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

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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

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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.

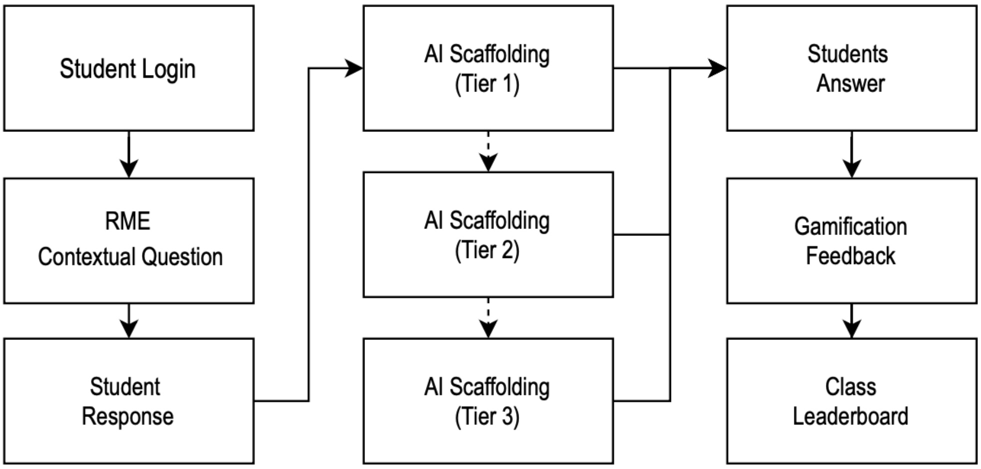

Figure 1. Instructional flow of the AI–RME–Gamification model with tiered AI scaffolding

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.

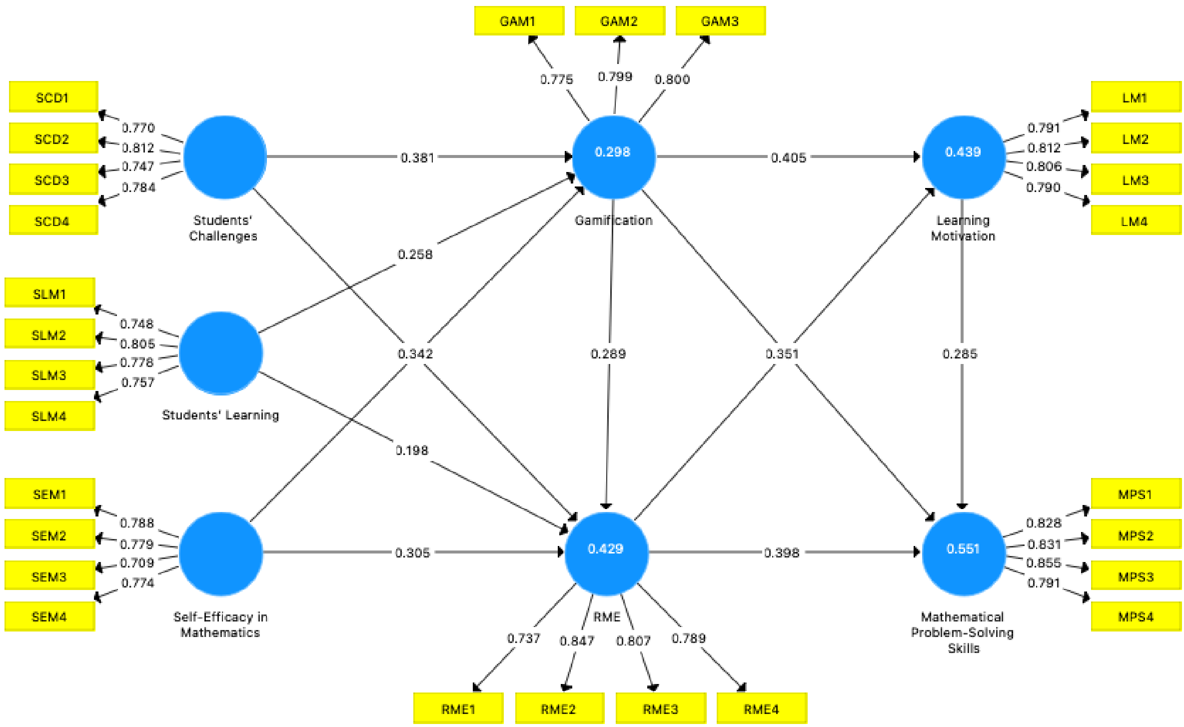

Figure 2. SEM-PLS structural model of the AI–RME–gamification framework

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.

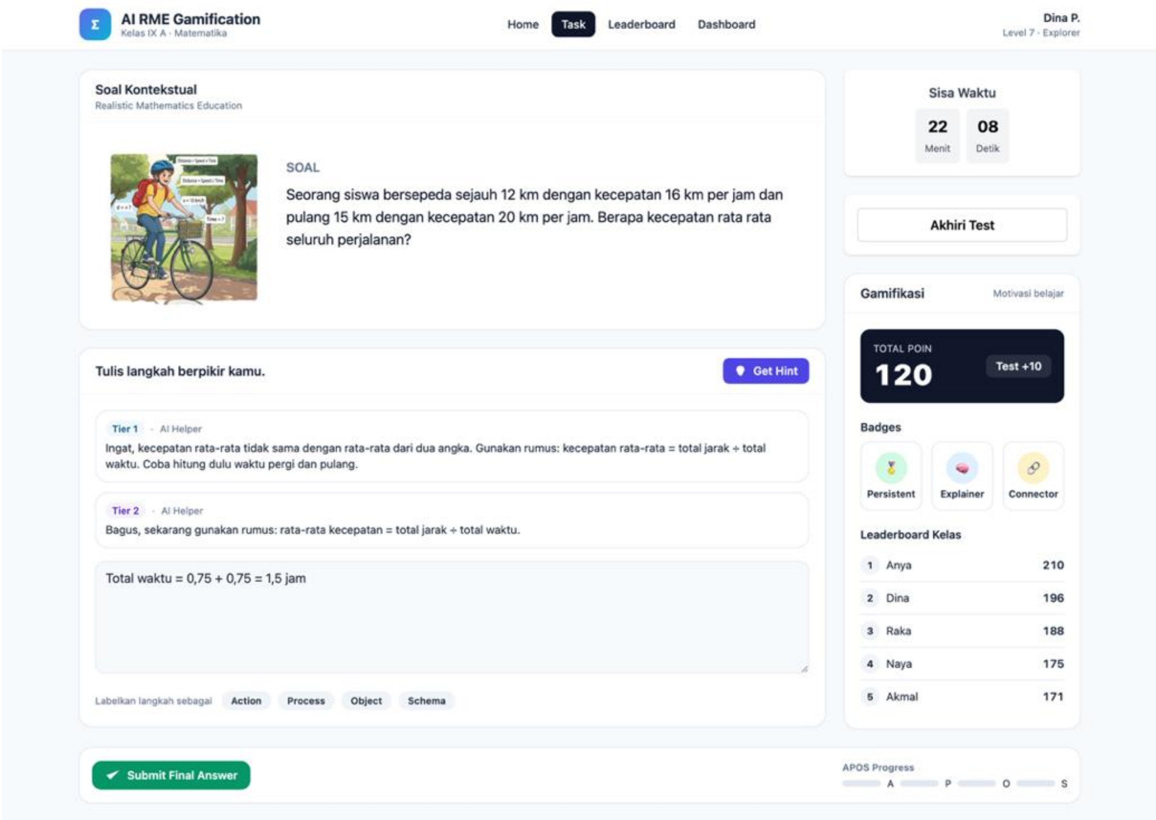

Figure 3. Screenshot of the AI–RME–Gamification prototype application

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.

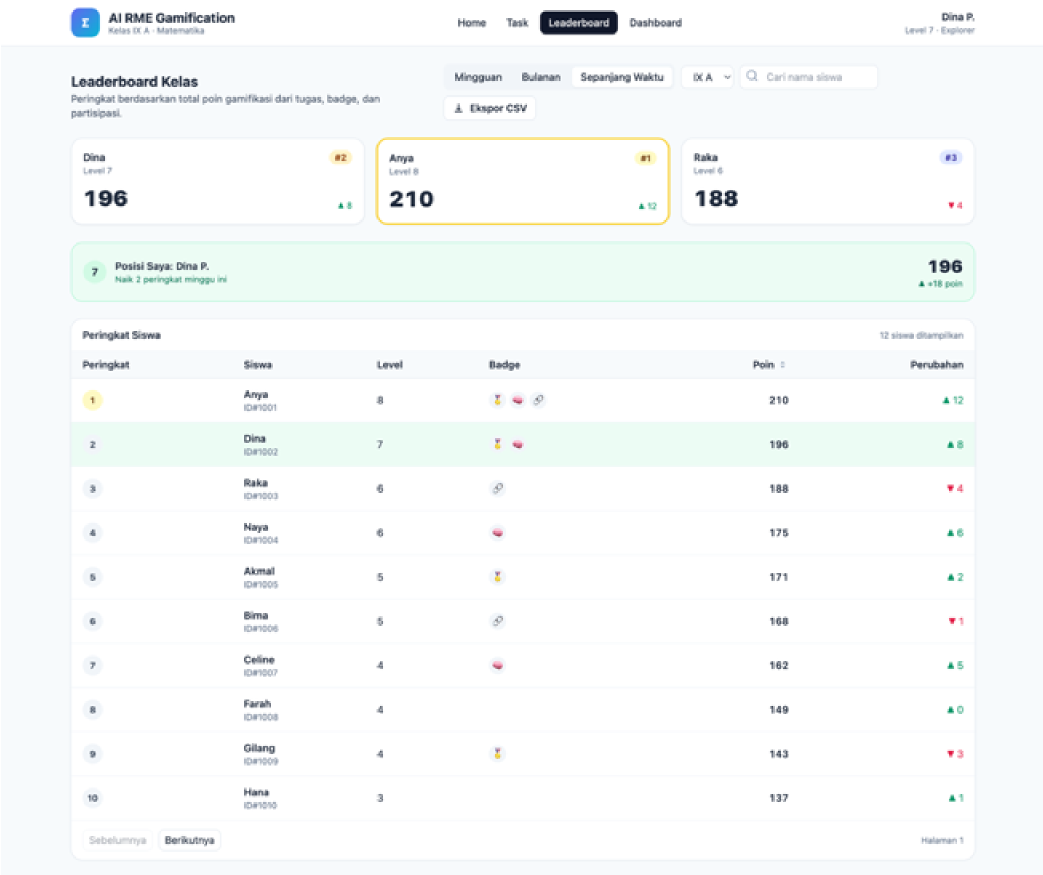

Figure 4. Teacher dashboard and leaderboard from the AI–RME–Gamification platform

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.

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