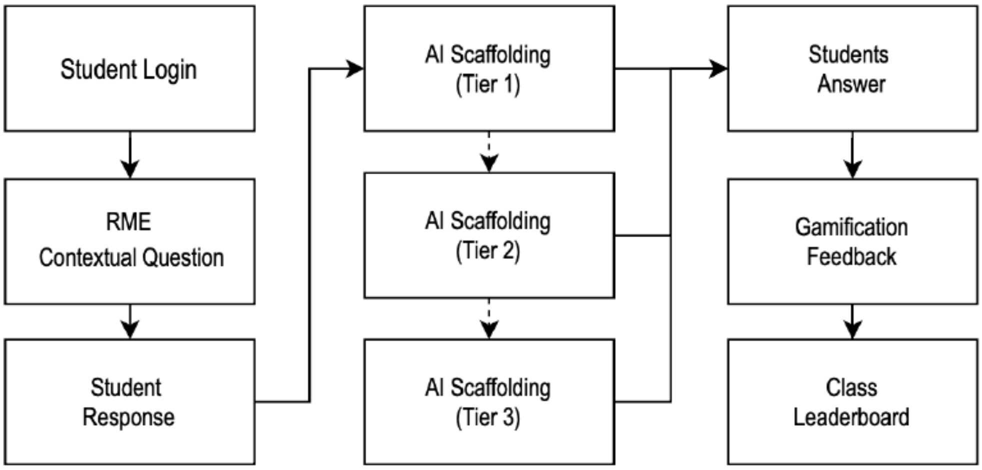


Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding

Hint escalation is adaptive and non-linear: it activates upon indicators of student impasse (e.g., repeated errors, nonproductive iterations, extended inactivity, or help requests) and ceases if progress is restored by a lower-tier prompt. Students may iterate within a tier during revision, and scaffolding is implicitly withdrawn upon resumption of independent progress. Importantly, hints are designed to avoid direct solution disclosure; each prompt demands a substantive mathematical response for further scaffolding to be triggered. Upon completion, students receive gamification feedback (points, badges), and class leaderboard status is updated to promote visibility of persistence and revision. The platform systematically records attempts, hint levels engaged, and revisions, providing a robust documentation of students' progress along the APOS continuum from informal strategies to formalized problem solving.

Participants

The study sample consisted of 300 Grade VIII students recruited from six junior secondary schools in Bandung and its surrounding areas using stratified sampling based on school sector, geographic region, and accreditation status. The sampling strata included four urban public junior secondary schools (*Sekolah Menengah Pertama*, SMP), each with superior accreditation, and two suburban private Islamic junior secondary schools (*Madrasah Tsanawiyah*, MTs), also of superior accreditation. Each school contributed two intact Grade VIII classes, selected at random from official class rosters. This approach preserved natural classroom groupings and minimized cross-class contamination, yielding a total of twelve participating classes. Stratification by sector (public vs. private), region (urban vs. suburban), and accreditation ensured adequate representation of diverse educational environments, with eight classes drawn from four urban SMP and four classes from two suburban MTs. Class sizes ranged from 25 to 30 students.

The final analytic sample comprised 300 students, following eligibility screening for current Grade VIII enrollment and confirmed attendance during scheduled data collection. Of these, 195 students were from public schools and 105 from private schools, with a gender distribution of 154 female and 146 male students, ages 13–14 years (consistent with national classification for Grade VIII). Permission and ethical compliance were maintained through institutional and school-level approvals and standardized parental consent and student assent procedures. All data collection activities were coordinated with school administrators and homeroom teachers to minimize disruption to instructional routines. Learning sessions and research measurements were integrated within standard mathematics lessons and distributed across seven scheduled periods to maintain naturalistic conditions.

For the explanatory qualitative phase, six students were purposively sampled from the quantitative cohort using latent profile analysis. This selection strategy ensured representation across achievement and motivation strata, with profiles corresponding to high, moderate, and low levels on both attributes. Additionally, three mathematics teachers with 5–10 years of pedagogical experience and prior involvement with contextual mathematics tasks participated in semi-structured interviews and classroom observations. This maximum-variation approach enabled mechanism-driven analysis of how the integrated RME, gamification, and AI instructional model functioned under authentic teaching and learning conditions, enriching insight from both student and teacher perspectives.

Data Collection Techniques

Quantitative data were obtained via a rigorously validated instrument comprising 27 items rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The questionnaire was designed to measure seven central constructs, as detailed in Table 1. The development process followed a structured, three-phase validation sequence. Initially, three mathematics education experts independently evaluated each item for theoretical alignment and content relevance. Subsequently, the instrument was piloted with a cohort of 50 students to identify and refine ambiguities in item wording and response patterns. Finally, psychometric validation in the outer model was performed using PLS analysis, assessing indicator loadings, average variance extracted (AVE), composite reliability (CR), discriminant validity, and Cronbach's alpha for every construct in accordance with established international standards (e.g., Hair et al., 2019). Full psychometric indices—including α, CR, AVE, and loading ranges—will be presented in the Results section under the measurement model.

The qualitative dataset was collected through semi-structured interviews with six students and three mathematics teachers; each session lasted between 30 and 40 minutes and was audio-recorded with informed consent. Student selection was based on a systematic tertile sampling approach using standardized metrics of motivation and problem-solving ability, yielding two high-performing, two mid-range, and two struggling participants to maximize representativeness. Interview protocols focused on three dimensions: (1) phenomenological experiences with contextualized RME tasks, (2) perceived effects of gamification mechanisms (points, badges, leaderboards) on engagement and persistence, and (3) the impact of AI scaffolding in facilitating the evolution from informal to formal mathematical understanding. Classroom observations during AI-RME-gamification lessons were conducted to capture behavioral markers of mathematical engagement, peer collaboration, and individual contributions. Observational field notes documented transitions between horizontal mathematization (within-context connections) and vertical mathematization (developing abstraction), situating these processes within the progressive mathematization framework. Triangulation of interview and observational data helped elucidate the empirical relationship between quantitative trends and classroom-level instructional dynamics.

Table 1. Operational definitions of research constructs

Construct	Theoretical Framework	Operational Definition	Sample Items	Items
Students' Challenges	Desirable Difficulties Theory (Bjork & Bjork, 2020)	Perceived level of productive difficulty in mathematical tasks	1. The problems required sustained effort over several steps 2. I needed to try more than one approach before making progress	4
Students' Learning (APOS)	APOS Theory (Dubinsky & McDonald, 2001)	Progression through Action-Process-Object-Schema stages	1. I can explain how my initial actions connect to a general rule 2. I translated concrete steps into a more formal representation"	4
Self-Efficacy in Mathematics	Self-Efficacy Theory (Bandura, 1997)	Confidence in one's ability to succeed in mathematical tasks	1. I am confident I can handle challenging mathematics problems 2. When I get stuck, I can find a way to move forward"	4
Gamification	Gamification Framework (Deterding et al., 2011)	Engagement with game elements in learning	1. Points and levels encourage me to continue working on the task 2. Badges or leaderboards make my effort feel visible"	3
RME AI	RME Principles (Freudenthal, 1991)	Integration of AI scaffolding with realistic contexts	1. AI hints helped me think without giving away the answer 2. AI guidance together with real-life contexts made the mathematics more meaningful"	4
Learning Motivation	Self-Determination Theory (Ryan & Deci, 2024)	Drive to engage and persist in mathematical learning	1. I wanted to keep trying even after making mistakes 2. These activities increased my interest in learning mathematics"	4
Mathematical Problem-Solving Skills	Mathematical Literacy Framework (OECD, 2019)	Ability to apply mathematical reasoning to non-routine problems	1. I can use multiple strategies to tackle non-routine problems 2. "I can justify why my solution works"	4

Ethical Considerations

The study conformed to rigorous ethical protocols, securing institutional review board approval and implementing standard informed consent and assent procedures for all student and teacher participants. Robust data protection strategies were deployed, including pseudonymization through coded identifiers and the segregation of identifying data on password-protected institutional drives accessible exclusively by the research team. API communications were configured to transmit only non-identifying metadata (study ID, timestamp, item content) and to avoid sharing any personally identifiable information with external services. Data retention and disposal procedures followed institutional guidelines, with specified timeframes and secure, permanent removal of sensitive information upon study completion.

Data Analysis Techniques

Quantitative data were analyzed utilizing SEM-PLS in SmartPLS, an approach well suited to predictive analyses with complex latent constructs (Hair & Alamer, 2022). The analytic procedure encompassed both measurement and structural modeling stages. The measurement model assessed reliability and validity through established criteria, including factor loadings above 0.70, AVE exceeding 0.50, and CR greater than 0.80. Discriminant validity for all constructs was confirmed using both the Fornell–Larcker criterion and the Heterotrait-Monotrait ratio (HTMT), ensuring conceptual distinctiveness and theoretical coherence (Hair et al., 2019). The subsequent structural model estimated path coefficients and evaluated predictive relevance, facilitating the examination of direct, indirect, and mediated effects between study variables.

Qualitative data derived from semi-structured interviews and classroom observations were analyzed through thematic analysis, following the procedural guidelines articulated by Braun and Clarke (2006). Initial coding was conducted inductively, allowing empirical themes to emerge from participant responses and classroom interactions. These themes were subsequently interpreted through the lens of RME didactical phenomenology, focusing on student engagement with contextual tasks, motivational outcomes linked to gamification, and the role of AI scaffolding in supporting the progression from informal to formal mathematical reasoning. Integrated interpretation brought together qualitative and quantitative findings, strengthening the explanatory narrative. For example, pronounced associations between gamification and motivation were linked to student enthusiasm for point-based and leaderboard mechanics, while teacher observations highlighted the impact of contextual reasoning tasks within RME on the development of problem-solving skills. Such triangulation reflects the cyclical nature of design research, in which empirical data and phenomenological insight are mutually reinforcing.

RESULTS AND DISCUSSION

The quantitative analysis consistently underscored the central importance of RME and learning motivation within the instructional framework. Gamification demonstrated a significant positive effect on learning motivation ($\beta = 0.406$) and directly contributed to mathematical problem-solving skills ($\beta = 0.191$). In addition to its direct effects, gamification indirectly enhanced problem-solving proficiency by sustaining learning motivation throughout the instructional cycle, affirming its function as a driver of student engagement. RME emerged as a pivotal component, exerting substantial direct effects on both learning motivation ($\beta = 0.351$) and problem-solving skills ($\beta = 0.336$). Learning motivation itself proved to be a robust predictor of problem-solving competencies ($\beta = 0.285$); this mediating relationship highlights the dual role of intrinsic and extrinsic motivational factors in fostering higher-order reasoning, conceptual connection making, and effective mathematical representations.

The mediating influence of learning motivation is a novel contribution of this study, demonstrating that both gamification and RME operate not only as formal instructional strategies but also as potent mechanisms directly shaping mathematical competence. Internal learner attributes further reinforced the effectiveness of RME, with self-efficacy ($\beta = 0.306$), perceived challenge ($\beta = 0.304$), and APOS-based learning ($\beta = 0.198$), all contributing significantly to meaning-making within the RME paradigm.

The overall structural relationships and their statistical significance are depicted in Figure 2, which presents the SEM-PLS model of the AI–RME–gamification instructional framework. Building on the relationships illustrated in Figure 2, further analysis was undertaken to ensure the validity and reliability of the findings. The measurement model was systematically evaluated to ascertain construct reliability and discriminant validity, while the structural model analysis assessed the magnitude and significance of the hypothesized pathways. These results from the quantitative analysis provide an evidence base for subsequent integration with qualitative findings, supporting a comprehensive mixed-methods interpretation in the following section.

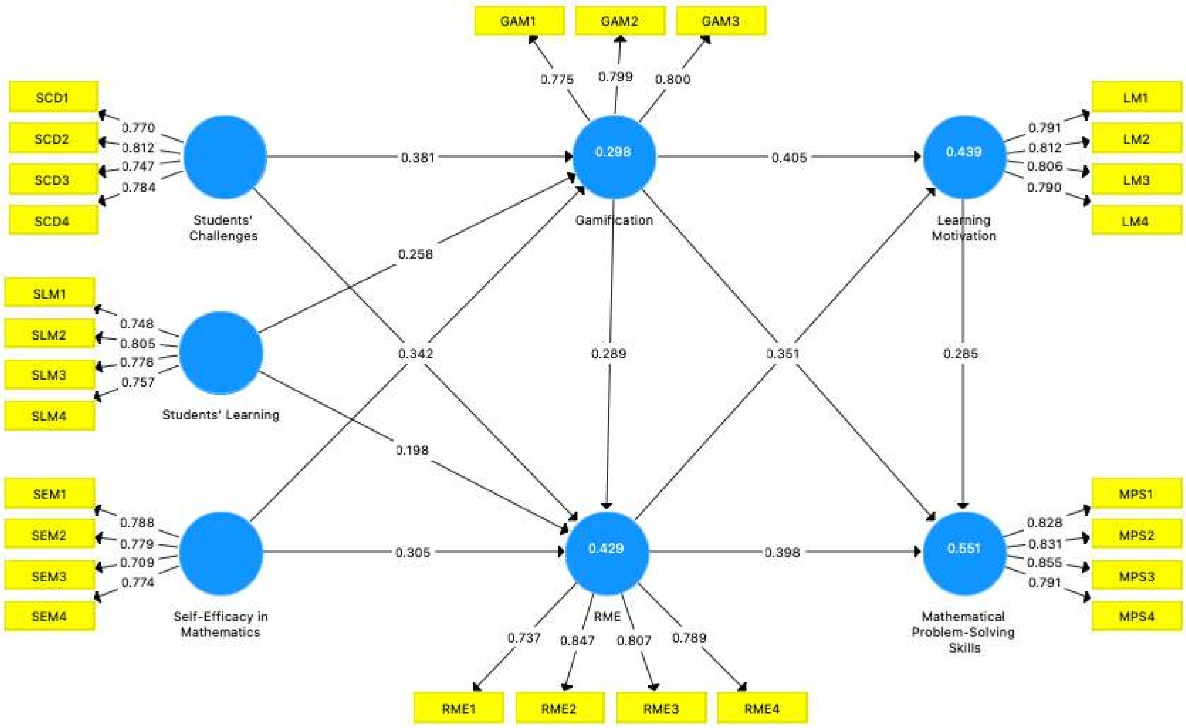


Figure 2. SEM-PLS structural model of the AI–RME–gamification framework

Quantitative Findings

The quantitative analysis began with the evaluation of the measurement model to confirm the reliability and validity of the constructs. All indicators demonstrated satisfactory outer loadings, with values exceeding the recommended threshold of 0.70, while the AVE for each construct was above 0.50. In addition, both CR and Cronbach's alpha values were greater than 0.80, indicating strong convergent validity and internal consistency. These results are summarized in Table 2.

Table 2. Measurement model results

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
Gamification	GAM1	0.775	0.64	0.86	0.81	Valid
	GAM2	0.802				
	GAM3	0.788				
Learning Motivation	LM1	0.791	0.67	0.88	0.83	Valid
	LM2	0.822				
	LM3	0.843				
	LM4	0.804				
Problem-Solving Skills	MPS1	0.812	0.66	0.87	0.82	Valid

Construct	Indicator	Loading	AVE	CR	Cronbach's α	Decision
	MPS2	0.826				
	MPS3	0.799				
	MPS4	0.811				
RME	RME1	0.740	0.65	0.88	0.84	Valid
	RME2	0.781				
	RME3	0.854				
	RME4	0.792				
Self-Efficacy	SEM1	0.781	0.62	0.85	0.80	Valid
	SEM2	0.812				
	SEM3	0.804				
	SEM4	0.794				
Challenges	SCD1	0.765	0.63	0.86	0.81	Valid
	SCD2	0.811				
	SCD3	0.828				
	SCD4	0.779				
APOS Students Learning	SLM1	0.751	0.61	0.84	0.79	Valid
	SLM2	0.784				
	SLM3	0.802				
	SLM4	0.773				

The results, presented in Table 2, indicate that all constructs (Gamification, RME, Learning Motivation, Problem-Solving, Self-Efficacy, Challenges, and APOS Learning) are measured accurately and consistently. Strong factor loadings (0.74–0.85) reinforce the robustness of the RME construct, while reliability indices (CR and α > 0.80) confirm internal consistency. Discriminant validity was then assessed using the Fornell–Larcker criterion. The square root of the AVE for each construct was higher than its correlations with other constructs, demonstrating that each construct measured distinct dimensions of the instructional model. This confirms that Gamification, RME, Learning Motivation, and Problem-Solving are empirically distinguishable, as shown in Table 3.

Table 3. Discriminant validity (Fornell–Larcker criterion)

Construct	Gamification	LM	Problem-Solving	RME
Gamification	0.80			
Learning Motivation	0.56	0.82		
Problem-Solving Skills	0.44	0.53	0.81	
RME	0.48	0.51	0.59	0.81

Note: The diagonal values represent $\sqrt{AVE}$. All diagonal values are greater than the inter-construct correlations, indicating that discriminant validity is established.

The results confirm discriminant validity: for example, Motivation ($\sqrt{AVE} = 0.82$) is statistically distinct from Gamification (r = 0.56) and RME (r = 0.51). This distinction is important because it validates the mediating role of Motivation between Gamification and Problem-Solving. Without sufficient discriminant validity, overlap among constructs could bias the interpretation of the mediation effect. The structural model analysis revealed several significant paths. Gamification exerted a substantial effect on Learning Motivation ($\beta = 0.405$) and a moderate effect on Problem-Solving Skills ($\beta = 0.191$). RME was found to be a pivotal construct, significantly predicting both Motivation ($\beta = 0.351$) and Problem-Solving Skills ($\beta = 0.398$). Learning motivation itself significantly predicted Problem-Solving ($\beta = 0.285$), confirming its mediating role. Furthermore, internal learner factors contributed significantly to strengthening RME: Self-Efficacy ($\beta = 0.305$), Students' Challenges ($\beta = 0.304$), and APOS-based Learning ($\beta = 0.198$). Together, these paths explained 48% of the variance in Learning Motivation, 52% of the variance in RME, and 55% of the variance in Problem-Solving Skills. A summary of these findings, including path coefficients, t-values, and f^2, is presented in Table 4.

Table 4. Structural model results

Path	β	t-value	p-value	f^2	Decision
Gamification → Learning Motivation	0.405	5.06	0.000	0.21	Supported
Gamification → Problem-Solving	0.191	2.60	0.009	0.08	Supported
RME → Learning Motivation	0.351	3.51	0.000	0.19	Supported
RME → Problem-Solving	0.398	4.98	0.000	0.25	Supported
Learning Motivation → Problem-Solving	0.285	2.85	0.004	0.17	Supported
Self-Efficacy → RME	0.305	4.20	0.000	0.12	Supported
Challenges → RME	0.304	4.10	0.000	0.11	Supported
APOS Learning → RME	0.198	3.00	0.002	0.07	Supported

The model fit indices confirmed the adequacy of the proposed framework. To assess explanatory power and predictive relevance, we report construct-level R^2 and Stone–Geisser Q^2 (blindfolding, d = 7). These indices are summarized in Table 5.

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

Endogenous construct	R^2	Q^2	Q^2 interpretation
Problem-Solving Skills	0.551	0.369	Large
Learning Motivation	0.439	0.275	Medium
RME	0.429	0.262	Medium
Gamification	0.298	0.179	Medium

Note: (Blindfolding d = 7; $Q^2 \approx 0.02/0.15/0.35$ = small/medium/large)

Complementing these fit statistics, Table 5 shows that the endogenous constructs have meaningful explanatory power and predictive relevance: PSS $R^2 = 0.551$ with $Q^2 = 0.369$ (large), LM $R^2 = 0.439$ with $Q^2 = 0.275$ (medium), RME $R^2 = 0.429$ with $Q^2 = 0.262$ (medium), and Gamification $R^2 = 0.298$ with $Q^2 = 0.179$ (medium). Collectively, these quantitative data confirm that the SEM-PLS model is both statistically and conceptually robust.

Qualitative Findings

Thematic analysis of interview transcripts and classroom observations resulted in the synthesis of four overarching themes: guided reinvention, interactivity, phenomenological exploration, and the enhancement of problem-solving skills. Collectively, these themes offer a nuanced understanding of how the AI–RME–Gamification instructional model shaped students' learning experiences and substantiate the core findings of the quantitative analysis.

Figure 3 presents the user interface of the AI–RME–Gamification application as employed during instructional sessions. The prototype exemplifies the delivery of contextual RME tasks, such as the following: "A student cycles 12 kilometers at 16 km/h and returns 15 kilometers at 20 km/h. Determine the average speed for the entire journey." AI scaffolding was implemented through a tiered hint system, accessible via the lower-right panel. For instance, Tier 1 (AI Helper) provided a prompt: "Remember, average speed is not the arithmetic mean of the two speeds. Use the formula: average speed = total distance ÷ total time." Upon encountering difficulty, the student accessed Tier 2 support: "Good. Now apply the formula: average speed = total distance ÷ total time to combine your results." Correct responses triggered immediate feedback, while gamification mechanisms—points, badges, and leaderboards—were simultaneously activated. This integration of scaffolded support and incentive structures visually corroborates the qualitative finding that students were motivated to construct their own solution strategies, rather than rely on direct answers, with digital rewards sustaining engagement.

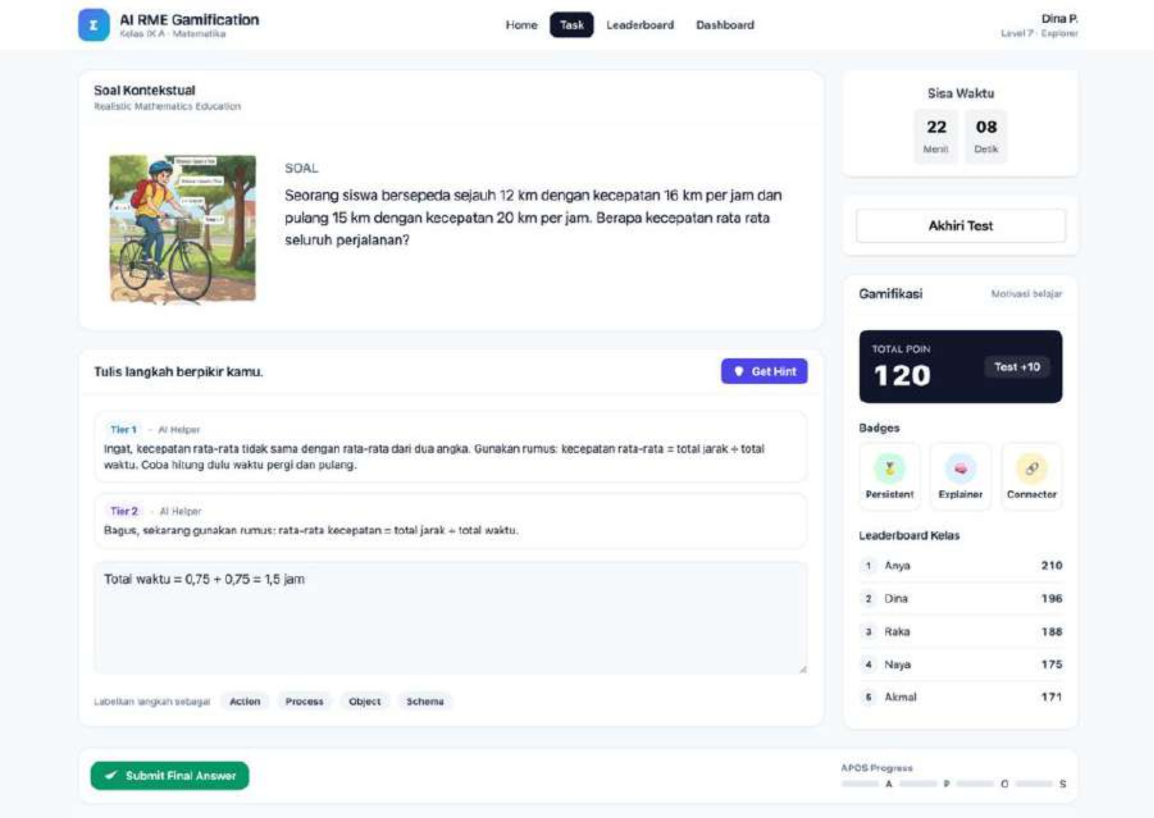


Figure 3. Screenshot of the AI–RME–Gamification prototype application

Student interview data consistently emphasized the application's function as a scaffold for autonomous problem solving. Codes such as "AI scaffolding," "hints," and "self-construction" predominated. One participant articulated, "The system gave me hints when I was stuck, but it did not show the answer. I had to try different ways until I found the solution." This pattern was mirrored in teacher observations; educators noted increased student independence: "They tried first, then used the hints only when they really needed them." These qualitative insights reflect the principle of guided reinvention central to RME and align with quantitative evidence that RME exerts strong predictive influence on both learning motivation ($\beta = 0.351$) and problem-solving ($\beta = 0.398$).

This transcript shows how the AI scaffolding guided by a large language model (LLM) accessed via an API initially led an actual student astray, treating average speed as a simple arithmetic mean, before guiding them toward the correct reasoning pathway (see Table 6). Through tiered hints, the AI first redirected the student to the appropriate formula (Tier 1), then corrected a calculation error (Tier 2), and finally consolidated the process by connecting total distance and total time (Tier 3). The progression of responses reflects the APOS framework: from Action (performing basic operations) to Process (organizing steps), to Object (treating distance and time as unified quantities), and ultimately to Schema (generalizing the concept of average speed). The gamification feedback further reinforced persistence and learning motivation, providing direct evidence that affective and cognitive processes were intertwined in this AI–RME–Gamification environment.

Another salient theme was interactivity, expressed in both social and digital dimensions. Codes such as peer collaboration, leaderboard competition, and teacher mediation highlighted the interactive character of the learning process. One teacher commented, "Even students who are usually quiet wanted to contribute because they were curious about their scores on the leaderboard." A student added, "I wanted to beat my friend's score, so I tried again until I got it right." These findings align with the RME characteristic of interactivity and confirm the statistical evidence that Gamification exerted a strong influence on Learning Motivation ($\beta = 0.405$). They also extend existing research on ICT in mathematics education, where digital tools are shown to foster dialogical and collaborative learning (Drijvers, 2015).

Table 6. Transcript of student–AI interaction on average task with tiered scaffolding LLM

Stage	Student Response	AI Scaffolding Example	Analysis (APOS/Didactical)
Initial answer	"Average = (16 + 20)/2 = 18 km/h."	"Remember, average speed = total distance ÷ total time. First calculate the time for the outbound and return trips." (Tier 1 – general strategy)	Student holds a misconception (incorrect schema → arithmetic average). AI redirects to the formal concept (Object).
Time calculation (wrong)	"Outbound time = 12 ÷ 16 = 0.75 h. Return time = 15 ÷ 20 = 0.8 h."	"Correct for the outbound time. But check again 15 ÷ 20. Is it really 0.8?" (Tier 2 – focused correction)	Student moves into Action → Process but miscalculates. AI focuses on correcting the specific operation.
Revision	"15 ÷ 20 = 0.75 h. So total time = 1.5 h."	"Good! Now total distance = 27 km, total time = 1.5 h. Use the formula average speed = distance ÷ time." (Tier 3 – near answer)	Student reaches the Process stage. AI scaffolds transition toward Object.
4. Final answer	"27 ÷ 1.5 = 18 km/h."	"Correct! You earn +10 points and the Master Speed badge for completing with a structured solution." (Feedback + Gamification)	Student achieves the Schema stage (general concept of average speed). Gamification reinforces learning motivation.

Further qualitative insights are provided by teacher dashboard and leaderboard data, as depicted in Figure 4. The dashboard features enabled monitoring of students' accrued points, badge achievements, and overall gamification performance, capturing not only final responses but also the full trajectory of student engagement. This afforded teachers a direct view into the quality of student reasoning and levels of persistence throughout the learning process. Teachers noted notable changes in representational practices, with one reporting, "They rarely did this before, but now I see more [students] using diagrams and tables to represent their thinking." Student self-reports corroborated this shift: "I usually just wanted the answer, but now I try to show how I got it." This evidence highlights the system's capacity to foster not only accuracy but also meta-cognitive engagement and representational fluency.

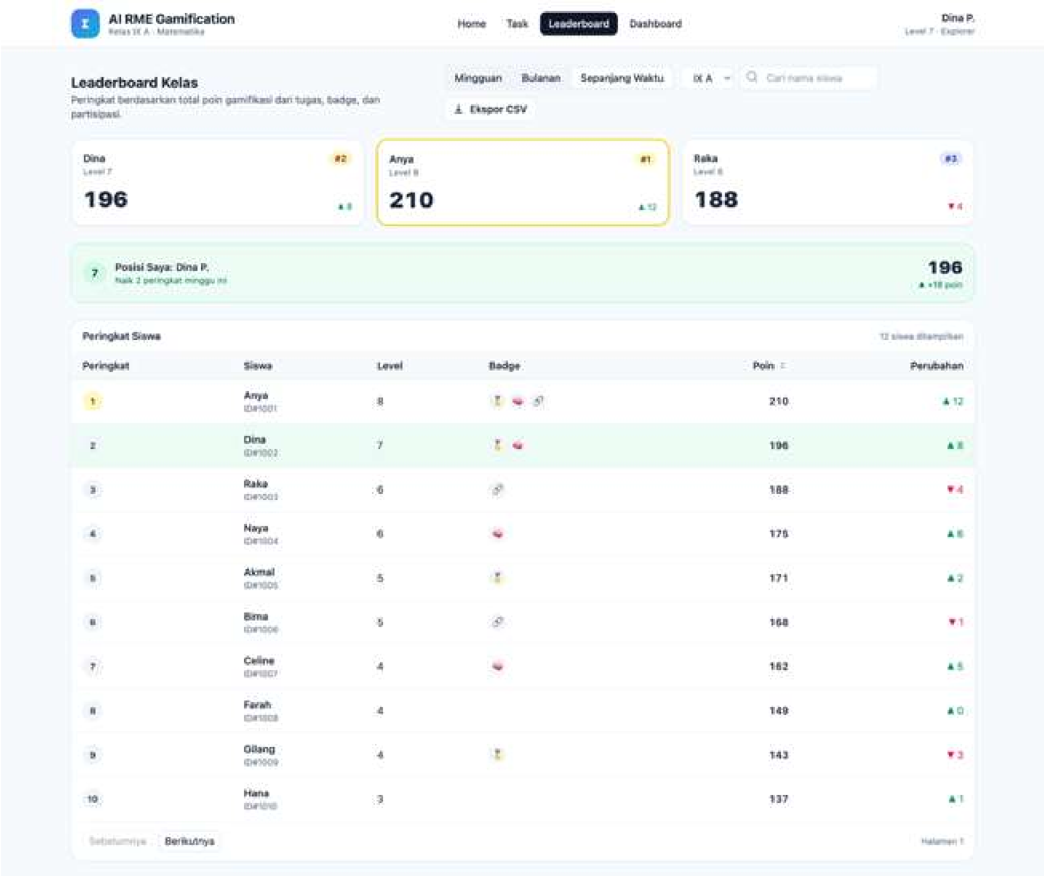


Figure 4. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

Figure 5 presents photographic evidence of classroom implementation, illustrating students' individual engagement with contextual mathematical tasks on the AI–RME–Gamification platform and their active monitoring of progress via leaderboards. Observation records confirm that the interactivity promoted by the gamification features extended beyond the digital realm, precipitating increased social engagement as students compared progress and exchanged strategies. The public visibility of performance spurred both peer collaboration and healthy competition, reinforcing findings that interactivity in this instructional context is both digital and inherently social.

Phenomenological exploration emerged as another salient theme (Treffers, 1991), with students consistently valuing tasks grounded in real-life contexts. Codes such as relevance, authenticity, and transferability recurred across cases. As one student expressed, "Because the problems looked like shopping or transport, I understood why we needed the formulas." Teachers echoed this value of authenticity: "When the questions are close to their daily life, the students are more serious. They see mathematics as something real." This qualitative evidence clarifies the pathway by which learning motivation significantly predicted problem-solving skill ($\beta = 0.285$): real-world contexts not only captured student interest but also facilitated meaningful application, supporting the OECD's conceptualization of mathematical literacy as the capacity to use mathematics in authentic scenarios (OECD, 2019).

Figure 5. Students engaging with the platform during classroom implementation

Both teachers and students observed a distinct improvement in problem-solving skills, as reflected in codes associated with reasoning, representation, explanation, and persistence (Anugraheni et al., 2025). Teachers reported not only greater accuracy but also enhanced quality of mathematical communication: "They could explain their steps better, not only write the result." These convergent findings situate the enhancement of problem-solving within the broader context of increased motivation, authentic task design, and interactive learning processes.

Integration of Findings

The integration of quantitative and qualitative findings underscores the robustness of the AI–RME–Gamification model in enhancing both affective and cognitive dimensions of mathematics learning. The results of the SEM-PLS structural model were systematically triangulated with thematic evidence obtained from interviews and classroom observations. This process allowed the statistical associations to be validated through authentic learning experiences, thereby strengthening the explanatory power of the model.

Table 7 demonstrates a consistent alignment between statistical significance and lived classroom experiences. The strong effect of gamification on learning motivation ($\beta = 0.405, t = 5.06$) was vividly reflected in observations of heightened student engagement. Teachers reported that even students who were usually reluctant to participate became more active due to the visibility of the leaderboard. This demonstrates that gamification is not limited to providing external rewards but also taps into social comparison and intrinsic curiosity, thereby amplifying the motivational pathway. The direct effect of gamification on problem-solving ($\beta = 0.191, t = 2.60$) was supported by students' testimonies, which indicated that the desire to progress to higher levels encouraged them to persevere with complex problems. This resonates with research on gamification as a source of sustained cognitive effort rather than superficial engagement.

The pivotal role of RME in the model was also evident. Statistically, RME predicted both learning motivation ($\beta = 0.351, t = 3.51$) and problem-solving ($\beta = 0.398, t = 4.98$). Qualitative evidence supported these effects through recurring themes of guided reinvention and phenomenological exploration. Students consistently emphasized that contextual problems made abstract concepts meaningful and that AI scaffolding, which provided hints without revealing solutions, pushed them to think independently. This aligns with Freudenthal's principle that mathematics must be connected to reality and progressively mathematized, as well as Gravemeijer (1994)'s notion that design features should guide learners' reinvention of formal strategies.

Table 7. Integrated structural and qualitative results

SEM-PLS	β	Qualitative Theme	Interview Quote	Integrated Interpretation
Gamification → Learning Motivation	0.405	Interactivity, Engagement	"Even quiet students wanted to join because of the leaderboard."(Teacher)	Gamification sustains motivation through competitive but supportive interaction.
Gamification → Problem-Solving	0.191	Problem-Solving Enhancement	"I tried harder to solve the tasks because I wanted to level up." (Student)	Gamification directly encourages persistence in problem-solving.
RME → Learning Motivation	0.351	Phenomenological Exploration	"Because the problems looked like shopping or transport, I understood the formulas better." (Student)	Contextualized tasks stimulate motivation through relevance.
RME → Problem-Solving	0.398	Guided Reinvention	"The system gave hints but not the answer, so I had to try different ways."(Student)	RME scaffolding supports progressive mathematization and problem-solving.
Motivation → Problem-Solving	0.285	Engagement, Persistence	"I kept trying because the points made me want to finish." (Student)	Learning Motivation bridges affective engagement and problem-solving skills.
Self-Efficacy → RME	0.305	Confidence, Self-construction	"I believed I could solve it myself if I tried step by step." (Student)	Self-efficacy strengthens the constructive aspect of RME.
Challenges → RME	0.304	Desirable Difficulties	"It was difficult, but the challenge made me think more carefully." (Student)	Challenges act as desirable difficulties enriching learning.
APOS Learning → RME	0.198	Conceptual Connections	"I understood how the steps connect to each other after trying again."(Student)	APOS progression supports formalization in RME processes.

The mediating effect of learning motivation on problem-solving ($\beta = 0.285, t = 2.85$) was also substantiated qualitatively. Students described a willingness to persist through challenges when motivated by the point and badge system. At the same time, teachers observed that motivated learners articulated their reasoning more clearly and made stronger conceptual connections. These findings support Suparatulatorn et al. (2023)'s perspective that problem-solving is not merely cognitive but also driven by affective engagement.

Finally, the contribution of internal learner factors to RME was validated by both data strands. Self-efficacy ($\beta = 0.305, t = 4.20$) emerged as a significant predictor, with students noting that confidence helped them persist with contextual tasks. Challenges ($\beta = 0.304, t = 4.10$) were reframed as opportunities rather than barriers, consistent with Bjork's principle of desirable difficulties (Bjork & Bjork, 2020). APOS-based learning ($\beta = 0.198, t = 3.00$) was evident in students' accounts of connecting informal steps to more formal strategies after repeated trials, highlighting the constructive role of AI scaffolding in supporting APOS transitions. The integrated findings reveal that gamification enhances learning motivation both directly and indirectly. RME serves as the central pedagogical mechanism for developing problem-solving skills, and internal learner factors strengthen the process of guided reinvention. The convergence of quantitative and qualitative evidence confirms that the AI–RME–Gamification model is not only statistically valid but also pedagogically grounded in classroom reality.

Learning Motivation as a Mediating Bridge in the AI–RME–Gamification Model

Mathematics is frequently perceived as a subject defined primarily by correct procedures, often lacking meaningful explanation (Martin & Towers, 2011). Many students view mathematics as a chore and feel uncertain about their ability to succeed, perceiving it as unusually complex and inaccessible (Raméntol & Camacho, 2016). This study directly addressed these challenges by evaluating whether the deliberate integration of Realistic Mathematics Education (RME) contexts, gamification mechanics, and artificial intelligence (AI)-driven scaffolding can effectively transform students' affective engagement into lasting gains in problem-solving skills and learning motivation within secondary mathematics classrooms. The structural model employed in this research estimated the effects of these components, conceptualizing self-efficacy, perceived challenge, and APOS-based learning progressions as antecedents to active participation in RME-centered activities.

The findings challenge a prominent assumption within the gamification literature. Rather than exerting a substantial direct effect on mathematical problem-solving, gamification's principal impact was on learning motivation, with only a modest secondary direct effect on problem-solving. Qualitative evidence corroborated this ordering of effects. Gamification features, such as points, leaderboards, and progression mechanics, cultivated a sense of challenge and drove persistence, but this effect often declined when students lacked sufficient informational support to complete tasks. To address this limitation, an AI-based tiered support system was implemented, delivering adaptive hints and feedback to facilitate student progress. Visibility of effort and achievement was enhanced through leaderboards, making social engagement both tangible and rewarding, thus supporting the development of learning motivation. Points and progression served to regulate the tempo of work, providing students with sustained reasons to persist as tasks increased in difficulty. Collectively, the evidence demonstrates that gamification, within this context, primarily operates as a motivational catalyst, rather than as a direct instructional tool. Improvements in problem-solving performance materialized through elevated motivation rather than the game elements themselves.

The study further elucidates the synergistic interplay among RME, AI, and gamification in advancing mathematics learning (Suparatulatorn et al., 2023). RME provided a meaningful foundation by connecting mathematics to students' lived experiences, producing strong effects on both motivation and problem-solving. Engagement with real-world contexts, such as shopping or transportation scenarios, enabled students to refine mathematical concepts and shift from informal to formal reasoning. The AI system functioned as an adaptive facilitator, deploying graduated support as needed without compromising students' problem ownership. Most significantly, the results reveal that learning motivation is not merely an educational outcome, but a critical mediating factor bridging pedagogical experiences and measurable improvements in problem-solving ability. This is manifest in students' persistence, willingness to continue problem-solving after receiving AI hints, and active engagement in peer discussions. The findings contest traditional conceptions of motivation as a peripheral benefit, instead establishing it as an essential conduit for transforming engaging instructional contexts into mathematical competence (Star et al., 2014). The empirical evidence confirms that, particularly in technology-enhanced environments, learning motivation facilitates the movement from contextual understanding to formal mathematical proficiency. Building upon this key insight, future research should examine how individual differences modulate this motivational pathway within integrated learning settings.

Additional results highlight the roles of student-specific factors in the AI–RME–Gamification environment. Notably, self-efficacy did not directly increase achievement; rather, it enhanced students' persistence with RME activities. Confident students were more likely to engage deeply with contextual problems, employ diverse representations, and iteratively revise their work in response to AI feedback (Bećirović et al., 2025; Fitria et al., 2025; Zheng & Tse, 2023). This underscores that confidence is most impactful when it promotes active participation in learning activities. Similarly, perceived challenge became a productive force when paired with appropriate scaffolding. Students reported that complex problems enhanced their thinking when three conditions co-occurred: meaningful RME-generated contexts, incremental AI hints that protected student agency, and gamification incentives that validated sustained effort. The APOS framework guided students' progression from concrete action to abstract understanding, with AI-supported hints and collaborative discourse supporting advancement from procedural to conceptual mathematical knowledge. This sequence established a transparent and reproducible learning trajectory from everyday contexts to formal mathematics—achieving a central goal of RME.

Contextual implementation factors further qualified the model's effectiveness across school types (Canonigo, 2024). While ICT access was not directly measured, distinctions between urban public schools and suburban private Islamic schools revealed differing priorities in implementation. In larger urban public schools, the competitive and social aspects of gamification—particularly leaderboard visibility and peer comparison—fueled engagement and effort. Conversely, in smaller suburban private Islamic schools, meaningful context and local relevance typical of RME tasks played a more prominent motivational role. These observations indicate that effective implementation of the integrated model requires adaptive strategies, rather than a universal approach. Large, diverse schools may prioritize social gamification features, while smaller, close-knit learning environments benefit from contextual authenticity and cultural resonance. Three core design principles emerge: (1) RME tasks must genuinely foster mathematical formalization rather than offer superficial context; (2) gamification elements should be balanced and serve to sustain learning persistence without displacing deep mathematical thinking; and (3) AI scaffolding should offer timely, individualized support calibrated to promote independent problem-solving, without creating overreliance or frustration. For maximal effectiveness, the AI system should account for individual learning histories, prior performance, common misconceptions, and the developmental stages typical of target student populations (Dabingaya, 2022; Soesanto et al., 2022). When these dimensions are successfully harmonized and thoughtfully adapted to context, motivation becomes the driving force that translates engagement into mathematical proficiency.

This study also offers several key theoretical contributions. Chief among these is the reconceptualization of learning motivation—not as a terminal outcome, but as a principal mediator connecting instructional design (RME, gamification, and AI support) to actual mathematical achievement. Unlike conventional theories positioning motivation as a consequence of effective teaching, these results establish motivation as the critical mechanism that converts meaningful engagement opportunities into advanced problem-solving proficiency (Wild & Neef, 2023; Xia et al., 2022). The research further clarifies the conditions under which challenging problems are rendered beneficial: when students engage with real-world tasks, receive graduated AI scaffolding, and are validated in their effort through gamification.

Moreover, self-efficacy's value is maximized when coupled with active participation—confidence is most potent when it incites action. Drawing on these findings, a practical instructional framework for mathematics emerges design RME tasks that enable progression from authentic contexts to mathematical abstraction, leverage gamification to sustain motivation without eclipsing substance, and implement AI-driven scaffolding that adapts responsively to student trajectories. Schools are encouraged to strategically accentuate social competition in larger settings and emphasize cultural and contextual relevance in smaller ones—all while keeping motivation as the central mediating construct.

In this integrated model, each element serves a distinct and complementary purpose: AI structures learning experiences and pacing; RME supplies conceptual grounding; gamification ensures momentum; and motivation unifies these influences into a cohesive and transformative mathematical learning process. This framework represents a paradigm shift—mathematics learning in digital contexts must not be limited to additive use of technology but rather considered as an integrated landscape where motivation transforms engagement into sustained competence. Beyond improvements in achievement, this reframing supports a transformative change in student attitudes—mathematics is repositioned from a subject to be endured to one that belongs meaningfully in students' educational and personal development. This evidence-based blueprint provides robust guidance for the design of technology-enhanced mathematics education that intentionally unites meaning, effort, and formal understanding.

CONCLUSION

This study examined the impact of integrating Realistic Mathematics Education (RME), gamification, and AI-driven scaffolding on secondary students' learning motivation and mathematical problem-solving skills. Employing a robust mixed-methods design, the evidence revealed that RME yielded the strongest direct effects on both problem-solving and motivation, achieved by grounding mathematical concepts in familiar, contextually meaningful experiences. Gamification was found to primarily enhance learning motivation, which in turn mediated improvements in problem-solving by sustaining student engagement. AI scaffolding provided tiered, adaptive hints that preserved productive struggle and maintained students' agency over problem-solving processes. Additionally, students' self-efficacy and their response to conceptual challenges fostered deeper participation in RME-centric activities, while APOS-based learning trajectories supported the shift from informal reasoning to formal mathematical thinking.

These findings advance existing theory by repositioning learning motivation as a structural mediator—rather than a simple outcome—that transforms engagement with technology-enhanced instruction into significant problem-solving achievement. This perspective challenges conventional models, demonstrating that in technology-rich environments, learning motivation functions as an essential, indispensable channel through which contextual experiences yield mathematical competence. Furthermore, the study offers empirical support for the notion of "desirable difficulties": challenges become productive when anchored in meaningful contexts, scaffolded appropriately, and validated through feedback and recognition—a synthesis corroborated by recent reviews and intervention studies.

Practical implications are clear for all educational stakeholders. Teachers are encouraged to select and design contexts that naturally elicit target mathematical concepts, to implement game elements that reinforce effort toward higher-order thinking, and to provide strategically tiered hints that sustain independent reasoning without foreclosing student problem-solving. Curriculum developers should sequence classroom activities to foster a progression from informal to formal cognition, structuring assessment to capture both process and outcome. Educational technology designers are advised to emphasize adaptive scaffolding—the design of digital dashboards should afford teachers visibility over student attempts, revisions, and explanations, rather than simply reporting completion metrics.

Several limitations of this research merit acknowledgment. The intervention comprised seven sessions with 300 students across six schools in a single region, which constrains the generalizability of results. The prototype learning environment, while functional, requires further development for larger-scale or long-term implementation. Additionally, reliance on both self-report and observational measures of motivation carries the risk of response bias. Future studies should pursue longitudinal designs to examine the persistence of motivation and problem-solving gains and should conduct replications across broader contexts—including varied student populations, technological infrastructures, and cultural settings—to refine the model's mechanisms. Overall, this study demonstrates that learning motivation is not simply a positive byproduct of mathematics instruction, but a central process enabling the effective translation of innovative pedagogical and technological approaches into enhanced mathematical problem-solving. This insight necessitates a rethinking of how technology-enhanced mathematics learning environments are designed and assessed, proposing that the intentional alignment of meaning, persistence, and formalization offers a powerful lever for improving student outcomes in the digital age.

Acknowledgments

The author would like to express his sincere gratitude to the Institute for Research and Community Service of Sunan Gunung Djati State Islamic University Bandung for supporting the research funding.

Declarations

Author Contribution	:	WS: Conceptualization, Writing - Original Draft, Methodology, Formal Analysis, and Investigation. SS: Review & Editing, and Validation. MP: Review & Editing, and Supervisor. HM: Data curation, Investigation, and Resources.
Funding Statement	:	This research was funded by the Research and Community Service Institute of Sunan Gunung Djati State Islamic University Bandung, UIN Sunan Gunung Djati Bandung.
Conflict of Interest	:	The authors declare no conflict of interest.
Additional Information	:	Additional information is available for this paper.

REFERENCES

Al-Barakat, A. A., El-Mneizel, A. F., Al-Qatawneh, S. S., AlAli, R. M., Aboud, Y. Z., & Ibrahim, N. A. H. (2025). Investigating the role of digital game applications in enhancing mathematical thinking skills in primary school mathematics students. *Decision Making: Applications in Management and Engineering, 8*(1), 132–146. https://doi.org/10.31181/dmame8120251301

Anugraheni, I., Gufron, A., & Purnomo, Y. W. (2025). The impact of realistic problem-based learning on mathematical connection abilities: evidence from elementary schools in Indonesia. *Cogent Education, 12*(1), 2523078. https://doi.org/10.1080/2331186X.2025.2523078

Ariffin, N. A. N., Ramli, N., Nik Badrul Alam, N. M. F. H., Yusof, Y., & Suparlan, A. (2022). Effectiveness of gamification in teaching and learning mathematics. *Journal on Mathematics Education, 13*(1), 173–190. https://doi.org/10.22342/jme.v13i1.pp173-190

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Bayaga, A. (2024). Enhancing M Enhancing mathematics problem-solving skills in AI-driven environment: Integrated SEM-neural network approach. *Computers in Human Behavior Reports, 16*, 100491. https://doi.org/10.1016/j.chbr.2024.100491

Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learning Environments, 12*, 29. https://doi.org/10.1186/s40561-025-00384-3

Beukes, B., Klock, A. C. T., Legaki, N.-Z., & Hamari, J. (2024). Gamified scaffolding in formal education: A scoping review. *Proceedings of the Annual Hawaii International Conference on System Sciences* (pp. 5144–5153). University of Hawai'i at Mānoa. https://dx.doi.org/10.24251/HICSS.2024.617

Bhardwaj, R. (2024). AI integrated model design for education system for analytical computation (Mathematics). *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2024* (pp. 1412–1417). IEEE. https://doi.org/10.1109/ICACITE60783.2024.10616503

Bjork, R. A., & Bjork, E. L. (2020). Desirable difficulties in theory and practice. *Journal of Applied Research in Memory and Cognition, 9*(4), 475–479. https://doi.org/10.1016/j.jarmac.2020.09.003

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Canonigo, A. M. (2024). Levering AI to enhance students' conceptual understanding and confidence in mathematics. *Journal of Computer Assisted Learning, 40*(6), 3215-3229. https://doi.org/10.1111/jcal.13065

Creswell, J. W. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dabingaya, M. (2022). Analyzing the effectiveness of AI-powered adaptive learning platforms in mathematics education. *Interdisciplinary Journal Papier Human Review, 3*(1), 1–7. https://doi.org/10.47667/ijphr.v3i1.226

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments* (pp. 9–15). ACM. https://doi.org/10.1145/2181037.2181040

Dewi, N. R., & Maulida, N. F. (2023). The development of STEM-nuanced mathematics teaching materials to enhance students' mathematical literacy ability through information and communication technology-assisted preprospec learning model. *International Journal of Educational Methodology, 9*(2), 409–421. https://doi.org/10.12973/IJEM.9.2.409

Drijvers, P. (2015). Digital Technology in Mathematics Education: Why It Works (Or Doesn't). In S. J. Cho (Ed.), *Selected Regular Lectures from the 12th International Congress on Mathematical*

Education (pp. 135–151). Springer International Publishing. https://doi.org/10.1007/978-3-319-17187-6_8

Dubinsky, E., Mcdonald, M. A. (2001). APOS: A Constructivist Theory of Learning in Undergraduate Mathematics Education Research. In Holton, D., Artigue, M., Kirchgräber, U., Hillel, J., Niss, M., Schoenfeld, A. (Eds.) *The Teaching and Learning of Mathematics at University Level. New ICMI Study Series* (pp. 275-282). Springer. https://doi.org/10.1007/0-306-47231-7_25

Fitria, W., Susilana, R., Priatna, N., & Rusman. (2025). Investigation of the impact online single and multiple representation scaffolding on mathematical concept mastery and mathematical problem-solving skill. *Journal on Mathematics Education, 16*(2), 709-728. https://doi.org/10.22342/jme.v16i2.pp709-728

Freudenthal, H. (1991). *Revisiting Mathematics Education: China Lectures*. Springer. https://doi.org/10.1007/0-306-47203-1

Gravemeijer, K. P. E. (1994). *Developing realistic mathematics education*. CD-ß Press.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hu, Y. Z., Wei, H. T., & Chignell, M. (2023). Impact of rewards on cognitive game performance: Competition with peers increases enjoyment in easy, but not difficult tasks. *Computers in Human Behavior, 149*, 107952. https://doi.org/10.1016/j.chb.2023.107952

Hui, H. B., & Mahmud, M. S. (2023). Influence of game-based learning in mathematics education on the students' cognitive and affective domain: A systematic review. *Frontiers in Psychology, 14*, 1105806. https://doi.org/10.3389/fpsyg.2023.1105806

Jun, M., & Lucas, T. (2025). Gamification elements and their impacts on education: A review. *Multidisciplinary Reviews, 8*(5), 2025155-2025155. https://doi.org/10.31893/multirev.2025155

Koskinen, A., McMullen, J., Hannula-Sormunen, M., Ninaus, M., & Kiili, K. (2023). The strength and direction of the difficulty adaptation affect situational interest in game-based learning. *Computers & Education, 194*, 104694. https://doi.org/10.1016/j.compedu.2022.104694

Lady, A., Utomo, B. T., & Lovi, C. (2018). Improving mathematical ability and student learning outcomes through realistic mathematic education (RME) approach. *International Journal of Engineering and Technology(UAE), 7*(2), 55–57. https://doi.org/10.14419/ijet.v7i2.10.10954

Lestari, R., Prahmana, R. C. I., Chong, M. S. F., & Shahrill, M. (2023). Developing realistic mathematics education-based worksheets for improving students' critical thinking skills. *Infinity Journal, 12*(1), 69–84. https://doi.org/10.22460/infinity.v12i1.p69-84

Li, M., & Noori, A. Q. (2024). Exploring the nexus of attitude, contextual factors, and AI utilization intentions: A PLS-SEM analysis among primary mathematics teachers in China. *Asian Journal for Mathematics Education, 3*(3), 289–311. https://doi.org/10.1177/27527263241269060

Malik, R., Abdi, D., Wang, R., & Demszky, D. (2025). Scaffolding middle school mathematics curricula with large language models. *British Journal of Educational Technology, 56*(3), 999-1027. https://doi.org/10.1111/bjet.13571

Martin, L. C., & Towers, J. (2011). Improvisational understanding in the mathematics classroom. In *Structure and Improvisation in Creative Teaching* (pp. 252-278). Cambridge University Press. https://doi.org/10.1017/CBO9780511997105.013

Maryani, I., Suyatno, S., Arfiani, I., Nizaar, M., Astuti, I. A. D., & Suliswaro, D. (2025). Gamified mobile-based learning approach: efforts to improve students' engagement and learning quality in remote schools in Indonesia. *Educational Process: International Journal, 15*(1), 1-17. https://doi.org/10.22521/edupij.2025.15.179

Matzakos, N., Doukakis, S., & Moundridou, M. (2023). Learning mathematics with large language models: A comparative study with computer algebra systems and other tools. *International Journal of Emerging Technologies in Learning (iJET), 18*(20), 51-71. https://doi.org/10.3991/ijet.v18i20.42979

Mitchell, B., & Co, M. J. (2024). The impact of implementing gamification elements on motivation, engagement and academic achievement. In *Proceedings of the International Conference on Education Research 2024* (pp. 184-193). Academic Conferences and Publishing International Ltd. http://dx.doi.org/10.34190/icer.1.1.3113

Mukuka, A., Mutarutinya, V., & Balimuttajjo, S. (2021). Mediating effect of self-efficacy on the relationship between instruction and students' mathematical reasoning. *Journal on Mathematics Education, 12(*1), 73–92. https://files.eric.ed.gov/fulltext/EJ1294665.pdf

Ndiung, S., & Menggo, S. (2025). Integrating ICT competencies into high-order thinking skills assessment for preparing students' mathematics learning autonomy in Indonesia. *International Journal of Innovative Research and Scientific Studies, 8*(1), 784–793. https://doi.org/10.53894/ijirss.v8i1.4423

Ng, D. T. K., Xinyu, C., Leung, J. K. L., & Chu, S. K. W. (2024). Fostering students' AI literacy development through educational games: AI knowledge, affective and cognitive engagement. *Journal of Computer Assisted Learning, 40*(5), 2049-2064. https://doi.org/10.1111/jcal.13009

OECD. (2019). *PISA 2018 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy*. OECD Publishing. https://www.oecd.org/publications/pisa-2018-assessment-and-analytical-framework-9789264305274-en.htm

Opesemowo, O. A. G., & Ndlovu, M. (2024). Artificial intelligence in mathematics education: The good, the bad, and the ugly. *Journal of Pedagogical Research, 8*(3), 333–346. https://doi.org/10.33902/JPR.202426428

Plomp, T. (2013). *Educational Design Research: Part A: An Introduction*. SLO.

Rahayu, C., Putri, R. I. I., Zulkardi, & Hartono, Y. (2022). Curiosity: A game-based early mathematics case. *Journal on Mathematics Education, 13*(2), 275–288. https://doi.org/10.22342/jme.v13i2.pp275-288

Raméntol, S. V, & Camacho, M. T. F. (2016). Students' perceptions towards mathematics. *Opcion, 32*(Special Issue 12), 964–986. https://dialnet.unirioja.es/descarga/articulo/5852339.pdf

Rane, N. (2023). Enhancing mathematical capabilities through ChatGPT and similar generative artificial intelligence: Roles and challenges in solving mathematical problems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4603237

Roldán-Álvarez, D., & Mesa, F. (2024). Intelligent deep-learning tutoring system to assist instructors in programming courses. *IEEE Transactions on Education, 67*, 153–161. https://doi.org/10.1109/te.2023.3331055

Ryan, R. M., & Deci, E. L. (2024). Self-determination theory. In *Encyclopedia of quality of life and well-being research* (pp. 6229-6235). Cham: Springer International Publishing.

Siregar, H. S., Munir, M., & Fikri, M. (2025). Enhancing Islamic education through technology integration: a study of teaching practices in Indonesia. *Jurnal Ilmiah Peuradeun, 13*(2), 959–986. https://doi.org/10.26811/peuradeun.v13i2.1875

Siswantari, Sabon, S. S., Listiawati, N., Wirda, Y., Zulkardi, & Riyanto, B. (2025). Bridging mathematics and communication: Implementing realistic mathematics education principles for skill development. *Journal on Mathematics Education, 16*(2), 729–752. https://doi.org/10.22342/jme.v16i2.pp729-752

Soesanto, R. H., Dirgantoro, K. P. S., & Priyanti, N. (2022). Indonesian students' perceptions towards AI-based learning in mathematics. *Journal on Mathematics Education, 13*(3), 531–548. https://doi.org/10.22342/jme.v13i3.pp531-548

Star, J., Chen, J., Taylor, M., Durkin, K., Dede, C., & Chao, T. (2014). Studying technology-based strategies for enhancing motivation in mathematics. *International Journal of STEM Education, 1*, 1–19. https://doi.org/10.1186/2196-7822-1-7

Suparatulatorn, R., Jun-on, N., Hong, Y.-Y., Intaros, P., & Suwannaut, S. (2023). Exploring problem-solving through the intervention of technology and Realistic Mathematics Education in the Calculus content course. *Journal on Mathematics Education, 14*(1), 103–128. https://doi.org/10.22342/jme.v14i1.pp103-128

Torres-Toukoumidis, A., Jiménez, M. M. F., Merchán-Romero, J., & Vega-Ramírez, J. F. A. (2025). Gamification and artificial intelligence in the educational context: Analysis of scientific literature. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 15348 LNCS* (pp. 349–354). Springer. https://doi.org/10.1007/978-3-031-78269-5_34

Treffers, A. (1991). Realistic Mathematics Education in the Netherlands. In L. Streefland (Ed.), *Realistic Mathematics Education in Primary School: On the Occasion of the Opening of the Freudenthal Institute* (pp. 11–20). CD-β Press. https://research-portal.uu.nl/en/publications/realistic-mathematics-education-in-the-netherlands

Wild, S., & Neef, C. (2023). Analyzing the associations between motivation and academic performance via the mediator variables of specific mathematic cognitive learning strategies in different subject domains of higher education. *International Journal of STEM Education*, *10*(1), 32. https://doi.org/10.1186/s40594-023-00423-w

Xia, Q., Yin, H., Hu, R., Li, X., & Shang, J. (2022). Motivation, engagement, and mathematics achievement: An exploratory study among Chinese primary students. *Sage Open*, *12*(4), 1-13. https://doi.org/10.1177/21582440221134609

Yin, D. S., & Yin, X. (2024). Scaffolding learning: From specific to generic with large language models. *Plos One, 19*(9), e0310409. https://doi.org/10.1371/journal.pone.0310409

Zabala-Vargas, S., de-Benito, B., Darder-Mesquida, A., Arciniegas-Hernandez, E., Reina-Medrano, J., & García-Mora, L. (2021). Strengthening motivation in the mathematical engineering teaching processes-A proposal from gamification and game-based learning. *International Journal of Emerging Technologies in Learning, 16*(6), 4-10. https://doi.org/10.3991/ijet.v16i06.16163

Zheng, W., & Tse, A. W. C. (2023). The impact of generative artificial intelligence-based formative feedback on the mathematical motivation of Chinese grade 4 students: A case study. In *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)* (pp. 1-8). IEEE. https://doi.org/10.1109/tale56641.2023.10398319

Zulkardi, & Kohar, A. W. (2018). Designing PISA-like mathematics tasks in Indonesia: Experiences and challenges. *Journal of Physics: Conference Series, 947*(1), 012015. https://doi.org/10.1088/1742-6596/947/1/012015