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Research Article

Factors influencing the effectiveness of realistic mathematics education instruction among pre-service mathematics teachers in Vietnam

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In the context of Vietnam's transition to a competency-based curriculum, Realistic Mathematics Education has emerged as a pivotal pedagogical framework. However, its successful implementation depends heavily on the professional readiness of pre-service teachers. This study develops and validates a structural model to investigate the key determinants of Realistic Mathematics Education-based teaching performance among mathematics education students. This paper uses a quantitative research design with an ex post facto approach was employed. Data were collected from 654 pre-service mathematics teachers across pedagogical universities in Vietnam using a multi-stage sampling strategy that combined cluster and convenience sampling. The primary instrument was a structured online survey consisting of 5-point Likert scale items adapted from established theoretical constructs. Partial Least Squares Structural Equation Modeling via SmartPLS 4.1 was utilized to analyze the measurement and structural relationships. The results confirm that Pedagogical Content Knowledge, Institutional Support, and Experience and Observation significantly and positively influence Realistic Mathematics Education teaching performance. Notably, Teacher Beliefs and Attitudes serve as a vital mediator, translating professional knowledge and support into practice. While the model demonstrates high predictive power, Importance-Performance Map Analysis identifies Experience and Observation as a critical priority area characterized by high impact but relatively lower performance levels. This shows teacher training programs should move beyond theoretical instruction to prioritize immersive clinical experiences, video analysis, and practical design skills. Enhancing these factors supports the development of effective, real-world-aligned numeracy instruction.

Keywords: Mathematics teachers; Pre-service mathematics teachers; Realistic Mathematics Education; Teaching mathematics; Teaching performance

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1. Introduction

In recent years, the Vietnamese educational landscape has undergone a strategic transformation toward a competency-based curriculum that emphasizes the learner's active role in constructing core competencies through creative engagement (Ministry of Education and Training, 2018). This

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shift directly addresses a critical systemic challenge: traditional, abstract mathematical instruction often disconnects students from the subject, fostering mathematics anxiety and eroding confidence rather than making mathematics feel relevant to reality (Al Umairi, 2024; Asiedu Menlah & Boateng, 2025; Smith et al., 2026). To bridge this gap, the theory of Realistic Mathematics Education [RME] has emerged as a pivotal pedagogical framework. Rooted in the humanistic philosophy that mathematics must be accessible and socially meaningful, RME treats mathematics as a "human activity" (Akosah et al., 2025; Van Den Heuvel-Panhuizen & Drijvers, 2020; Yığ, 2022). By utilizing real-world contexts, RME facilitates the transition from informal knowledge to formal mathematical structures, empowering students to rediscover concepts by anchoring new information in their prior experiences (Fauzan et al., 2024; Zulkardi et al., 2020).

Building on these foundations, RME transcends simple contextualization by leveraging personal experiences to catalyze logical reasoning and creative thought (Zulkardi et al., 2020). Recent scholarship emphasizes that anchoring mathematics in student-generated ideas not only cultivates robust problem-solving skills but also ensures the seamless integration of mathematical principles into daily existence (Dare et al., 2021). Furthermore, the inherent relevance of RME bolsters intrinsic motivation and classroom engagement, as learners derive concepts directly from real-world phenomena (Hasibuan et al., 2019). This pedagogical effectiveness is increasingly amplified by digital tools and virtual environments, which offer interactive platforms for students to reconstruct complex mathematical structures (Listyaningrum et al., 2025). However, the successful implementation of such a sophisticated framework depends less on the availability of materials and more on the internal and external factors influencing the teacher's delivery (Akosah et al., 2024; Arhin et al., 2026; Berhe et al., 2025).

While the development of RME-based materials in Vietnam has begun to bridge the gap between theory and practice (Loc et al., 2020), the effective institutionalization of this method hinges primarily on the competency and psychological readiness of pre-service teachers (Phuong et al., 2025). The rationale behind this investigation is the critical need to understand the underlying mechanisms that enable future teachers to adopt innovative, student-centered pedagogies in a rapidly modernizing educational system. Although numerous studies acknowledge the benefits of RME, there remains a significant gap in empirical research detailing how teacher-level and institutional-level factors translate into actual instructional practices in the Vietnamese context.

Consequently, the novelty of this study lies in its empirical exploration of the intersection between pre-service teachers' Pedagogical Content Knowledge [PCK], Teacher Beliefs and Attitudes [BEA], Institutional Support [INS], and practical Experience and Observation [EAO] within the specific context of RME teaching effectiveness among pre-service mathematics teachers in Vietnam. By utilizing Structural Equation Modeling [SEM] to examine the direct and mediating pathways among these factors, the study provides a nuanced, data-driven perspective on relationships that have received limited empirical attention in Vietnam's current educational reform phase. The findings offer practical insights for teacher training institutions to design evidence-based professional development programs, thereby supporting efforts to align future mathematics instruction with contemporary educational standards.

2. Theoretical Consideration

2.1. RME and Teacher Effectiveness

The effect of instructional quality on student outcomes is not a static phenomenon; rather, it varies significantly across countries, students' age, and subject domains (Blömeke & Olsen, 2019). Existing research emphasizes that this impact is contingent upon the specific nature of the outcome—whether cognitive or affective (Blömeke & Olsen, 2019; Nilsen et al., 2016)—and is often sensitive to the methodological design, particularly whether the analysis utilizes cross-sectional or longitudinal data (Nilsen et al., 2016). Within this complex landscape, teaching effectiveness in the RME paradigm emerges as a specialized, multi-dimensional construct. Rooted in Freudenthal's

(1991) view of mathematics as a human activity, effectiveness in RME is conceptualized not as a collection of isolated instructional skills, but as the teacher's ability to facilitate "guided reinvention" through horizontal and vertical mathematization (Ali et al., 2025; Gravemeijer, 1994; Treffers, 1987). This process requires teachers to act as instructional designers who utilize "models-of" and "models-for" to bridge the gap between informal, context-linked knowledge and formal mathematical systems (Siswantari et al., 2025; Treffers, 1987; Van den Heuvel-Panhuizen, 2003).

Moving beyond mere cognitive outputs, recent literature emphasizes that effective RME practice is inseparable from the affective domain and professional reflection (Ofem et al., 2024). Specifically, models such as the RME-based Lesson Study for Learning Community [LSLC] have proven vital in enhancing teachers' pedagogical competence, self-efficacy, and systematic reflection (Rusiyanti et al., 2022). This professional growth directly mirrors the learner's affective domain, transforming mathematics from a rigid discipline into an engaging, meaningful subject that fosters intrinsic motivation and voluntary participation (Juandi et al., 2022; Mulbar & Zaki, 2018). Rather than requiring uniform proficiency across all areas, high-quality RME teaching relies on adaptive instruction and the strategic use of didactical scaffolding, where the teacher’s ability to balance structured guidance with student autonomy synergistically aligns with learning outcomes (Van den Heuvel-Panhuizen & Drijvers, 2020). This effectiveness is further amplified when teachers design context-rich learning trajectories that foster both cognitive growth and positive affective engagement (Gravemeijer et al., 2017; Ulandari et al., 2019; Zulkardi et al., 2020). Empirical evidence suggests that when teachers-both pre-service and in-service-effectively implement these principles using context-rich tools, from cultural heritage to digital platforms like GeoGebra, they foster significant improvements in students' problem-solving proficiency and intrinsic motivation (Davor et al., 2026; Dereje, 2023; Kassa et al., 2025; Listyaningrum et al., 2025; Tong et al., 2022; Wibawa et al., 2025). By synthesizing these perspectives, the current study posits that teaching effectiveness in RME is a dynamic, transformative process where teacher competence and instructional quality are integrated with long-term mathematical literacy gains (Zulkardi et al., 2020). Consequently, the model operationalizes this effectiveness as a synergistic integration of instructional practices, affective engagement, and professional reflection, specifically tailored to the professional development of pre-service mathematics teachers in Vietnam.

2.2. Pedagogical Content Knowledge

PCK is a fundamental determinant of instructional quality, as teachers with robust PCK can effectively translate complex mathematical concepts into accessible learning experiences, thereby enhancing student achievement and situational interest (Kadarisma et al., 2019; Njiku, 2025). In the specific context of RME, PCK requires not only content mastery but also the sophisticated ability to anticipate student conjectures and identify diverse mathematical thinking processes, areas that often necessitate continuous, targeted professional development (Fauzan et al., 2024).

Building upon this foundation, the transition from theoretical knowledge to practical application is mediated by practical EAO. This process allows pre-service teachers to internalize pedagogical strategies by observing real-world RME implementations and reflecting on instructional challenges (Zulkardi et al., 2020). Consequently, integrated training models and collaborative inquiry have proven essential in bridging the gap between knowledge and classroom practice, directly improving teachers' capacity to transform subject matter into high-quality instructional materials and fostering positive pedagogical beliefs (Babichenko et al., 2024; Kadarisma et al., 2019; Njiku, 2025). Furthermore, the integration of mathematical content knowledge and pedagogical content knowledge is crucial for effective mathematics teaching. A balanced integration of these domains allows educators to implement more effective teaching practices, particularly when handling challenging mathematical topics like ratio and proportion (Mailizar et al., 2026; Norton, 2019; Yang & Kaiser, 2022). Thus, cultivating a comprehensive PCK framework-supported by practical classroom experience and institutional guidance-is essential for optimizing instructional effectiveness within real-world mathematical contexts. Therefore, the following hypothese was proposed in this study:

Hypothesis 1 (H1). Pedagogical Content Knowledge has a positive and significant direct impact on the effectiveness of mathematics teaching [MTE] through the Realistic Mathematics Education approach among pre-service mathematics teachers.

2.3. Beliefs as Mediator

RME represents a transformative pedagogical framework that prioritizes the construction of mathematical knowledge through engagement with real-world contexts, effectively bridging the gap between abstract theory and experiential learning (Abrahamson et al., 2020; Ariati et al., 2022; Fauzan et al., 2024). Empirical evidence suggests that RME significantly outperforms conventional, decontextualized methods by enhancing student learning outcomes, retention, and positive attitudes toward the discipline (Van den Heuvel-Panhuizen, 2023). Central to the successful translation of RME theory into instructional practice is the professional competence of the educator. According to the Professional Competence Model (Halász & Looney, 2019; Xue et al., 2025), a teacher's PCK serves as the cognitive foundation that enables them to design and implement complex, context-based learning environments. When teachers possess a deep understanding of how to represent mathematical concepts through realistic contexts-an essential component of implementing RME (Zubaidah et al., 2023)-it directly enhances their psychological readiness and professional valuation of the method. Grounded in the Theory of Planned Behavior (Ajzen, 2020) and recent empirical findings, a favorable orientation toward active learning methodologies reinforces a teacher's intrinsic motivation and attitudes toward instructional innovation (Dunn et al., 2018; Gülsün et al., 2026). Consequently, a higher level of PCK equips educators with the confidence and competence needed to develop positive beliefs and attitudes [BEA] regarding the efficacy of RME. Furthermore, drawing on Social Cognitive Theory (Bandura, 2020), the interplay between a teacher's internal psychological states-such as beliefs, attitudes, and self-efficacy-and their actual instructional behaviors is a critical determinant of educational outcomes (Biçer & Yıldırım, 2023; Depaepe & König, 2018; Mengiste, 2025; Li & Ma, 2025). Teachers who hold strong, positive beliefs about the value of context-based mathematics are more likely to execute high-quality instructional practices and adapt the curriculum flexibly to meet student needs (Llinares, 2021; Piyakun & Phusee-Orn, 2025; Schoen & LaVenia, 2019). Therefore, a robust pedagogical belief and attitude system acts as the primary conduit through which teacher capability translates into the effectiveness of mathematics teaching. Accordingly, the following hypotheses were proposed:

Hypothesis 2 (H2). Pedagogical Content Knowledge significantly and positively influences Teacher's Beliefs and Attitudes.

Hypothesis 3 (H3). Teacher’s Beliefs and Attitudes positively influence the effectiveness of mathematics teaching.

2.4. Institutional Support

INS serves as a fundamental determinant in the successful implementation of innovative pedagogical frameworks like RME. Within the framework of the Theory of Planned Behavior [TPB] and Teacher Efficacy Theory, organizational resources and support mechanisms act as critical facilitating conditions that shape teachers' cognitive, affective, and behavioral responses toward new instructional practices. Specifically, robust INS—encompassing physical infrastructure, high-quality academic resources, and sustained professional development environments—directly alleviates the anxiety associated with adopting complex pedagogical models (Nahrowi et al., 2025). When institutions provide access to structured programs such as Lesson Study and Didactic Suitability Criteria, teachers' PCK and instructional competencies are substantially enhanced (Chacón-Rivadeneira et al., 2024). From an affective perspective, this continuous support system—through mentoring, collaboration platforms, and facilitating conditions—fosters teacher engagement, self-efficacy, and optimism, which are essential for reinforcing positive beliefs and attitudes toward RME (Liljedahl, 2020; Peddell et al., 2025; Siswantari et al., 2025). By cultivating a conducive environment that aligns organizational resources with RME-specific goals, training institutions not only stabilize the transition from theoretical training to practical classroom application but also improve the actual effectiveness of RME-based mathematics teaching. Consequently, a higher level of INS leads to stronger intrinsic motivation and more positive beliefs among educators. Therefore, this study constructs the following hypothesis:

Hypothesis 4 (H4). Institutional Support positively influences Teacher's Beliefs and Attitudes.

Hypothesis 5 (H5). Support from training institutions has a positive influence on the effectiveness of RME-based mathematics teaching.

2.5. Practical Experience

The transition from teaching and observation experience to the effectiveness of mathematics teaching within the RME approach is grounded in a developmental and collaborative pedagogical framework. Teaching and observation experience within the RME framework is a collaborative process where educators and students engage in experimenting with and reflecting on mathematical practices anchored in real-world contexts. Recent research indicates a significant correlation between teaching seniority and instructional quality; specifically, educators with over three years of experience demonstrate a superior ability to facilitate learning, adjust pedagogical activities, and design practical scenarios that align with learners' needs compared to their less experienced counterparts (Armiati et al., 2022; Kanbolat et al., 2023; Rifandi et al., 2021; Van den Heuvel-Panhuizen & Drijvers, 2020).

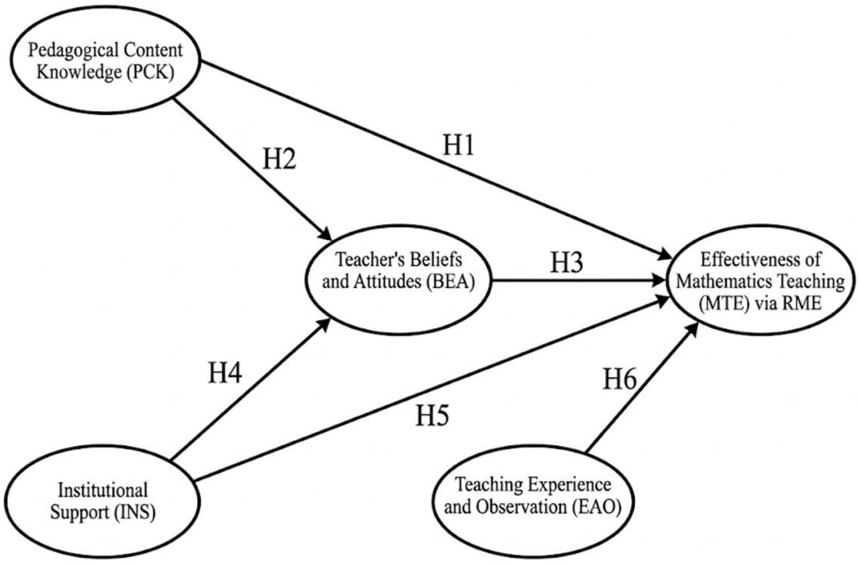
Furthermore, the accumulation of practical field experiences and guided observations significantly enhances the PCK and self-efficacy of pre-service mathematics teachers, allowing them to better scaffold students' mathematical learning in realistic contexts (Njiku, 2025). By systematically monitoring student problem-solving processes and identifying cognitive hurdles through classroom observation, instructors not only refine their mathematical knowledge for teaching but also significantly bolster their self-efficacy (Matsumoto-Royo et al., 2021; Togmey, 2025). This accumulation of practical knowledge allows teachers to better anticipate student difficulties and scaffold the reinvention of mathematical concepts, which is the cornerstone of RME. When combining Project-Based Learning [PjBL] and reflective learning, pre-service teachers can translate these teaching experiences into individualized and effective instruction (Fakhrudin et al., 2025; Poonputta, 2023; Poonputta et al., 2025; van Es et al., 2017).

Furthermore, sustained professional development through models such as Lesson Study and mentoring is essential for translating RME principles into effective classroom practice. Active learning initiatives-including the use of video observations and the integration of indoor/outdoor environments-enable teachers to notice critical aspects of classroom dynamics and optimize their instructional strategies (Aslan & Arabacı, 2023; Kanbolat et al., 2023; Pambudi et al., 2022, 2023). Specifically, the RME-based Lesson Study for Learning Community model has proven vital in enhancing teachers' capacity to design and execute meaningful mathematical contexts, thereby fostering students' communication skills through structured guidance (Rusiyanti et al., 2022; Siswantari et al., 2025). In addition, integrating digital tools (such as MathCityMap or GeoGebra) into outdoor RME activities helps pre-service teachers connect real-world experiences to formal mathematical concepts effectively (Barlovits et al., 2024; Martínez-Gómez & Nicolalde, 2025; Wulandari et al., 2023). Consequently, ongoing professional development and practical classroom observation serve as critical mechanisms for maintaining teacher motivation and institutionalizing high-quality instructional practices within the RME paradigm. Therefore, experience and systematic classroom observation act as foundational drivers that directly enhance the pedagogical and content-specific skills required to execute RME effectively. Thus, the following assumption was proposed.

Hypothesis 6 (H6). Teaching experience and observation have a positive and significant direct impact on the effectiveness of mathematics teaching based on the RME approach among pre-service mathematics teachers.

Figure 1 depicts the proposed conceptual model based on the hypotheses. Each factor is represented by an ellipse, and the prediction is denoted by an arrow.

Figure 1
The proposed conceptual model



3. Methods

3.1. Research Design

This study employs a quantitative research design with an ex post facto approach to investigate the relationships between variables. The analysis is performed using Structural Equation Modeling [SEM] to evaluate the impact of the constructs through a systematic two-stage process: the measurement model (outer model) and the structural model (inner model). Initially, the outer model is assessed for convergent validity—utilizing Cronbach's alpha, composite reliability (CR), and average variance extracted [AVE]—and discriminant validity, which is verified via the Fornell-Larcker criterion to ensure each construct is distinct and non-overlapping. Subsequently, the inner model is evaluated to test the research hypotheses, where the t-value and p-value serve as the primary indicators for determining the statistical significance of the structural paths (Hair et al., 2020, 2022).

3.2. Participants and Data Gathering Tools

Adopting a quantitative research design based on the systematic survey methodology of Taşkın et al. (2022), this study engaged a substantial sample of 654 pre-service mathematics teachers across pedagogical universities in Vietnam. Pre-service mathematics teachers were chosen because they are the frontline implementers of the new math curriculum. The selection criteria require participants to be second-year students majoring in Mathematics Education, who have completed core pedagogical courses and teaching practice. To ensure both sample diversity and alignment with real-world educational contexts, a multi-stage sampling strategy was employed, combining cluster sampling with convenience sampling. This sample size was strategically targeted to provide robust statistical power, ensuring representative insights into a critical demographic of the future education landscape.

3.3. Instrument Development and Validation

The survey instrument was developed through a rigorous three-stage process to ensure its theoretical alignment and psychometric soundness.

3.3.1. Step 1: Construct operationalization and scaling

The questionnaire was designed to operationalize five core constructs: PCK, BEA, INS, EAO, and RME Implementation Performance. To ensure content validity, the items for PCK and BEA were adapted from the validated scales of Lamichhane (2017), Carlson and Daehler (2019), Kasa et al. (2024), Spangenberg et al. (2019), and Behling et al. (2022), while the scales for INS and RME Implementation Performance were developed based on the theoretical framework of RME (Liljedahl, 2020; Siswantari et al., 2025). All items were measured on a 5-point Likert scale (1: Strongly Disagree to 5: Strongly Agree).

3.3.2. Step 2: Expert review and content validity

Before the pilot study, the initial draft of the instrument underwent a formal review by a panel of three experts in Mathematics Education and Educational Measurement. The experts evaluated each item for its relevance to the Vietnamese pedagogical context, theoretical consistency, and linguistic clarity. Based on their feedback, four items were reworded to eliminate technical ambiguity, and two items in the BEA construct were refined to better capture the nuances of pre-service teachers' attitudes toward modern pedagogical models like RME.

3.3.3. Step 3: Pilot study and linguistic refinement

A pilot study was conducted with a small group of 50 pre-service mathematics teachers (not included in the final sample) to evaluate the instrument's reliability and face validity. The pilot results yielded Cronbach’s alpha coefficients ranging from .865 to .945 across all constructs, indicating good internal consistency. Furthermore, feedback from pilot participants was used to address "grammatically awkward" phrasing, ensuring that the Vietnamese translation accurately reflected the original pedagogical concepts and was easily understood by the target demographic.

3.3.4. Step 4: Final diagnostic testing

Prior to the main structural equation modeling in SmartPLS 4, the final data underwent rigorous diagnostic tests, including assessments for normality, convergent validity, and discriminant validity. This comprehensive validation process ensures that the instrument provides a high-precision measurement of the factors influencing RME teaching effectiveness.

Table 1 shows the construct of rhe instrument.

3.4. Data Analysis Plan

To evaluate the proposed theoretical model and test the research hypotheses, this study followed a multi-stage analytical framework using Partial Least Squares Structural Equation Modeling [PLS-SEM] via SmartPLS 4.1. This approach was selected for its robustness in handling complex models with multiple latent constructs and its superior predictive capabilities. The analysis was executed through a systematic three-phase process.

3.4.1. Phase 1: Measurement model evaluation (Outer Model)

The initial phase focused on ensuring the psychometric properties of the scales. Internal consistency was assessed through Cronbach’s alpha and Composite Reliability [CR], with a target threshold of > .70. Convergent validity was established using Average Variance Extracted values exceeding 0.50. Finally, discriminant validity was rigorously verified using both the Fornell-Larcker criterion and the Heterotrait-Monotrait [HTMT] ratio, ensuring that each construct is empirically distinct.

Table 1
List of latent variables and corresponding indicators

Construct	*Scale items*	*Origin of the scale*
Pedagogical Content Knowledge (PCK)		
PCK1	I can anticipate the patterns (ideas/reactions) that students might come up with in an RME lesson	Babichenko et al. (2024); Behling et al. (2022); Carlson and Daehler (2019); Kadarisma et al. (2019); Kasa et al. (2024); Lamichhane (2017); Njiku (2025); Spangenberg et al. (2019); Zulkardi et al. (2020)
PCK2	I know how to structure activities to help students transition from a real-world context to a formal mathematical model	
PCK3	I can explain the connection between the content of the lessons and the core principles of RME	
PCK4	I understand how students can use informal models (e.g., diagrams, everyday language) to solve mathematical problems	
PCK5	I can easily create horizontal connections between different real-world contexts to clarify the same mathematical concept	
Teacher's Beliefs and Attitudes (BEA)		
BEA1	I feel confident designing and conducting a math lesson entirely using the RME method	Abrahamson et al. (2020); Ariati et al. (2022); Behling et al. (2022); Carlson and Daehler (2019); Fauzan et al. (2024); Kasa et al. (2024); Lamichhane (2017); Llinares (2021); Piyakun and Phusee-Orn (2025); Schoen and LaVenia (2019); Spangenberg et al. (2019); Zulkardi et al. (2020)
BEA2	I have a strong desire to apply the RME method when I become a full-time teacher.	
BEA3	I am comfortable with the idea that lectures can deviate from the intended topic due to spontaneous student contributions (interactivity principle)	
BEA4	I believe that RME is a practical method and can be successfully applied even in large classrooms	
Institutional Support (INS)		
INS1	The RME materials/curriculum provided to me at the school are very comprehensive and of high quality	Nahrowi et al. (2025); Chacón-Rivadeneira et al. (2024); Peddell et al. (2025); Siswantari et al.(2025); Liljedahl (2020), Siswantari et al. (2025); Liljedahl (2020)
INS2	The RME method has been explicitly integrated into many different pedagogical subjects (not just one)	
INS3	My school/department regularly organizes micro-teaching sessions focusing on the principles of RME	
INS4	My school provides sufficient facilities/technology (e.g., flexible classrooms, digital resources) to support RME teaching	
INS5	I feel connected to the RME learning community (e.g., clubs, research groups) supported by the university	
INS6	There is a formal mechanism for students to provide feedback on the quality of teaching and RME support provided by the department	

Table 1 continued

Construct	Scale items	Origin of the scale
Experience and observation (EAO)		
EAO1	I've had plenty of opportunities to observe many hours of high-quality RME math lessons from excellent teachers	Rifandi et al. (2021); Van den Heuvel-Panhuizen & Drijvers (2020); Armiati et al. (2022); Pambudi et al. (2023); Rusiyanti et al. (2022); Siswantari et al. (2025); Martínez-Gómez & Nicolalde (2025); Wulandari et al. (2023); Barlovits et al. (2024) Pambudi et al. (2023); Togmey (2025); Matsumoto-Royo et al. (2021);Nahrowi et al. (2025)
EAO2	I have completed enough trial/practice lessons to feel comfortable with RME	
EAO3	I regularly participate in video analysis and reflection on my own and my peers' RME teaching sessions.	
EAO4	I receive detailed and helpful feedback from my instructor regarding my RME application	
RME-based Teaching Effectiveness (MTE)		
MTE1	I believe that my RME lessons adhere well to the core principles of RME	Ali (2022); Bakker (2018); Gravemeijer (1994); Gravemeijer et al. (2017); Listyaningrum et al. (2025); Saraswati et al. (2026); Siswantari et al. (2025); Sutarni et al. (2024); Tong et al. (2022); Treffers (1987); Ulandari et al. (2019); Van den Heuvel-Panhuizen (2003); Wibawa et al. (2025); Zulkardi et al. (2020)
MTE2	After my lesson, students demonstrate active participation and interaction (e.g., discussion, asking questions)	
MTE3	I believe that your RME lessons help students achieve both mathematical goals and practical application goals	
MTE4	I typically receive positive feedback from my instructors regarding your proficiency in using RME	
MT5	I will always have the opportunity for detailed reflection on how well me have applied the RME principles after each teaching session	
MTE6	During the lesson, I successfully used language and models provided by the students to build knowledge	
MTE7	I believe you are capable of assessing student progress in the transition from practical applications to formal mathematics (modeling)	
MTE8	I can assess students' learning process (not just the final outcome) using RME theory	
MTE9	I can manage your time and classroom activities effectively, even when using complex real-world scenarios	
MTE10	I am proficient in guiding students to transition from everyday/informal language to formal mathematical language	
MTE11	I know how to encourage and guide students to create their own tools/models to solve problems	

3.4.2. Phase 2: Structural model assessment (Inner model)

Once the measurement model was validated, the structural relationships were examined. The significance and magnitude of the path coefficients (β) were determined using a bootstrapping procedure (5,000 resamples). The model's explanatory power was evaluated through the Coefficient of Determination (R^2), while the Effect Size (f^2) was analyzed to determine the substantive impact of each independent variable on the dependent constructs.

3.4.3. Phase 3: Predictive power and robustness testing

To move beyond simple association, the study employed a predictive-oriented evaluation. This involved calculating Stone-Geisser's Q^2 to assess cross-validated redundancy. Furthermore, the PLSpredict algorithm was utilized to evaluate the model's out-of-sample predictive relevance, focusing on Root Mean Square Error [RMSE] and Mean Absolute Error [MAE] indices to ensure the model's generalizability to new data.

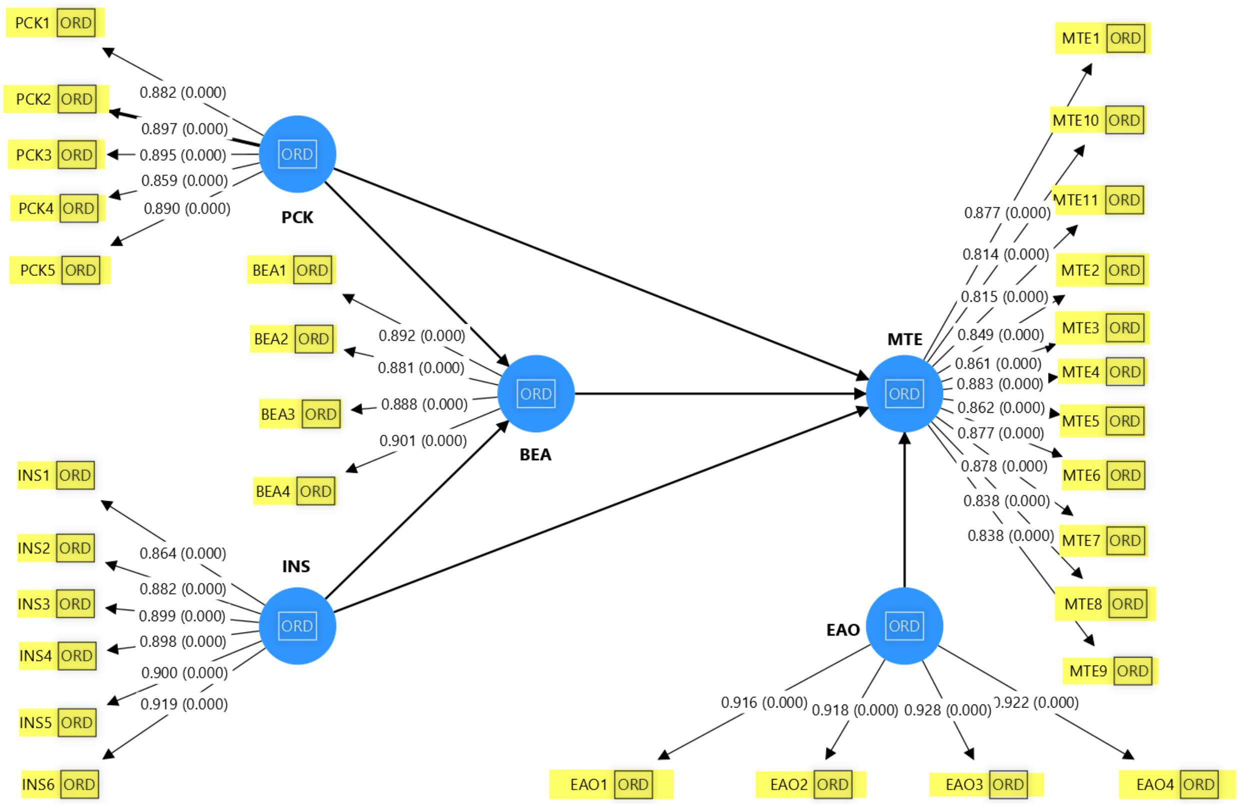
4. Results

4.1. Evaluating the Measurement Model

4.1.1. Factor loadings

The results of the measurement model analysis show that the scales in the study all ensure the necessary convergence and reliability to proceed with the next structural analysis steps (see Figure 2).

Figure 2
PLS-SEM model



Specifically, all indicators belonging to the five latent factors, including PCK, BEA, INS, EAO, and MTE, have very high factor loadings, ranging from 0.814 to 0.928. This value far exceeds the standard threshold of 0.707, demonstrating that the observed variables very well reflect their corresponding latent concepts. Notably, these loadings all achieve absolute statistical significance with a p-value of $p < .001$ (shown as .000 in parentheses), confirming the strong relationship between the indicators and factors. With this statistical evidence, the measurement model has achieved ideal convergent validity, providing a solid foundation for testing hypotheses about the interactions between variables in the structural model. This is a reliable scientific basis for us to continue with the next steps in evaluating the measurement model and the structural model in the following sections of this paper.

4.1.2. Construct reliability & convergent validity

Using SmartPLS 4, the measurement model was evaluated based on Cronbach's alpha, composite reliability (ρ_a, ρ_c), and AVE. According to Hair et al. (2022), thresholds of 0.7 for reliability and .5 for AVE indicate satisfactory consistency and convergent validity. As shown in Table 2, all constructs (MTE, EAO, INS, and PCK) exhibited high internal consistency, with Cronbach's alpha exceeding .913 and both ρ_a and CR (ρ_c) surpassing .93 (Hair et al., 2022). Additionally, AVE values ranged from .730 to .848, well above the .5 benchmark, confirming that the observed variables explain a substantial portion of the latent variance (Hair et al., 2022). These results validate the model's reliability and convergent validity for further PLS-SEM analysis.

Table 2
Construct reliability and convergent validity

	Cronbach's alpha	*Composite reliability (rho_a- ρ_a)*	*Composite reliability (rho_c- ρ_c)*	*Average variance extracted (AVE)*
BEA	0.913	0.914	0.939	0.793
EAO	0.940	0.941	0.957	0.848
INS	0.950	0.950	0.960	0.799
MTE	0.963	0.963	0.967	0.730
PCK	0.931	0.931	0.947	0.783

4.1.3. Discriminant validity

Discriminant validity was established using the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait ratio. As shown in Table 3, the square root of the Average Variance Extracted for all constructs-BEA (.891), EAO (.921), INS (.894), MTE (.854), and PCK (.885)-exceeded their respective inter-construct correlations. These results confirm the absence of conceptual overlap and multi-collinearity, satisfying the requirements for discriminant validity.

Table 3
Discriminant Validity-Fornell larcker criterion

	BEA	*EAO*	*INS*	*MTE*	*PCK*
BEA	.891				
EAO	.584	.921			
INS	.700	.770	.894		
MTE	.711	.831	.834	.854	
PCK	.714	.689	.716	.798	.885

The output shows that the cross-loading values of the indicators of each of the five measurement models are larger than their cross-loading values in other measurement models (as shown in the other four columns-Table 4). Hence, the hypothesized model achieves discriminant validity for cross-loadings.

The output in Table 5 shows that the HTMT values for the ten pairs of the measurement models are far smaller than .90, confirms that the scales have good discriminant validity (Hair et al., 2022). This strongly suggests that the four reflective measurement models have achieved discriminant validity.

Table 4
Discriminant Validity –Cross loadings

ITEMS	*BEA*	*EAO*	*INS*	*MTE*	*PCK*	*ITEMS*	*BEA*	*EAO*	*INS*	*MTE*	*PCK*
BEA1	.892	.582	.658	.667	.679	MTE10	.588	.691	.704	.814	.700
BEA2	.881	.461	.598	.623	.617	MTE11	.595	.637	.709	.815	.703
BEA3	.888	.513	.605	.598	.617	MTE2	.619	.677	.686	.849	.639
BEA4	.901	.518	.628	.642	.627	MTE3	.636	.685	.687	.861	.661
EAO1	.535	.916	.714	.747	.640	MTE4	.588	.772	.734	.883	.653
EAO2	.522	.918	.673	.748	.612	MTE5	.584	.745	.710	.862	.684
EAO3	.539	.928	.708	.773	.644	MTE6	.611	.745	.726	.877	.700
EAO4	.553	.922	.738	.793	.643	MTE7	.626	.709	.717	.878	.690
INS1	.638	.668	.864	.738	.659	MTE8	.622	.689	.720	.838	.696
INS2	.648	.659	.882	.738	.636	MTE9	.606	.705	.719	.838	.691
INS3	.621	.689	.899	.749	.621	PCK1	.631	.617	.619	.708	.882
INS4	.597	.693	.898	.728	.629	PCK2	.655	.615	.637	.722	.897
INS5	.614	.705	.900	.749	.646	PCK3	.593	.604	.617	.692	.895
INS6	.633	.713	.919	.771	.645	PCK4	.641	.571	.647	.693	.859
MTE1	.609	.746	.725	.877	.677	PCK5	.635	.642	.644	.713	.890

Table 5
Heterotrait-monotrait ratio

Relationship	*HTMT*	*Relationship*	*HTMT*
EAO ↔ BEA	.628	MTE ↔ INS	.872
INS ↔ BEA	.750	PCK ↔ BEA	.773
INS ↔ EAO	.814	PCK ↔ EAO	.737
MTE ↔ BEA	.758	PCK ↔ INS	.761

Note. HTMT: Heterotrait-monotrait ratio.

The output in Table 5 shows that the HTMT values for the ten pairs of the measurement models are far smaller than .90, confirms that the scales have good discriminant validity (Hair et al., 2022). This strongly suggests that the four reflective measurement models have achieved discriminant validity.

4.1.4. Collinearity analysis

In a hypothesized model, an indicator in a measurement model should not highly correlate with other indicators in the same measurement model. Multicollinearity occurs when the indicators are highly correlated with each other, and if collinearity exists between the indicators, the output of the analysis is violated. Multicollinearity occurs when Variance inflation factor [VIF] of any indicator in a measurement model > 5.0. Table 6 shows that multicollinearity does not occur among all indicators of the five measurement models, with VIF values meet the benchmark of < 5.0.

Table 6
Collinearity Statistics (VIF)

ITEMS	*VIF*	*ITEMS*	*VIF*	*ITEMS*	*VIF*	*ITEMS*	*VIF*	*ITEMS*	*VIF*	*ITEMS*	*VIF*
BEA1	2.752	EAO2	3.727	INS3	3.819	MTE10	3.064	MTE6	4.117	PCK1	2.963
BEA2	2.674	EAO3	4.125	INS4	3.800	MTE11	3.351	MTE7	4.117	PCK2	3.277
BEA3	2.818	EAO4	3.815	INS5	4.027	MTE2	3.433	MTE4	4.552	PCK3	3.416
BEA4	3.036	INS1	2.931	INS6	4.617	MTE3	3.892	MTE8	3.415	PCK4	2.557
EAO1	3.680	INS2	3.247	MTE1	4.050	MTE5	3.543	MTE9	3.556	PCK5	3.167

4.2. Structural Model Assessment

4.2.1. Analyzing the mediating effect

For the mediation model, the main concerns of interpreting the relationships between the latent variables in the structural model are the direct effect, indirect effect, and total effect. After running bootstrapping, we obtained the following results for *path coefficient and p values*.

Structural model analysis confirms that all hypothesized relationships are statistically significant and positive, supporting the robustness of the theoretical framework (all T-values > 1.96, p < .05). Regarding direct effects, PCK exerted the strongest influence on the mediator, Teacher's Beliefs and Attitudes (BEA) (β = 0.437, t = 9.320, p < .001), followed by INS (β = 0.387, t = 9.038, p < 0.001). In predicting the primary outcome variable, Mathematics Teaching Effectiveness (MTE), Emotional Anthropic Orientation (EAO) emerged as the most substantial direct predictor (β = 0.363, t = 8.935, p <.001), followed by significant contributions from INS (β = 0.292, t = 7.132, p < .05) and PCK (β = 0.261, t = 7.077, p < .05), while BEA exhibited the smallest direct effect on MTE (β = 0.108, t = 3.384, p = 0.001). Furthermore, the mediating role of BEA was statistically confirmed as a complementary partial mediator for PCK and INS. Specifically, BEA significantly mediated the relationship between INS and MTE ($\beta_{indirect}$ = 0.042, t = 3.135, p < .05), increasing the total effect of INS on MTE to 0.334 (t = 8.252, p < .001). Similarly, a significant indirect effect was observed between PCK and MTE via BEA ($\beta_{indirect}$ = 0.047, t = 3.289, p < .05), resulting in a total effect of 0.308 (t = 9.221, p < .001). Ultimately, when considering total effects, EAO maintains the strongest overall influence on MTE (β = 0.363), followed closely by INS (β = 0.334) and PCK (β = 0.308), underlining the stable and multifaceted nature of these structural relationships (see Figure 3 and Tables 7).

Figure 3

Structural Model Results with Path Coefficients and p-values

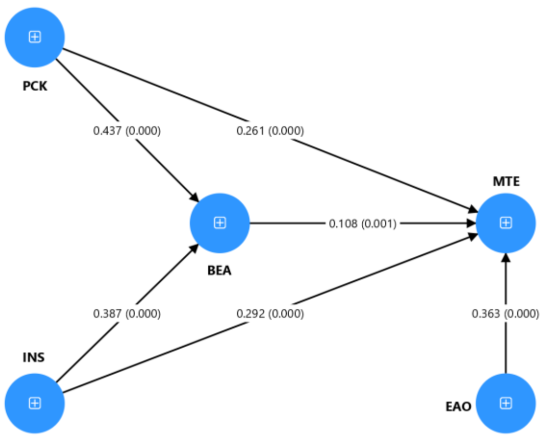


Table 7

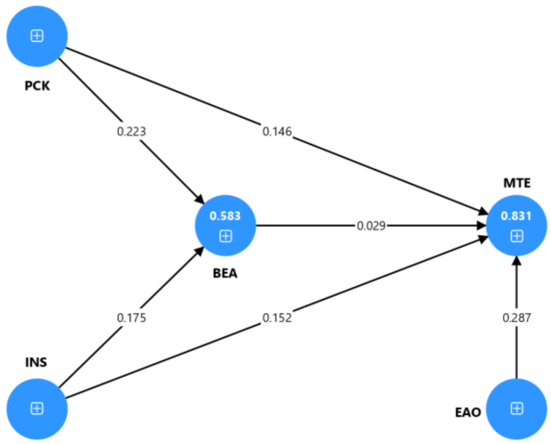
Structural Model Results and Hypothesis Testing

Types of effects	*Hypothesized Path*	*Original sample*	*Sample mean*	*Standard deviation*	*T statistics (|O/STDEV|)*	*P values*	*Decision*
Direct	BEA → MTE	0.108	0.107	0.032	3.384	.001	support
Direct	EAO → MTE	0.363	0.364	0.041	8.935	<.001	support
Direct	INS → BEA	0.387	0.387	0.043	9.038	<.001	support
Direct	INS → MTE	0.292	0.292	0.041	7.132	<.001	support
Direct	PCK → BEA	0.437	0.437	0.047	9.320	<.001	support
Direct	PCK → MTE	0.261	0.261	0.037	7.077	<.001	support
Indirect	INS → BEA → MTE	0.042	0.042	0.013	3.135	.002	support
Indirect	PCK → BEA → MTE	0.047	0.047	0.014	3.289	.001	support
Total effects	INS → MTE	0.334	0.334	0.041	8.252	<.001	support
Total effects	PCK → MTE	0.308	0.308	0.033	9.221	<.001	support

4.2.2. The effects in the structural model

Based on the data in Figure 3, Table 7, and Figure 4, it is evident that PCK has a significant direct impact on MTE (β = 0.261, T statistic = 7.077, p < .05; f^2 = 0.029, small effect). Similarly, the direct impacts of INS and Experience and Observe (EAO) on MTE were significant. The path coefficients, T, p, and f were (β = 0.292, T statistic = 7.132, p < .05, f^2 = 0.152) and (β = 0.363, T statistic = 8.935, p < 0.05, f^2 = 0.287), respectively. This means that the deeper students' professional understanding of RME and the greater their EAO in teaching, the higher the impact on teaching effectiveness. Furthermore, there was a significant impact of PCK (with β = 0.437, T statistic = 9.320, p < .05; f^2 = 0.223: medium effect) and INS (β = 0.487, T statistic = 9.038, p < .05; f^2 = 0.175: medium effect) on MTE. [Please note that f^2 = 0.02, 0.15, and 0.35 respectively represent small, medium, and large effect sizes - according to Chua (2024)]. According to Hair et al. (2022), the model demonstrates strong explanatory power, with an R^2 value of 0.831 for MTE. This indicates that the proposed PLS-SEM model is appropriate and provides a reliable basis for further analysis and pedagogical implications.

Figure 4
Effects sizes in the hypothesized model



4.2.3. Model fit assessment

This study uses model fit indices to assess the suitability of the structural model. According to common recommendations, a model is considered to have good fit when the SRMR index is less than .08 and the NFI index approaches 1 (Hair et al., 2022). The results presented in Table 8 show that the model fit indices all meet the acceptable thresholds, with SRMR = 0.036, NFI = 0.905 (> 0.9), d_ULS = 0.6610, and d_G = 0.349; simultaneously, the Chi-square values of the saturated model and the estimated model are comparable (χ^2 = 2030.141). These results indicate that the proposed structural model has a good fit with the research data and does not exhibit serious problems with model bias.

Table 8
Analysis of Model Fit Assessment

	SRMR	*d_ULS*	*d_G*	*Chi-square*	*NFI*
Saturated model	0.036	0.610	0.514	2030.141	0.905
Estimated model	0.036	0.617	0.514	2033.953	0.905

4.3. Predictive Power Asessment

4.3.1. PLSpredict LV summary-PLS-SEM prediction error (descriptives)

Descriptive analysis of 6.540 observations revealed that while both the mediator (BEA) and the endogenous variable exhibited a mean of 0.000, their dispersion patterns differed significantly (see Table 9 and Table 10).

Table 9
PLS Predict Assessment of Endogenous Constructs

	$Q^2_{predict}$	*RMSE*	*MAE*
BEA	0.579	0.651	0.456
MTE	0.823	0.423	0.305

Table 10
Prediction Error Analysis

	Mean	*Median*	*Observed min*	*Observed max*	*Standard deviation*	*Excess kurtosis*	*Skewness*	*No*	*CMts*	*CMts-p*
BEA	0.000	0.005	−2.466	3.083	0.651	2.094	0.232	6540.000	18.702	0.000
MTE	0.000	−0.075	−1.438	2.325	0.423	2.881	0.842	6540.000	21.603	0.000

Note. No=Number of observations used; CMts=Cramér-von Mises test statistic; CMts-p=Cramér-von Mises test statistic.

Specifically, BEA showed higher variability (SD = 0.651) relative to MTE (SD = 0.423). Non-normality was confirmed for both constructs via the Cramér-von Mises test ($p < .001$), supported by positive skewness and excess kurtosis, indicating right-skewed and leptokurtic distributions. Most notably, PLS-predict results underscored the model's robust predictive relevance. The $Q^2_{predict}$ for MTE reached a substantial 0.823-markedly higher than that of BEA (0.579)-demonstrating superior predictive power for MTE. Furthermore, MTE exhibited higher predictive accuracy with lower error metrics (RMSE = 0.423; MAE = 0.305) compared to the mediator. These findings suggest that the structural paths converge more stably when explaining the primary outcome variable, MTE.

4.3.2. PLSpredict MV summary–overview

Based on the PLSpredict results (see Table 11), the model's predictive relevance was evaluated by comparing its performance against the Indicator Average [IA] and Linear Model [LM] benchmarks. All indicators for both BEA and MTE yield Q2predict values greater than zero, ranging from 0.428 to 0.639, which confirms that the PLS-SEM model provides higher predictive accuracy than a simple mean-value baseline. Specifically, when comparing prediction errors, the PLS-SEM RMSE and MAE values for all indicators are substantially lower than those of the IA benchmark, indicating a significant reduction in information loss. Furthermore, a comparison with the LM benchmark reveals that for the majority of indicators-such as BEA1 (0.617 vs. 0.628) and MTE1 (0.521 vs. 0.533)-the PLS-SEM error metrics are consistently lower. According to the criteria established by Hair et al. (2022), since the PLS-SEM model outperforms the LM benchmark across all (or the vast majority of) indicators, it can be concluded that the model possesses strong predictive power. This evidence confirms that the proposed structural path effectively captures the underlying data patterns and offers high reliability for out-of-sample predictions.

Table 11
PLSpredict MV

	Q^2predict	*PLS-SEM_RMSE*	*PLS-SEM_MAE*	*LM_RMSE*	*LM_MAE*	*IA_RMSE*	*IA_MAE*
BEA1	0.517	0.617	0.441	0.628	0.436	0.888	0.755
BEA2	0.428	0.678	0.497	0.682	0.488	0.896	0.740
BEA3	0.431	0.671	0.470	0.689	0.486	0.889	0.750
BEA4	0.455	0.656	0.462	0.662	0.468	0.888	0.746
MTE1	0.626	0.521	0.337	0.533	0.345	0.853	0.714
MTE10	0.593	0.530	0.372	0.543	0.376	0.830	0.694
MTE11	0.564	0.541	0.396	0.551	0.396	0.819	0.673
MTE2	0.541	0.587	0.397	0.595	0.400	0.866	0.714
MTE3	0.557	0.554	0.393	0.559	0.391	0.832	0.684
MTE4	0.635	0.531	0.340	0.536	0.343	0.879	0.738
MTE5	0.621	0.535	0.356	0.549	0.368	0.869	0.730
MTE6	0.639	0.515	0.355	0.530	0.364	0.856	0.717
MTE7	0.605	0.534	0.368	0.552	0.378	0.850	0.706
MTE8	0.599	0.522	0.382	0.527	0.382	0.824	0.674
MTE9	0.605	0.526	0.376	0.541	0.383	0.838	0.699

4.3.3. Predictive performance assessment

To evaluate the model's predictive relevance, a comparative analysis was conducted using the PLSpredict procedure against two established benchmarks: the Indicator Average (IA) and the Linear Model.

The predictive superiority of the PLS-SEM model was rigorously validated through benchmarking against Indicator Average and Linear Model (see Tables 12). Comparative analysis with IA revealed significantly lower prediction errors for both BEA and MTE, with mean

Table 12
CVPAT LV Summary-Comparison of PLS-SEM, IA and LM

Comparative structure	PLS loss	IA model				LM model			
		IA loss	Ald	*t* value	*p* value	LM loss	Ald	*t*-value	*p*-value
BEA	0.430	0.792	−0.363	10.100	<.001	0.443	−0.013	2.274	0.023
MTE	0.287	0.718	−0.430	12.589	<.001	0.300	−0.012	3.792	0.000
Overall	0.325	0.738	−0.412	12.555	<.001	0.338	−0.012	4.048	0.000

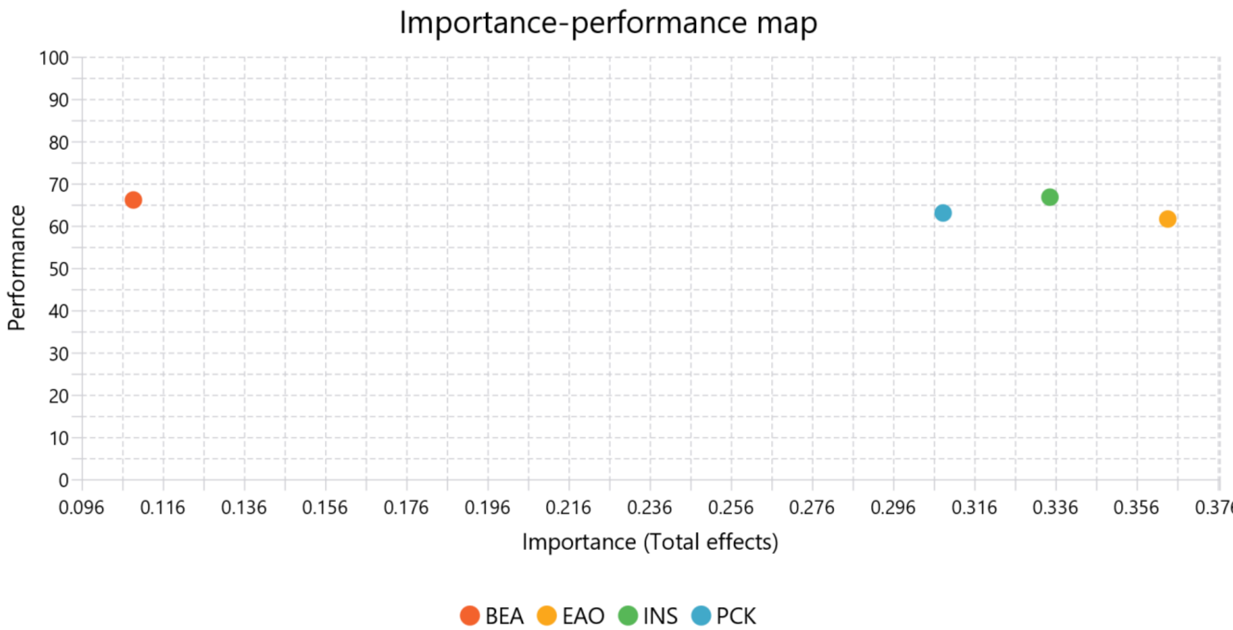
Note. Ald=Average loss difference.

loss differences of −0.363 and −0.430, respectively ($p < .001$). Notably, for MTE, the PLS loss (0.287) was substantially lower than the IA loss (0.718). Following Hair et al. (2022), these negative differences, supported by a robust t-statistic of 12.589 ($p < .001$), confirm the model's superior capability in reconstructing observed data with minimal bias. Furthermore, the PLS-SEM approach significantly outperformed the LM benchmark for both BEA ($p = .023$) and MTE ($p < .001$), indicating that the proposed structural framework captures complex data patterns more effectively than simple linear regressions. Collectively, the consistent outperformance of PLS-SEM over both naive and linear benchmarks provides compelling evidence for the high predictive relevance and stability of the conceptual model.

4.3.4. Importance-performance map analysis

The model's predictive and strategic relevance were confirmed through PLS-predict and Importance-performance map analysis [IPMA] (see Tables 9-11, Figure 5).

Figure 5
Importance-Performance Map Analysis



PLS-predict analysis demonstrated high predictive power for the primary outcome, with MTE achieving a substantial $Q^2_{predict}$ of 0.823, significantly higher than BEA (0.579), alongside lower error metrics (RMSE = 0.423; MAE = 0.305). Simultaneously, the IPMA results identified EAO as the most critical factor, yielding the highest importance (approx 0.363) but moderate performance (approx 61.588), signaling a primary area for improvement. In contrast, while Teacher's Beliefs and Attitudes (BEA) showed high performance (approx 66), its low total impact (0.108) suggests a structural "bottleneck" where its mediating role is overshadowed by the direct effects of EAO and INS. These findings suggest that to maximize MTE, resources should be prioritized toward optimizing EAO and enhancing the transmission mechanism of the BEA mediator rather than further increasing its performance.

Indicator-level performance analysis, as shown in Table 13, reveals a clear disparity in contribution levels across construct groups. INS and Teacher's Beliefs and Attitudes (BEA) exhibited the highest performance indices (65.099–67.966 and 63.876–67.928, respectively), indicating that organizational support and teacher mindset are currently being effectively leveraged. In contrast, EAO indicators showed lower performance (60.359–63.417) despite their high structural importance. PCK remained at an intermediate, stable level (62.271–64.182). Synthesizing importance and performance metrics, EAO1 and EAO2 emerge as critical "low-performance, high-importance" indicators. Consequently, these specific elements should be prioritized in strategic interventions to maximize overall MTE.

Table 13

Performance values of indicators for the MTE construct

ITEMS	MV-per	ITEMS	MV-per	ITEMS	MV-per	ITEMS	MV-per	ITEMS	MV-per
BEA1	63.876	EAO3	62.041	INS5	66.934	MTE5	65.138	MTE11	67.699
BEA2	67.928	EAO4	63.417	INS6	66.514	MTE6	66.055	PCK1	62.271
BEA3	65.979	INS1	65.099	MTE1	64.717	MTE7	66.934	PCK2	63.609
BEA4	66.781	INS2	67.966	MTE2	66.896	MTE8	67.737	PCK3	62.653
EAO1	60.359	INS3	67.339	MTE3	67.699	MTE9	66.399	PCK4	64.182
EAO2	60.359	INS4	66.628	MTE4	64.832	MTE10	65.711	PCK5	62.385

Note: per: performance.

5. Discussion

This study confirms the structural robustness of the proposed model, with all hypotheses (H1–H6) statistically supported. The findings underscore that MTE within the RME framework is a multifaceted construct driven by professional, organizational, and psychological determinants. Specifically, INS and PCK emerged as the primary direct antecedents. The significant impact of PCK aligns with the seminal work of Shulman (1987) and more recent findings by Ball et al. (2008), who argued that specialized content mastery is the 'engine' of effective mathematics instruction. This is further reinforced by Carrillo et al. (2018), who emphasize that specialized knowledge is essential for identifying real-world mathematical affordances. Without a deep understanding of how to transform abstract concepts into 'realizable' contexts-a core tenet of RME-preservice teachers struggle to bridge the gap between theory and classroom application, a challenge recently highlighted in the systematic review by Alsina et al. (2024) regarding the practical limitations of initial PCK training. Furthermore, the influence of INS suggests that pedagogical innovation does not occur in a vacuum. As noted by Thurlings et al. (2015), the availability of institutional resources and a supportive climate are critical for fostering innovative teaching behaviors. In the context of RME, this support provides the necessary scaffolding for preservice teachers to move beyond traditional rote-memorization methods. Notably, Teacher's Beliefs and Attitudes functioned as a significant partial mediator, optimizing the paths from INS and PCK toward MTE. Although the indirect effects were modest, BEA's presence enhanced the total impact of INS from 0.292 to 0.334. This finding resonates with Fives and Gill (2015), who posited that beliefs serve as a dynamic 'filter' through which new knowledge and environmental factors are interpreted. Even with high PCK, a teacher's effectiveness in RME is limited if they do not possess a constructive attitude toward student-centered learning—a sentiment echoed by Cross Francis (2009) regarding the critical alignment between mathematical beliefs and actual classroom practice. Furthermore, the significant influence of EAO aligns with Zeichner (2012), confirming that practical exposure and real-world modeling are indispensable for developing RME-based pedagogical competencies. In line with Morris et al. (2017), vicarious experience through observing expert mentors remains a powerful source of self-efficacy in teacher education. For preservice teachers, seeing RME 'in action' provides a mental blueprint that raw theory cannot replace, allowing them to internalize complex pedagogical moves through professional modeling. Collectively, these results suggest that while professional knowledge and organizational support provide the foundation, fostering positive psychological attitudes is essential for maximizing the value chain of mathematics teaching effectiveness.

Beyond the statistical significance of these mediating pathways, a deeper strategic perspective is revealed when examining the alignment between the importance of these variables and their actual performance in practice. While the structural model confirms the theoretical necessity of Beliefs and Attitudes as a psychological bridge, the Importance-Performance Map Analysis provides a more nuanced critical evaluation of how these factors manifest in the current training reality. This transition from "path impact" to "execution efficiency" highlights a crucial gap between what pre-service teachers believe and what they actually experience in their professional development journey. Recent studies emphasize that high importance in a structural model does not always translate to high performance in educational settings. For instance, Hair et al. (2020, 2022) argues that IPMA is essential for identifying "low-hanging fruit"—areas where importance is high but performance is lagging, necessitating urgent policy intervention.

In the context of RME, this 'Belief-Practice Gap' is a well-documented challenge. Lutovac and Kaasila (2018) found that while pre-service teachers may hold sophisticated beliefs about student-centered mathematics, their actual classroom performance is often constrained by a lack of practical exposure and the inability to reconcile theoretical ideals with school realities. This misalignment suggests that positive attitudes alone cannot compensate for insufficient "situated learning" opportunities. This suggests that structured practicum experiences, supported by observation, collaboration, and reflection, are necessary to help pre-service teachers transform student-centered beliefs into context-sensitive classroom practices (Sounoglou et al., 2026). Furthermore, Korthagen (2017) highlights that the "reality shock" experienced during initial teaching phases often stems from a disconnect between the idealized pedagogical frameworks taught in universities and the pragmatic constraints of school environments. This gap is particularly evident in complex approaches like RME, where institutional pressures often override theoretical ideals.

The IPMA results prioritize EAO as a strategic area for improvement. As noted by Grossman et al. (2009) and Gravemeijer et al. (2017) in recent studies of pedagogical training, professional development programs must move beyond theoretical mastery of PCK and focus on "clinical" practice to bridge the gap between cognitive beliefs and actual teaching effectiveness. Consequently, these findings suggest that the value chain of mathematics teaching is only as strong as its weakest link-which, in this case, appears to be the practical execution of RME principles in real-world settings.

In teacher training based on RME, "learning by doing" transcends purely theoretical accumulation. The lower performance of EAO compared to other factors suggests a "theory-heavy, practice-light" imbalance in current curricula. This finding aligns with Korthagen (2017), who argues that professional growth in teaching is not a linear transfer of theory to practice, but a cyclical process of reflection-in-action. Practicum experiences, case-based discussions, video analysis, and lesson study cycles can help bridge this gap by enabling pre-service teachers to connect theoretical principles with students' thinking, classroom interaction, and context-based mathematical tasks (Bozkuş, 2025; Kanbolat et al., 2023; Kılıç, 2022). Without sufficient practical context, even the most sophisticated RME theories remain "inert knowledge."

A paradigm shift is required from passive instruction to micro-teaching and clinical practice, where pre-service teachers directly engage with real-world mathematical situations. Recent meta-analyses by Ball and Forzani (2009) reinforce that the most effective teacher preparation programs are those that integrate coursework with intensive, supervised clinical experiences. In the absence of these experiences, the potential of RME to transform classroom dynamics remains unrealized.

The IPMA results provide a critical revelation: although BEA performs relatively well, its importance is the lowest on the map. This statistical reality suggests that while positive beliefs and attitudes are necessary "psychological prerequisites," they are not sufficient drivers of Teaching Effectiveness. This supports the "Enacted PCK" framework proposed by Carlson et al. (2019) and expanded by Behling et al. (2022), which posits that a teacher's internal dispositions only contribute to student outcomes when mediated through active pedagogical enactment. Thus, while BEA acts as a vital 'bridge,' it is not the ultimate destination. As Kennedy (2016) noted in her analysis of pedagogical reform, improving teacher attitudes without providing a platform for practical application creates a gap where teachers know what to do but lack the situated experience to do it effectively. Consequently, for RME training to be truly transformative, the focus must shift from fostering 'believers' to developing 'practitioners' who can navigate the complexities of real-world classrooms."

EAO Group (EAO1, EAO2, EAO3): These indicators are located in the right-hand area of the chart (high importance), but their performance only fluctuates around 60-62 points. This confirms that teacher training students are very eager for practical observation experiences to transform PCK knowledge into teaching competence. INS and PCK Group: Variables such as INS5, INS7, PCK3, and PCK5 are concentrated in the group with fairly good performance and stable importance. This shows that support from the training institution and PCK are a solid foundation, creating a "launching pad" for practical activities. In addition, the study confirms that RME helps develop the ability to transform knowledge into practice. The results support all research hypotheses, showing an organic interaction between PCK (RME knowledge), INS (Training support), and EAO (Practice). This combination helps students not only solve math problems but also learn how to design "learning scenarios" based on reality–the core of the RME philosophy.

The recent scholarly discourse in Infinity Journal underscores a significant evolution in Realistic Mathematics Education, moving toward digital integration and cultural contextuality. While Fauzan et al. (2024) highlighted how RME enhances fundamental literacy through teacher experience, and others like Johar et al. (2025) and Nursyahidah et al. (2025) developed sophisticated e-modules and ethnomathematics trajectories, a critical prerequisite remains under-examined: the internal readiness and systemic support of the educators themselves. This study addresses this gap, suggesting that the success of the advanced frameworks proposed in contemporary literature depends heavily on a fundamental shift in teacher training models.

From this reality, the empirical evidence from our PLS-SEM analysis necessitates a transition from traditional problem-solving focal points to a more comprehensive, multi-dimensional training paradigm. Firstly, to realize the 'authentic experiences' cited by Fauzan et al. (2024), training programs must increase the intensity of practical sessions, granting pre-service teachers the autonomy to lead model lessons rather than remain passive observers. Secondly, resource allocation must be strategic; rather than over-investing in areas with already high performance, such as Teacher Beliefs, institutions should prioritize the EAO group to achieve meaningful breakthroughs in teaching effectiveness.

Furthermore, aligning with the digital shift noted by Johar et al. (2025), our results emphasize that PCK is the essential bridge that allows teachers to transform abstract concepts into accessible content via visual and technological tools. However, these individual competencies cannot function in a vacuum. There is an urgent need for a synchronized INS system, providing the academic and environmental stability required for pedagogical innovation. Ultimately, the 'catalyst' for activating this entire ecosystem is the fosterage of professional confidence. When pre-service teachers possess a proactive attitude and faith in their students' potential, the synergy between pedagogical knowledge and institutional resources is maximized, fundamentally elevating the quality of mathematics teacher education in the modern era.

Finally, although the study achieved many valuable results, some limitations still need to be considered: (1) The convenient sampling method may cause bias: The survey sample was collected through a survey form and mainly from groups of teacher training students at some universities, therefore the level of representativeness of all Vietnamese students is still not achieved; (2) The study only used the PLS-SEM method: Although PLS-SEM has predictive advantages, it does not provide strong global fit indicators like CB-SEM, leading to limitations in comparing competing models; (3) Lack of empirical data on RME activities in the classroom: The study measured awareness of RME but did not directly observe the actual implementation process. From there, the next research direction could be: (1) Expanding the sample across multiple regions, educational levels and types of training institutions: This helps to improve the generalizability of the research results; (2) Incorporating more qualitative data: In-depth interviews, classroom observations, and learning journals can help to understand how learners actually experience and apply RME.

6. Conclusion

This study developed and tested a predictive model of factors affecting the teaching effectiveness of mathematics education students. Through PLS-SEM analysis with a dataset of 654 learners, the analysis results showed that the measurement model achieved high reliability and demonstrated strong predictive power for the central outcome variable, teaching effectiveness. All research hypotheses were supported, affirming the role of knowledge of RME, support from the training institution, and practice and observation in teaching effectiveness according to RME. Among these, the Experience and observe variable showed the strongest impact, indicating that practical experience, participation in modeling activities, and problem-solving play a decisive role in the development of students' RME competence. The IPMA results show that although factors such as skills and guidance performed well, the experience factor, despite being the most important, performed lower. Therefore, instructors or instructors should increase opportunities for practice, observation, handling pedagogical situations, and organizing model teaching activities based on RME for students. The study has partly provided empirical evidence confirming that RME not only helps teacher-students deeply understand the nature of mathematics but also develops their ability to translate knowledge into practical contexts, meeting the requirements of current educational reform.

7. Limitations and Recommendations of the Study

A notable limitation of this research pertains to the operationalization of the dependent variable, Mathematics Teaching Effectiveness, which was measured via subjective self-appraisals rather than objective performance metrics. While self-efficacy and perceived competence are foundational to professional development, relying solely on self-reported data may elicit social desirability bias or an overestimation of pedagogical proficiency, potentially inflating the structural path coefficients within the model. To mitigate this 'common method' concern and establish a more nuanced understanding of RME implementation, future inquiries should employ a multi-informant approach. This could involve triangulating self-perceptions with empirical evidence such as standardized classroom observation protocols, mentor supervisor evaluations, and longitudinal student achievement data. Incorporating formal teaching practicum rubrics would further bridge the gap between perceived and actual teaching effectiveness, ensuring a more rigorous validation of the factors influencing RME success in the Vietnamese context.

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Data Availability: The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

Ethics Declaration: This study was conducted in accordance with established ethical standards for research involving human participants. Informed consent was obtained from all participants prior to data collection, and participation was voluntary. The confidentiality and anonymity of the participants were ensured throughout the research process.

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