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Research Article

Realistic Mathematics Education and Learning Interest as Simultaneous Predictors of Mathematics Achievement: Evidence from a Teacher-Perspective SEM-PLS Study

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ABSTRACT

Purpose of the study: Despite widespread recognition of Realistic Mathematics Education (RME) and student learning interest as critical factors in mathematics learning, their simultaneous contribution to performance, as perceived by classroom teachers, remains insufficiently examined. This study investigates the concurrent relationships between RME implementation quality and student learning interest with teacher-rated mathematics learning performance in elementary schools.

Methodology: A quantitative cross-sectional survey involved n = 55 purposively selected elementary school mathematics teachers. Using validated questionnaires with 5-point Likert scales, teachers rated RME practices, student interest, and mathematics performance across nine competency dimensions based on year-long classroom observations. Structural Equation Modeling–Partial Least Squares (SEM-PLS) with bootstrapping (5,000 resamples) was employed. The measurement model demonstrated robust psychometric properties (AVE > 0.70, CR > 0.93, HTMT < 0.90).

Main Findings: RME implementation significantly predicted teacher-rated performance ($\beta = 0.468$, $p < 0.001$, $f^2 = 0.312$, medium-to-large effect), as did student learning interest ($\beta = 0.382$, $p < 0.001$, $f^2 = 0.198$, medium effect). Both predictors jointly explained 58.4% of performance variance ($R^2 = 0.584$, $Q^2 = 0.398$), indicating substantial explanatory and predictive capacity.

Novelty/Originality of this study: This study uniquely integrates pedagogical and psychological predictors within a single SEM-PLS framework from the practitioner perspective, addressing a methodological gap in Indonesian elementary mathematics research that has predominantly relied on separate, small-scale analyses. Findings carry direct implications for teacher professional development and curriculum design, particularly in advancing RME adoption and interest-fostering strategies within Indonesia's Merdeka Curriculum context.

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1. INTRODUCTION

The mathematics learning crisis in Indonesia has reached a critical point requiring urgent attention from all education stakeholders. Data from the Program for International Student Assessment (PISA) 2022 revealed that Indonesia ranked 69th out of 81 participating countries with a mean mathematics score of 366, significantly below the Organization for Economic Co-operation and Development (OECD) average of 472 [1]. This score represents a concerning decline from Indonesia's 2018 PISA mathematics score of 379, signaling persistent and worsening challenges in mathematics education despite various reform efforts implemented over the past decade [1], [2]. The trend of stagnating or declining mathematics performance has been observed consistently across multiple PISA cycles, with Indonesia's scores remaining substantially below international benchmarks since the country's first participation in 2000, indicating systemic issues in mathematics instruction and learning that transcend individual policy interventions [3]. The situation was further exacerbated by the COVID-19 pandemic, which resulted in extended school closures affecting 60% of Indonesian students for more than three months, compared to 51% across OECD countries, leading to significant learning loss, particularly in foundational mathematical concepts and skills [1].

The fundamental issue stems from the persistent dominance of traditional, mechanistic learning approaches that prioritize algorithmic procedures and rote memorization over deep conceptual understanding and meaningful application [4]. Systematic classroom observations across Indonesian elementary schools reveal that the majority of mathematics teachers continue to employ conventional drill-and-practice methods characterized by teacher-centered instruction, procedural emphasis without conceptual grounding, and decontextualized problem sets disconnected from students' lived experiences [5]. These instructional practices result in students being required to memorize formulas without understanding their mathematical foundations or real-world applications, complete repetitive computational exercises without developing essential problem-solving strategies, and learn mathematics in isolation from authentic contexts, ultimately rendering mathematics abstract, intimidating, and seemingly irrelevant to their daily lives [6]. The consequences of these inappropriate pedagogical approaches are profound and far-reaching, manifesting in elevated mathematical anxiety among students, progressive decline in learning interest and engagement, and the development of deeply entrenched negative attitudes toward mathematics as a difficult, inaccessible subject with no perceived relevance to their present or future lives [7], [8].

Realistic Mathematics Education (RME) has emerged as a promising pedagogical paradigm to address fundamental problems in mathematics instruction. Developed based on Freudenthal's (1991) philosophy that mathematics should be learned as a human activity rather than as a ready-made system to be transmitted, RME positions students as active constructors of mathematical knowledge through engagement with realistic contexts and situations meaningful to their experiences [9], [10]. Unlike conventional approaches that begin with formal abstractions and algorithmic procedures presented in decontextualized formats, RME utilizes contextual problem situations as starting points for learning, facilitating a progressive mathematization process whereby students gradually develop from informal, context-specific strategies to increasingly formal and general mathematical concepts and procedures [11], [12].

Empirical research demonstrates substantial positive effects of RME on various dimensions of mathematical competence. A systematic review by van den Heuvel-Panhuizen and Drijvers (2020) examining RME implementation across international contexts found consistent evidence of improved conceptual understanding, problem-solving capabilities, and positive attitudes toward mathematics among students who experienced RME compared to traditional instruction [11]. In the Indonesian context specifically, longitudinal research tracking elementary students' mathematical development under RME-based curriculum showed significant gains in realistic problem-solving abilities, mathematical reasoning, and capacity to apply mathematical concepts to authentic situations [13], [14]. Furthermore, empirical studies synthesizing evidence from multiple classroom implementations indicate substantial positive effects for RME interventions on mathematical achievement, with particularly strong outcomes for measures of conceptual understanding and contextual application compared to procedural fluency measures alone [15]-[19].

However, RME implementation proves insufficient without concurrent attention to students' psychological factors, particularly learning interest, which educational research identifies as a robust predictor of academic achievement across domains [20]-[23]. Contemporary research in educational psychology reveals that interest plays a fundamental role in learning through multiple mechanisms. Interest enhances cognitive processing by focusing attention on relevant information, facilitates deeper elaboration and organization of learning materials, and promotes persistence when encountering challenging tasks or obstacles [20]. Students demonstrating high interest in mathematics exhibit qualitatively different patterns of engagement, including more frequent voluntary practice, greater willingness to tackle difficult problems, and more elaborate self-explanation during problem-solving processes [24]-[26].

Meta-analytic evidence examining the relationship between interest and academic achievement across diverse educational contexts reveals consistent positive associations. Schiefele et al., synthesizing multiple studies across different age groups and subject areas, found average correlations ranging from 0.31 to 0.38

between subject-matter interest and achievement, with effects demonstrating particular strength and consistency at the elementary school level compared to secondary or tertiary education [27]. More recent longitudinal research tracking students over extended periods confirms bidirectional relationships whereby initial interest predicts subsequent achievement, and achievement experiences in turn shape the development or decline of interest over time, creating reciprocal feedback loops that can be either virtuous or vicious depending on early experiences [28]-[31].

Although research on RME and learning interest has been extensively conducted over the past two decades, there are fundamental gaps that have not been adequately addressed in the literature. First, the majority of research analyzes RME and learning interest separately as independent predictors, ignoring potential interaction effects and the complexity of relationships between them. However, Self-Determination Theory by Ryan and Deci suggests that learning approaches as environmental factors and interest as individual factors interact complexly in influencing learning outcomes [20], [21]. Existing research fails to capture this complexity due to methodological limitations of analysis that only use simple univariate or bivariate approaches without considering simultaneous effects [22].

Second, RME research in Indonesia is dominated by qualitative studies or experiments with small samples limited to one particular school or classroom [6]. A bibliometric analysis of RME publications in Indonesian elementary schools between 2013 and 2022 found that among 265 articles published in accredited journals, the majority were single-school studies with quantitative research designs, but only a small percentage employed complex structural analysis such as SEM or multilevel modeling [32], [33]. Moreover, no integrated teacher perspectives were considered key stakeholders in RME implementation. The teacher's perspective is very crucial because they are the ones who implement RME directly in the classroom and observe student interest in daily learning contexts.

Third, there is a serious methodological limitation in construct measurement in previous studies. The majority of research uses single indicators or simple composite scores to measure complex constructs, ignoring the multidimensional nature of RME, interest, and learning performance, which actually consist of various interrelated dimensions [34], [35]. This oversimplified approach fails to capture the nuances and complexity of each construct, potentially leading to biased estimates and inaccurate conclusions about the magnitude and nature of the relationships studied.

Fourth, the context of implementing the Merdeka Curriculum, which began to be applied nationally in 2022, emphasizing differentiated learning and formative assessment, creates a new landscape that has not been explored in empirical research. How RME and learning interest operate in this new curriculum context, with emphasis on student agency and personalized learning, remains an open question requiring empirical investigation. This research carries particular urgency in the Indonesian context, given the country’s substantial demographic dividend, with approximately 50 million students currently enrolled in the K-12 education system, representing both an enormous opportunity and a critical challenge for national development [1]. The quality of mathematics education these students receive will fundamentally shape Indonesia's capacity to compete effectively in an increasingly knowledge-based global economy and to successfully navigate the digital transformation reshaping labor markets worldwide [36]. Current global trends toward automation, artificial intelligence, and data-driven decision-making demand increasingly sophisticated mathematical literacy encompassing not merely computational proficiency but also computational thinking, data interpretation, statistical reasoning, and complex problem-solving capabilities, competencies that traditional mathematics instruction fails to adequately develop [36], [37].

This research is theoretically significant because it integrates pedagogical perspectives represented by RME with psychological perspectives represented by learning interest using a sophisticated analytical framework, namely SEM-PLS, which allows testing of simultaneous relationships and structural model complexity. Practically, research findings can inform teacher professional development programs, more evidence-based curriculum design, and education policy to improve mathematics learning quality systematically and sustainably. Therefore, this study aims to examine the relationship between RME implementation quality and mathematics learning performance as observed by teachers, investigate the association between student learning interest and mathematics learning performance from teacher perspectives, and evaluate the simultaneous relationships among RME implementation, learning interest, and teacher-rated mathematical competencies using SEM-PLS analysis. By examining these relationships from the perspective of elementary school teachers as direct implementers who observe students daily across diverse learning contexts, this study provides practitioner-grounded evidence about how pedagogical innovation and student engagement manifest in observable classroom competencies.

2. RESEARCH METHOD

This study employs a quantitative non-experimental research design with a cross-sectional survey approach. This design was selected because the variables of interest, namely RME implementation quality, student learning interest, and mathematics learning performance, represent naturally occurring classroom phenomena that cannot be manipulated through experimental intervention [38]. Data analysis used Structural Equation Modeling-Partial Least Squares (SEM-PLS) via SmartPLS 4.0. SEM-PLS was selected because it is robust to non-normal distributions commonly found in ordinal Likert-scale data, enables simultaneous estimation of multiple structural paths within a single model, and performs well with small-to-medium sample sizes relative to covariance-based SEM [34], [39].

The structural relationships hypothesised in this study are presented in Figure 1. The model positions RME Implementation (X1) and Student Learning Interest (X2) as two independent predictor constructs, each hypothesised to exert a direct positive influence on Mathematics Achievement (Y) as the dependent construct. H1 represents the hypothesised path from RME Implementation to Mathematics Achievement, while H2 represents the hypothesised path from Student Learning Interest to Mathematics Achievement. A bidirectional correlation arrow between X1 and X2 acknowledges the expected co-occurrence of contextual instructional quality and student psychological engagement within the same classroom.

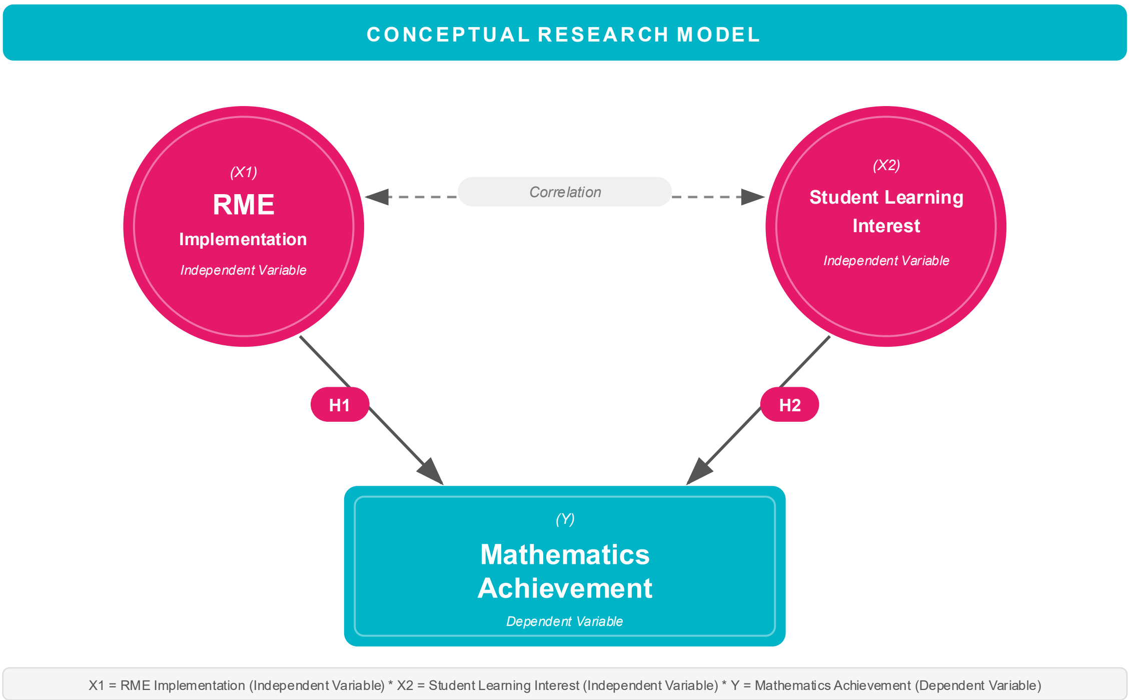

Figure 1. Conceptual Research Model

As shown in Figure 1, the model is limited to direct effects without mediating or moderating pathways, reflecting the exploratory nature of the present study within the Indonesian elementary school context. This parsimonious structure is appropriate given the sample size and the dual-predictor focus of the research questions. The target population comprised elementary school mathematics teachers actively teaching during the 2024-2025 academic year. Three inclusion criteria were applied: (1) teaching mathematics in Grades 3 to 6, (2) possessing a minimum of two years of teaching experience, and (3) holding at least a Bachelor's degree in Education in accordance with Indonesian national teacher qualification standards.

Purposive sampling was employed to select 55 respondents who additionally demonstrated documented exposure to innovative learning approaches through training or professional development workshops within the preceding two years, confirmed through training certificates referenced during data collection. Purposive sampling was appropriate because the study required respondents with a minimum relevant experience in RME-aligned instructional practices [38]. The final sample comprised 70.9% female and 29.1% male teachers, with a mean age of 37.2 years (SD = 6.5) and a mean teaching experience of 8.7 years (SD = 4.1). Schools were distributed across urban (47.3%), suburban (32.7%), and rural (20.0%) settings.

Data were collected using a structured questionnaire consisting of 27 items across three latent constructs, each measured by nine indicators on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Instrument development followed three validation stages. Content validity was established through expert judgment by three mathematics education specialists using the Content Validity Index (CVI greater than or equal to 0.79). Construct validity was verified through Confirmatory Factor Analysis, with all items achieving factor loadings above 0.70 and AVE exceeding 0.50. Reliability was confirmed through Cronbach's Alpha and Composite Reliability, both exceeding 0.90 [38].

Data collection was conducted from February to May 2025. After obtaining formal research permits from the Regional Education Office and school principals, teachers were briefed on study objectives and voluntary participation. Questionnaires were distributed with the researcher's assistance, and teachers were instructed to base their ratings on accumulated observations across the full academic year. All 55 returned questionnaires passed quality screening, yielding a 100% usable response rate. The complete instrument grid is presented in Table 1.

Table 1. Data Collection Instrument Grid

Variable	Theoretical Basis	Dimension	Item Description	No.
RME Implementation (X1)	Gravemeijer and Doorman (1999) [40]	Use of real-world contexts	The teacher uses authentic daily-life situations as learning starting points	1
		Authentic problem-solving	The teacher designs problems connected to students' lived experiences	2
		Mathematical models and representations	The teacher facilitates the use of diagrams, manipulatives, and visual models	3
		Social interaction	The teacher encourages mathematical discussion and collaborative problem-solving	4
		Horizontal mathematization	Teacher guides students from contextual situations to informal models	5
		Vertical mathematization	The teacher supports the transition from informal strategies to formal procedures	6
		Reflection and evaluation	The teacher facilitates student reflection on learning processes	7
		Integration across topics	The teacher connects current content with related mathematical concepts	8
		Guided reinvention	Teacher structures activities enabling students to rediscover mathematical principles	9
Student Learning Interest (X2)	Renninger and Hidi (2016) [24]	Enthusiasm for learning	Students show visible enthusiasm during mathematics lessons	10
		Attention and concentration	Students maintain sustained attention during mathematical tasks	11
		Active participation	Students actively engage in activities, discussions, and problem-solving	12
		Persistence in difficulties	Students continue working on challenging problems without giving up	13
		Mathematical curiosity	Students ask questions and explore ideas beyond required tasks	14
		Self-confidence	Students demonstrate confidence when attempting and presenting solutions	15
		Intrinsic motivation	Students engage with mathematics out of genuine interest	16
		Perseverance	Students invest sustained effort in complex multi-step problems	17

Variable	Theoretical Basis	Dimension	Item Description	No.
		Appreciation of mathematics	Students express recognition of the utility and relevance of mathematics	18
		Conceptual understanding	Student demonstrates understanding of mathematical concepts and relationships	19
		Problem-solving ability	Student applies appropriate strategies to varied contextual problems	20
		Mathematical communication	Student articulates reasoning clearly in verbal and written forms	21
		Mathematical reasoning	Student constructs logical arguments and justifies conclusions	22
Mathematics Learning Performance (Y)	NCTM (2000) [41]	Contextual application	Student applies mathematical concepts to real-world situations	23
		Performance in assessments	Student achieves consistent results across quizzes and assignments	24
		Mathematical representation	The student uses symbols, graphs, and diagrams to represent mathematical ideas	25
		Conceptual connections	Student identifies connections among mathematical concepts across topics	26
		Critical thinking	Student evaluates problems and solutions with analytical reasoning	27

Note: All items were rated by classroom teachers on a five-point Likert scale based on year-long accumulated observations. X1 = RME Implementation; X2 = Student Learning Interest; Y = Mathematics Learning Performance.

A priori statistical power analysis was conducted to determine the adequacy of the sample size. For a multiple regression model with two predictor variables ($k = 2$), a medium effect size ($f^2 = 0.15$), and a significance level of $\alpha = .05$, a minimum sample of $n = 55$ is required to achieve the target statistical power of 0.80 [16]. The present study's sample of $N = 55$ meets this threshold precisely. Post hoc estimation based on actual obtained effect sizes confirmed that retrospective power exceeded this criterion for both predictors: RME Implementation achieved a power level of 0.97 ($f^2 = 0.312$), while Student Learning Interest achieved 0.87 ($f^2 = 0.198$), both substantially above the minimum 0.80 benchmark. This confirms adequate statistical sensitivity for the detected effects across both hypothesised paths. The sample additionally satisfies the PLS-SEM rule of ten times the maximum number of paths pointing to any single construct, which requires a minimum of $n = 20$ for the present two-predictor model [16].

Data analysis followed Hair et al.'s two-step procedure for PLS-SEM [34]. Step 1 evaluated the outer measurement model through four sequential criteria: (a) indicator reliability, assessed through standardised outer loadings (lambda greater than or equal to 0.708, meaning each indicator shares at least 50% of its variance with the assigned construct); (b) internal consistency, assessed through Composite Reliability (CR greater than or equal to 0.70) and Cronbach's Alpha (alpha greater than or equal to 0.70); (c) convergent validity, confirmed through Average Variance Extracted (AVE greater than or equal to 0.50); and (d) discriminant validity, assessed through the Heterotrait-Monotrait Ratio (HTMT less than 0.90), which Henseler et al. (2015) demonstrated to outperform the traditional Fornell-Larcker criterion in detecting discriminant validity violations [15].

Step 2 evaluated the inner structural model. Before examining path coefficients, multicollinearity among predictors was assessed through the Variance Inflation Factor (VIF less than 5.00). Path coefficients (beta) were estimated and tested for significance using bias-corrected bootstrapping with 5,000 resamples at alpha = .05 (t greater than 1.96, two-tailed) [34]. Explanatory capacity was quantified through R2, with predictive relevance assessed via the Stone-Geisser Q2 through Blindfolding with omission distance d = 7 (Q2 greater than 0 confirms out-of-sample predictive capability). Effect size for each predictor was calculated using Cohen's f2, benchmarked as 0.02 (small), 0.15 (medium), and 0.35 (large) [16]. Overall model fit was evaluated through the Standardised Root Mean Squared Residual (SRMR less than 0.08) and Normed Fit Index (NFI greater than 0.90) [38]. The complete evaluation criteria are summarised in Table 2.

Table 2. Statistical Analysis Criteria for PLS-SEM Two-Step Evaluation

Step	Assessment	Index	Threshold
Step 1: Outer Model	Indicator Reliability	Outer Loading (lambda)	greater than or equal to 0.708
	Internal Consistency	CR and Cronbach's Alpha	greater than or equal to 0.70
	Convergent Validity	AVE	greater than or equal to 0.50
	Discriminant Validity	HTMT	less than 0.90
	Multicollinearity	VIF	less than 5.00
Step 2: Inner Model	Path Significance	t-statistic, p-value	t greater than 1.96; p less than .05
	Explanatory Power	R2	greater than 0.50 = substantial
	Effect Size	Cohen's f2	0.02 / 0.15 / 0.35
	Predictive Relevance	Q2 (Blindfolding)	greater than 0
	Model Fit	SRMR and NFI	less than 0.08 and greater than 0.90

Note: CR = Composite Reliability; AVE = Average Variance Extracted; HTMT = Heterotrait-Monotrait Ratio; VIF = Variance Inflation Factor; SRMR = Standardised Root Mean Squared Residual; NFI = Normed Fit Index. All analyses were conducted in SmartPLS 4.0.

3. RESULTS AND DISCUSSION

The profile of 55 research respondents shows diverse and representative characteristics of the elementary school mathematics teacher population. Gender distribution shows 70.9% of respondents are female, totaling 39 people, and 29.1% are male, totaling 16 people, reflecting the composition of elementary mathematics teachers in Indonesia who are predominantly female. The average age of respondents is 37.2 years with a standard deviation of 6.5 years, indicating the majority of respondents are in the mid-career phase with quite mature experience and professional stability. Respondent education levels include 89.1% who have a Bachelor's degree in Education, totaling 49 people, and 10.9% who have a Master's degree, totaling 6 people, showing that all respondents meet the minimum qualifications required in national education regulations.

The average teaching experience of respondents is 8.7 years with a standard deviation of 4.1 years, showing that most respondents have sufficient teaching experience to implement various learning approaches, including innovative approaches. Grade distribution taught includes 49.1% teaching grades 5 and 6, totaling 27 people, 36.4% teaching grades 3 and 4, totaling 20 people, and 14.5% teaching grades 1 and 2, totaling 8 people. The location of schools where respondents teach is distributed between 47.3% in urban areas, totaling 26 people, 32.7% in suburban areas, totaling 18 people, and 20.0% in rural areas, totaling 11 people. A total of 78.2% of respondents have attended innovative learning training in the last 2 years, showing that the majority of respondents have exposure to current learning approaches, including RME.

Descriptive statistics of research variables presented in Table 1 reveal that all three constructs demonstrate normal data distribution with positive perceptions. The RME Implementation variable shows the most variability among respondents, suggesting diverse experiences in implementing this approach across schools. The Student Learning Interest variable exhibits the highest mean, indicating teachers perceive students as more engaged than current RME adoption levels. The Mathematics Learning Performance variable shows the most consistent perceptions across respondents. All constructs meet the normality requirements for PLS-SEM analysis, skewness and kurtosis values between -1 and +1, confirming appropriate data distribution for structural modeling.

Table 3. Descriptive Statistics and Normality Assessment (n = 55)

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	Assessment
RME Implementation	3.49	0.91	1.33	5.00	-0.398	0.271	Normal
Student Learning Interest	3.68	0.78	1.78	5.00	-0.372	0.198	Normal
Mathematics Achievement	3.32	0.78	1.67	5.00	-0.508	0.365	Normal

Note: All variables were measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Skewness and Kurtosis values between -1 and +1 indicate approximate normality, appropriate for PLS-SEM analysis.

Table 3 confirms that the distributional properties of all three constructs satisfy the assumptions required for PLS-SEM analysis. The absence of extreme skewness or kurtosis values across variables indicates that the teacher-rated Likert data are suitable for structural modelling without requiring transformation or non-parametric alternatives. Evaluation of the measurement model or outer model begins with assessment of convergent validity through outer loadings presented in Table 4, Panel A. All indicators demonstrate strong loadings on their respective constructs, indicating that each item reliably measures its intended dimension. The consistency of loadings across constructs, ranging from 0.76 to 0.90, demonstrates robust measurement without weak indicators requiring removal. Convergent validity is further confirmed through Average Variance Extracted (AVE) and Composite Reliability (CR) indices, all exceeding recommended thresholds with AVE > 0.70 and CR > 0.93. The high CR values indicate excellent internal consistency among indicators within each construct.

Table 4. Measurement Model Assessment - Outer Model Quality Indices

Construct	AVE	CR	Cronbach's α	Indicator Range	Highest Indicator	Lowest Indicator
RME Implementation	0.701	0.938	0.925	0.762–0.897	IR4: 0.897	IR1: 0.762
Student Learning Interest	0.708	0.933	0.918	0.768–0.889	MB5: 0.889	MB1: 0.768
Mathematics Achievement	0.718	0.945	0.935	0.781–0.901	PBM8: 0.901	PBM6: 0.781

Note: AVE = Average Variance Extracted; CR = Composite Reliability. All values exceed quality thresholds (AVE > 0.70, CR > 0.93), confirming excellent convergent and internal consistency reliability.

The results presented in Table 4 demonstrate that all three constructs satisfy the minimum quality thresholds for convergent validity and internal consistency reliability. These findings confirm that the teacher-rated measurement instruments possess adequate psychometric properties to proceed to structural model evaluation.

The visual representation of the outer model, including all indicator loadings and their relationships to the three latent constructs, is presented in Figure 2. The path diagram allows for direct visual inspection of loading magnitudes across all 27 indicators and confirms the reflective measurement structure of each construct.

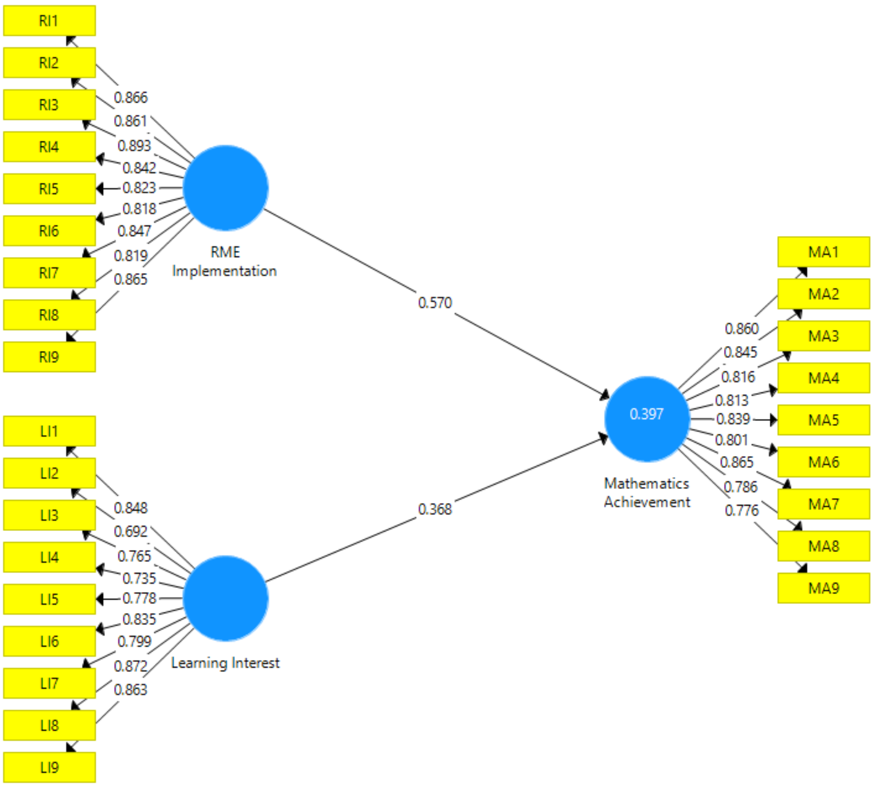

Figure 2. Outer Model (Measurement Model)

As illustrated in Figure 2, all indicator loadings are consistently high across the three constructs, with no cross-loading anomalies detected. The uniformity of loadings within each construct visually reinforces the convergent validity findings reported in Table 4.

Discriminant validity, which assesses the degree to which constructs are empirically distinct from one another, was evaluated using the Heterotrait-Monotrait Ratio of Correlations (HTMT) as recommended by Henseler et al. [15]. The HTMT results are presented in Table 5. All HTMT values must fall below the threshold of 0.90 to confirm adequate discriminant validity between construct pairs.

Table 5. Discriminant Validity Assessment (HTMT)

	RME Implementation	Learning Interest	Mathematics Achievement
RME Implementation	0.837	—	—
Learning Interest	0.687	0.841	—
Mathematics Achievement	0.742	0.658	0.848

Note: Diagonal values represent the square root of AVE. Off-diagonal values represent HTMT ratios. All HTMT values < 0.90 confirm adequate discriminant validity.

As shown in Table 5, all HTMT values fall below the 0.90 threshold, confirming that RME Implementation, Student Learning Interest, and Mathematics Achievement are empirically distinguishable constructs. This finding satisfies the discriminant validity requirement and supports the independence of the three latent variables in the structural model.

Evaluation of the structural model begins with an assessment of multicollinearity. Variance Inflation Factor (VIF) values for both predictors are well below the 5.0 threshold, with RME at 1.89 and Interest at 1.91, indicating no collinearity concerns and ensuring reliable parameter estimation. Path coefficients and model fit indices derived from bootstrapping with 5,000 resamples are presented in Table 6. Panel A reports hypothesis testing results for H1 and H2, while Panel B presents the model's explanatory capacity, predictive relevance, and overall fit indices.

Table 6. Structural Model Results - Path Coefficients and Model Fit Indices

Panel A: Hypothesis Testing (Bootstrapping with 5,000 samples)

Hypothesis	Path	β	SE	t-value	p-value	f²	Effect	Decision
H1	RME → Achievement	0.468	0.087	5.379	<0.001***	0.312	Med-Large	Accepted
H2	Interest → Achievement	0.382	0.084	4.548	<0.001***	0.198	Medium	Accepted

Panel B: Model Fit and Explanatory/Predictive Capacity

Index	Value	Criterion	Interpretation
R^2	0.584	>0.50	58.4% variance explained
Adjusted R^2	0.562	—	Robust after adjustment
Q^2	0.398	>0	Strong predictive capability
SRMR	0.052	<0.08	Good fit
NFI	0.912	>0.90	Good fit
VIF (RME)	1.89	<5.00	No collinearity
VIF (Interest)	1.91	<5.00	No collinearity

Note. β = Standardized path coefficient; SE = Standard Error; t = t-statistic; *** $p < 0.001$. Q^2 = Predictive Relevance (Stone-Geisser); SRMR = Standardized Root Mean Squared Residual; NFI = Normed Fit Index. Both hypotheses strongly supported (all $t > 1.96$, all $p < 0.05$).

The results in Table 6 provide strong statistical support for both research hypotheses. Panel A confirms that both H1 and H2 are accepted at $p < 0.001$, with RME Implementation exhibiting a medium-to-large effect ($f^2 = 0.312$) and Student Learning Interest a medium effect ($f^2 = 0.198$). Panel B confirms that the model achieves substantial explanatory power ($R^2 = 0.584$), adequate predictive relevance ($Q^2 = 0.398$), and satisfactory model fit (SRMR = 0.052; NFI = 0.912), indicating that the structural model is both statistically significant and practically meaningful.

The complete structural model with standardised path coefficients and R^2 value is visualised in Figure 3. This diagram integrates the findings from Table 4 into a single path model, enabling direct visual interpretation of the relative strength of H1 and H2 and the overall explanatory capacity of the model.

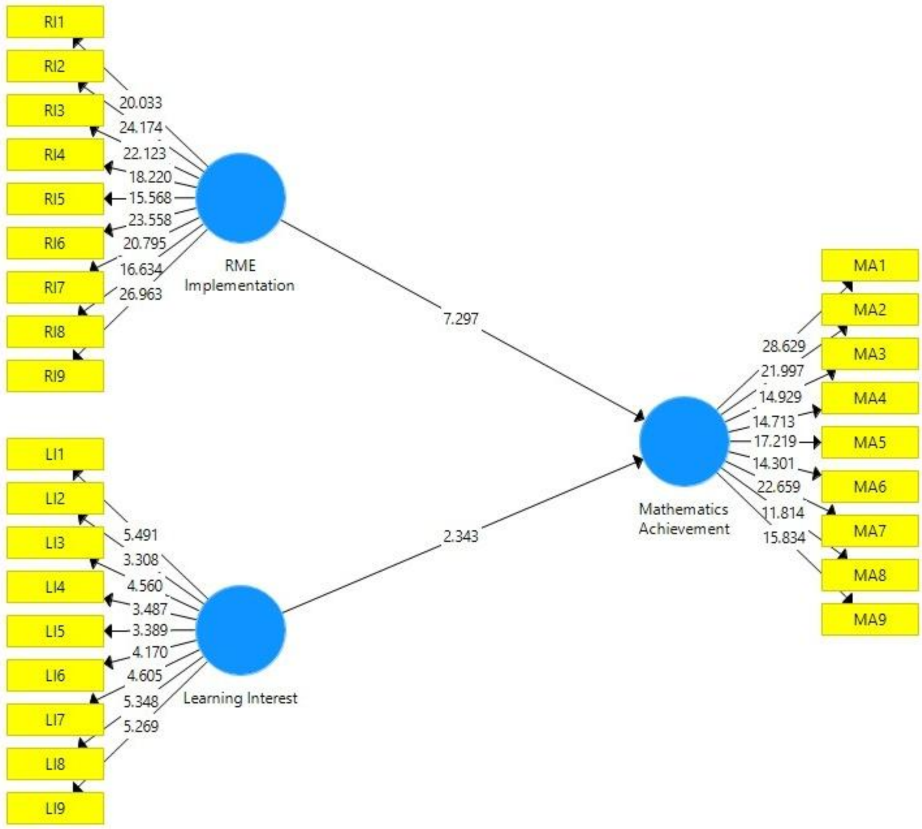

Figure 3. Inner Model (Structural Model)

The first hypothesis, that RME implementation has a positive and significant relationship with mathematics learning performance, is accepted with strong statistical support ($\beta = 0.468$, $t = 5.379$, $p < 0.001$, $f^2 = 0.312$). This result is consistent with theoretical frameworks and empirical evidence on the effectiveness of RME in promoting deep mathematical understanding [11]. The mechanism through which RME is associated with improved performance can be understood through several interrelated pathways that align with contemporary learning theories. First, RME's emphasis on contextual problem situations as learning starting points activates students' prior knowledge and creates meaningful connections between abstract mathematical concepts and concrete real-world applications [9], [42]. aligning with cognitive constructivism, which posits that learning occurs most effectively when new information is built upon existing knowledge structures through active mental construction. Second, the progressive mathematization process in RME, comprising horizontal mathematization and vertical mathematization, facilitates gradual abstraction from informal, intuitive strategies to formal mathematical procedures [40], [43], supporting development of both procedural fluency and conceptual understanding rather than requiring students to memorize decontextualized algorithms. Third, RME's guided reinvention approach, where students are supported to rediscover mathematical principles through structured problem-solving, promotes deeper engagement and ownership of learning compared to direct transmission of ready-made mathematical knowledge [44].

The second hypothesis, that student learning interest has a positive and significant relationship with mathematics learning performance, is also accepted with strong statistical support ($\beta = 0.382$, $t = 4.548$, $p < 0.001$, $f^2 = 0.198$). This finding provides empirical support for theoretical frameworks emphasizing the central role of motivation and affect in learning, aligning with Self-Determination Theory and Interest Development Theory, which posit that intrinsic motivation and genuine interest serve as powerful psychological forces that enhance learning processes and outcomes through multiple mechanisms [20], [45]. While RME demonstrates a slightly stronger association with mathematics achievement, both factors remain substantively important. Collectively, both variables jointly explain 58.4% of the variance in mathematics learning performance, demonstrating that combining pedagogical quality with psychological engagement represents a comprehensive approach to improving mathematics learning outcomes as observed by teachers in Indonesian elementary schools.

From a practical perspective, the research findings carry several important actionable implications for educational stakeholders. For teachers, results indicate that professional development focused on high-quality RME implementation should be prioritized [32], [46], with emphasis on developing competencies in designing contextual problem situations, facilitating progressive mathematization, and creating classroom environments that support student collaboration and mathematical discourse [47], [48]. Simultaneously, teachers should cultivate student learning interest through strategies such as connecting mathematics to students' lives and interests, providing appropriately challenging tasks, offering autonomy-supportive instruction [20], [49], and creating a classroom climate where mathematical curiosity and exploration are valued and rewarded.

The use of teacher ratings to assess mathematics learning performance in this study warrants careful interpretation. Teacher ratings represent a specific perspective on student competencies that differs from, yet complements, objective achievement measures such as standardized test scores. The ratings in this study reflect accumulated judgments based on prolonged observation of students across multiple contexts over an entire academic year, providing ecological validity that is particularly relevant to RME, which emphasizes authentic mathematical reasoning in realistic situations. Research on the validity of teacher judgments provides important context: Südkamp et al., found median correlations of $r = 0.63$ between teacher ratings and standardized test scores across 75 studies [50], indicating that teacher ratings capture overlapping but distinct aspects of mathematical competence, including typical effort investment, improvement trajectories, and engagement patterns. Nonetheless, teacher ratings are susceptible to various biases, including halo effects, expectation effects, and implicit biases related to student demographics. The potential for common source bias, where the same teachers rated both independent and dependent variables, should be acknowledged as a limitation that may inflate observed correlations. The findings should therefore be interpreted as demonstrating relationships among RME implementation, student interest, and learning performance as perceived from the teacher perspective, based on observations in authentic classroom contexts, rather than as establishing causal effects on objectively measured achievement gains.

4. CONCLUSION

This study provides empirical evidence that both the quality of Realistic Mathematics Education (RME) implementation and student learning interest are significantly and positively associated with mathematics learning performance as observed by elementary school teachers in Indonesia. RME implementation demonstrates a medium-to-large direct effect ($\beta = 0.468$, $p < 0.001$, $f^2 = 0.312$), while student learning interest demonstrates a medium effect ($\beta = 0.382$, $p < 0.001$, $f^2 = 0.198$), with both predictors jointly explaining 58.4% of variance in teacher-rated mathematics achievement. These findings confirm that pedagogical quality and psychological engagement are not competing priorities but mutually reinforcing determinants of mathematical competence in classroom practice. Based on these findings, a theoretical proposition is advanced: effective mathematics learning in elementary school is governed by the convergence of instructional authenticity and affective engagement, where neither pedagogical innovation nor motivational readiness alone is sufficient to produce optimal learning outcomes. This proposition extends existing frameworks by positioning RME not merely as a teaching method but as an environmental condition that simultaneously stimulates cognitive construction and sustains student interest, a dynamic that is particularly salient within the Kurikulum Merdeka framework, which demands differentiated and student-centred instruction. For practice, teachers should integrate contextual problem design with deliberate interest-cultivation strategies, as both dimensions contribute independently to performance outcomes. School leaders and policymakers should treat RME professional development and classroom climate improvement as complementary investment priorities rather than sequential or alternative interventions, ensuring that instructional reform and affective engagement are addressed as an integrated whole in Indonesia's ongoing mathematics education improvement agenda.

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AUTHOR CONTRIBUTIONS

Conceptualization, A.D.; Methodology, A.D.; Software, A.D.; Validation, F.K.; Formal Analysis, F.K. and A.D.; Investigation, F.K.; Resources, F.K.; Data Curation, F.K. and A.D.; Writing – Original Draft Preparation, F.K. and A.D.; Writing – Review & Editing, A.D.; Visualization, A.D.; Supervision, F.K.; Project Administration, F.K. Both authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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