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PAPER

Designing an AI-Supported Formative Assessment Model for Pre-Service Mathematics Teacher Self-Study in Vietnam

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ABSTRACT

Amid Vietnam's accelerated digital transformation, teacher education is undergoing a pivotal shift—demanding innovative pedagogical and assessment strategies to foster self-directed learning (SDL) competencies. This need is particularly acute in Mathematics, a discipline that requires advanced logical reasoning, autonomy, and metacognitive engagement. In response, this study proposes a theoretically grounded and empirically validated formative assessment (FA) model designed to enhance SDL among pre-service primary Mathematics teachers. The model integrates both internal factors (e.g., motivation, metacognitive skills, and self-assessment competences) and external elements (e.g., technological tools, instructional support, and learning environments). Data were collected from 438 pre-service Mathematics teachers across multiple universities and analyzed using structural equation modeling (SEM). The findings identify two primary predictors of effective SDL: learners' perceptions and attitudes toward FA and their intrinsic motivation and persistence. These factors significantly impact learning outcomes and are further amplified when supported by AI-driven tools and digital learning platforms. The study highlights the mediating role of technological and pedagogical scaffolds in strengthening SDL and emphasizes the critical integration of formative feedback, metacognitive strategies, and adaptive instructional design. Despite encouraging results, several challenges remain, including limited learner autonomy, inconsistent technology adoption, and reliance on instructor-led practices. This study contributes to a deeper understanding of how AI-enhanced FA can promote learner autonomy, critical thinking, and sustainable learning behaviors in Mathematics education. It offers actionable insights for policymakers and educators in designing resilient, context-sensitive teacher training frameworks aligned with the demands of the digital era. Future research should focus on piloting the model across diverse educational settings and leveraging big data and emerging technologies to improve predictive validity and pedagogical impact.

KEYWORDS

formative assessment (FA), mathematics self-study, digital transformation, AI technology, teacher education

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1 INTRODUCTION

In the era of digital transformation and lifelong learning, self-directed learning (SDL) plays a pivotal role in teacher professional development, particularly in Mathematics, which demands conceptual understanding, logical reasoning, and disciplined problem-solving. AI technologies—such as Photomath, Wolfram Alpha, and adaptive platforms—enhance SDL by offering personalized tasks, real-time feedback, and tools for error analysis, thereby fostering critical thinking and self-assessment [10], [11], [18], [42]. However, over-reliance on technology raises concerns, underscoring the need for digital competence and ethical AI use [2].

Despite its potential, formative and process-oriented assessment in Vietnam remains underdeveloped. The system continues to emphasize summative tests, while students show limited self-assessment and regulation skills, leading to passive learning behaviors [16], [22]. Technological supports for assessment remain fragmented and instructors often lack the training to design effective, technology-enhanced formative assessments (FAs) [20], [29]. This limits SDL development and risks producing "performative teachers" with shallow pedagogical insight, undermining educational quality [17], [35], [38].

Given these challenges, it is imperative to design and validate AI-supported, process-oriented assessment models for Mathematics self-study. Such models can cultivate learner autonomy, self-regulation, and teaching competence, addressing both current gaps and long-term demands of teacher education. While prior studies highlight formative assessment FA's benefits [3], few have empirically examined its link with SDL in Mathematics or applied structural equation modeling (SEM) to analyze how factors such as motivation, AI use, and assessment practices shape outcomes. This study addresses that gap, drawing on FA theory, self-study theory, and SDL models to investigate how AI-supported assessment can enhance Mathematics self-study among pre-service teachers.

1.1 Objectives of the study

Specifically, this study seeks to:

1. Establish a theoretical foundation for the relationship between FA, AI application, and Mathematics self-learning competencies among pre-service teachers;
2. Propose a SEM-based model identifying key influencing factors and their interrelationships in relation to self-directed Mathematics learning;
3. Empirically validate the model with data from pre-service primary Mathematics teachers at selected universities in Vietnam; and
4. Recommend pedagogical strategies and policy interventions to enhance teacher education programs in alignment with digital transformation in education.

This approach not only aims to improve assessment practices within teacher training programs but also contributes to the theoretical discourse on integrating feedback, technology, and critical thinking into the design of modern learning curricula. The study's outcomes are expected to provide practical evidence for developing effective self-study training programs and establishing robust FA systems in teacher education across Vietnam.

2 LITERATURE REVIEW

In the context of modern educational transformation, the development of students' self-directed learning (SDL) capacity has become an essential requirement to meet the demands of lifelong learning and adapt to the rapid evolution of knowledge [13],[6]. In Mathematics—an inherently theoretical and cognitively demanding discipline—self-directed learning is not only a means to support learning but also a decisive factor in learners' ability to master knowledge and solve problems independently [43].

2.1 The context of contemporary education and the imperative of developing self-directed learning competency

Modern education is shifting from traditional teacher-centered models to learner-centered approaches that emphasize autonomy, flexibility, and the capacity for lifelong learning. This paradigm shift positions self-directed learning as a core competency, particularly in fields requiring logical reasoning and creative thinking, such as Mathematics. Candy [6] asserts that SDL is central to 21st-century education, enabling learners to adapt learning strategies to specific contexts. Echoing this perspective, [43] emphasizes the critical role of SDL in cultivating independent thinking and problem-solving abilities, especially in disciplines with complex logical structures such as Mathematics. Garrison and Vaughan [8] further highlight that in blended learning environments, SDL plays a pivotal role in optimizing learning outcomes and fostering critical thinking.

In Vietnam, [24] identify the development of SDL as a key objective in teacher education. However, they point out that its implementation remains fragmented and lacks a coherent strategy. Similarly, [14] underscores the importance of self-assessment—a crucial component of SDL—particularly in systematic and abstract subjects such as Mathematics. According to [13], the ability to direct one's learning enhances not only access to knowledge but also decision-making skills and lifelong learning autonomy. In the era of digital transformation and open education, cultivating Mathematics-related SDL competencies is both a necessary demand and a foundational element for shaping proactive learners capable of adapting to educational innovation.

2.2 Self-directed learning in mathematics teacher education

Candy [6] defines SDL as learners' active process of setting goals, choosing strategies, monitoring, and adjusting behaviors to achieve outcomes. In Mathematics teacher education, SDL is viewed as a key pedagogical strategy for reflection and improvement, fostering critical thinking and deeper engagement [32]. Narrative inquiry, for example, helps teachers connect personal and learners' experiences, promoting dialogue and collaboration [34]. Empirical studies show that SDL and self-regulated learning frameworks enhance pedagogical competence, diversify strategies, and improve Mathematics learning outcomes [12], with task modification linked to assessment efficacy and performance [5]. SDL also underpins critical thinking, problem-solving, and lifelong learning [25], yet its implementation faces challenges. Effective adoption requires institutional support to overcome Mathematics anxiety among pre-service teachers [32]. In Vietnam, although SDL has been integrated into training, systemic application and suitable assessment tools remain limited [15].

2.3 Formative assessment and its relationship to mathematics self-directed learning among pre-service teachers

Formative assessment is an ongoing process that provides timely feedback, enabling learners to adjust strategies and improve outcomes [3], [31]. In Mathematics, integrating FA into SDL fosters autonomy, strengthens self-assessment, and enhances academic performance [28]. Research shows that self-regulated learning (SRL)—the ability to set goals, monitor progress, and reflect—is a strong predictor of Mathematics achievement [27], while competency- and activity-based learning approaches further promote both mastery and independence [19]. However, challenges such as low motivation and academic anxiety may hinder these benefits. In Vietnam, assessment practices remain dominated by summative evaluation, with limited systematic adoption of FA, despite its potential to build students' self-assessment skills and teaching competencies [26], [14]. Overall, FA is a core mechanism for cultivating SDL and critical thinking, especially in Mathematics education, where logical and structural reasoning are essential.

2.4 Artificial intelligence and its potential in supporting formative assessment for mathematics self-directed learning in teacher education

Artificial intelligence (AI) is reshaping higher education, offering powerful tools for personalization, self-assessment, and competency development [18]. In Mathematics, where reasoning and problem-solving are central, AI enhances self-directed learning and FA through real-time feedback, progress tracking, and adaptive systems such as [33]; [10], [41]. International studies affirm that AI-based dashboards, feedback systems, and applications such as Photomath and Wolfram Alpha not only support knowledge acquisition but also foster critical thinking and error analysis [11], [18]. In Vietnam, however, research shows that AI use in Mathematics teacher training is still fragmented, constrained by limited capacity, infrastructure, and integration with assessment strategies [23]; [29]; [30]. While AI holds promise for fostering self-directed learning and adaptive teaching competencies, its effective adoption requires systemic frameworks that align pedagogical soundness with technological innovation [39].

2.5 Current status and challenges in formative assessment of mathematics self-directed learning among pre-service teachers in Vietnam

In the context of digital transformation and lifelong learning, FA is recognized as a key driver of educational quality and self-directed learning [31]. Unlike summative approaches, it provides continuous feedback that enables students to adapt strategies, sustain motivation, and strengthen self-regulation—an especially critical need in cognitively demanding fields such as Mathematics [43]. In Vietnam, however, FA remains limited. [26] note that teacher training institutions still rely heavily on periodic testing, while [30] highlight difficulties in adopting flexible, technology-supported tools. A further challenge is students' weak self-assessment skills, which hinder reflection and improvement [15]; meanwhile, instructors face constraints due to insufficient training and systemic support [20]. Broader structural barriers—such as exam-oriented pressures, passive learning culture, and traditional teaching—further impede progress [36]. In contrast, international studies affirm that well-designed FA enhances performance, autonomy, and motivation [1], [7]. These gaps highlight the urgency of examining FA practices for Mathematics pre-service teachers in Vietnam to inform context-appropriate strategies that advance competency-based and technology-enhanced education. Find below the summary of related research conducted in Vietnam.

Recent studies on formative assessment in higher education in Vietnam have revealed numerous challenges and directions for improvement. [25] indicated that assessment practices remain formalistic, fragmented, and lack appropriate tools, emphasizing the need to enhance lecturers' assessment competence and develop goal-oriented assessment systems. [14] highlighted that students often lack self-assessment skills and should be guided through reflective feedback and learning journals. [17] affirmed that technology—particularly artificial intelligence—effectively supports progress monitoring, error detection, and learning strategy adjustment, suggesting its integration into teacher education programs. [21] noted that lecturers still face difficulties in designing formative assessments, calling for more intensive professional development. [35] demonstrated that formative assessment fosters intrinsic motivation, student engagement, and active learning, while [22], [23] proposed linking assessment with lifelong learning competencies and innovation through technology and personalization. Finally, [17] found that assessing critical thinking through open-ended tasks and authentic situations promotes critical reflection, self-regulation, and active learning [47].

2.6 Developing a formative-based assessment model in mathematics self-study for pre-service teachers with AI support

Self-directed learning competence is shaped by both internal and external factors influencing students' readiness for autonomous learning. Internally, metacognition, psychological capital, and intrinsic motivation build the foundation for self-regulation and sustained engagement, while externally, support from family, peers, institutions, and classroom assessment—especially self-assessment—enhances reflection and critical thinking [40]. However, barriers such as overreliance on teachers and unstable motivation remain challenges. Overall, key factors affecting SDL through process-based assessment include self-assessment and self-regulation [43], [16], quality feedback and support tools, technological assistance (notably AI) [10], and individual motivation [36].

3 RESEARCH METHODOLOGY

This study employed a quantitative research design. The study surveyed 438 undergraduate Primary Education majors from Hanoi and northern Vietnam teacher training universities. A questionnaire, validated by experts and piloted with 30 students, was structured into six sections covering demographic and academic information, FA in self-study (Assessment for Learning), Mathematics self-study

(Knowles, Garrison), AI tools in learning (TAM, TEL), effectiveness of self-study (Bloom, OBE), and open-ended reflections. Items were measured mainly on 5-point Likert scales. Data were coded, screened, and processed using SPSS 20.0. Descriptive statistics, Exploratory Factor Analysis (EFA), and linear regression were applied to examine the impact of process-based assessment (PBA) on self-directed learning, with a focus on the mediating role of AI-supported Mathematics learning.

4 RESULTS

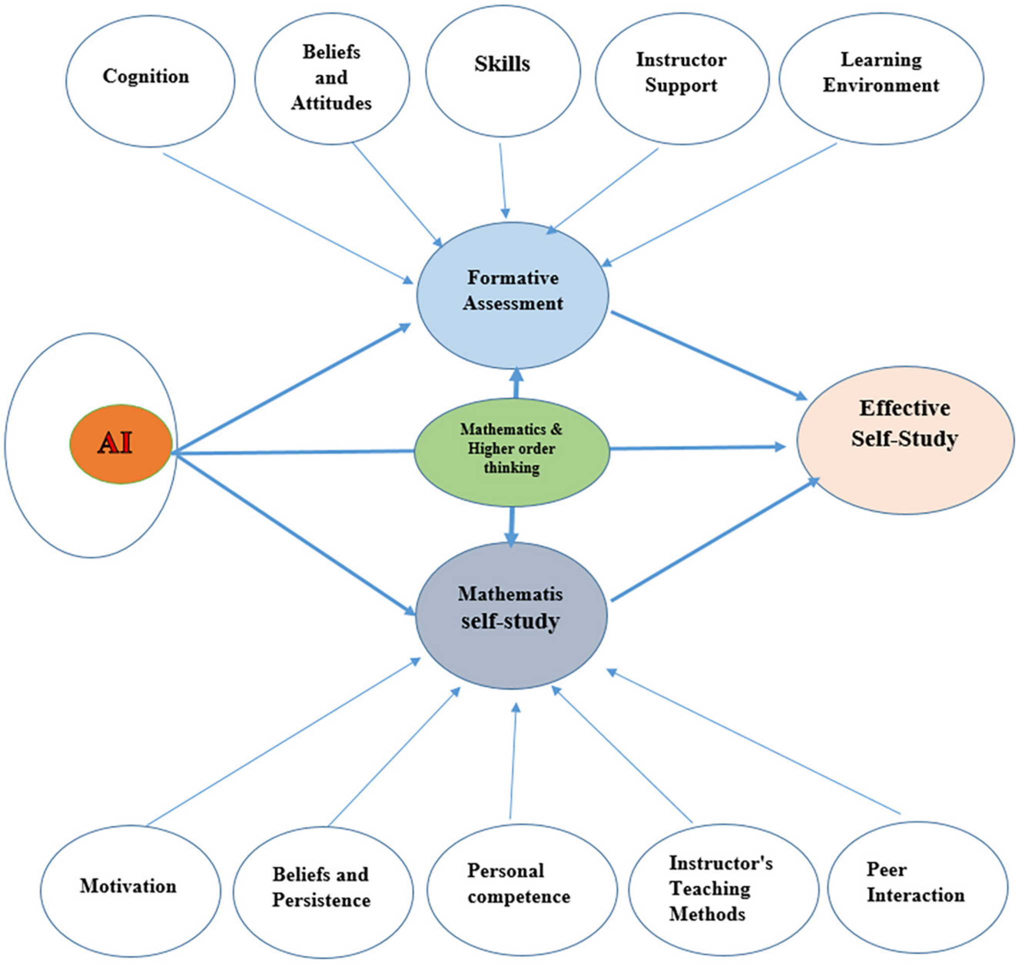

Fig. 1. Formative-based assessment model in Mathematics self-study for pre-service teachers with AI support

4.1 Theoretical model and core components of the study

This study proposes a theoretical model to evaluate the effectiveness of self-directed learning in Mathematics among pre-service teachers within the context of digital transformation. The model is constructed around four core components: formative assessment FA, self-directed learning, support from AI tools, and learning outcomes. These components are operationalized through a structured survey instrument developed based on foundational theories in education and educational technology.

4.2 Formative assessment

This component captures various forms of continuous and multifaceted assessments embedded in the self-learning process. It is influenced by students' cognitive understanding, attitudes, self-assessment skills, instructor support, and the learning environment. Measurement is conducted using 27 observed variables (B1–BE4), grouped into five dimensions: 1) cognitive awareness, 2) beliefs and attitudes, 3) self-assessment skills, 4) instructor support, and 5) environmental conditions.

4.3 Self-directed learning

This component reflects the degree to which students autonomously set learning goals, plan their studies, and seek and utilize learning resources—particularly in the domain of Mathematics. Six subcomponents are identified: 1) motivation, 2) volition, 3) individual competence, 4) instructional methods, 5) peer interaction, and 6) the learning environment. Each subcomponent is measured through a corresponding set of observed variables.

4.4 AI-supported learning tools

This component assesses students' perceptions of the effectiveness of AI tools in supporting both self-learning and FA. The observed variables are designed based on the technology acceptance model (TAM), emphasizing perceived usefulness, interactivity, and personalization capabilities of AI tools in enhancing learning.

4.5 Learning outcomes

As the outcome component, this reflects the learning achievements resulting from students' self-directed efforts in Mathematics. It includes content knowledge, mathematical thinking skills, ability to apply knowledge, self-assessment competence, and lifelong learning capacity. This component is evaluated through observed variables that represent expected learning outcomes.

4.6 The impact of AI on formative assessment and self-directed learning in mathematics

This study demonstrates the multidimensional influence of AI on FA and SDL in Mathematics education. AI enhances beliefs and attitudes, assessment skills, instructional practices, and the learning environment by providing feedback, personalization, and interactive support. It strengthens teachers' adaptability, students' autonomy, and peer collaboration, with its strongest effect observed in shaping beliefs and sustaining motivation. The proposed model identifies core constructs of FA (cognition, attitudes, skills, support, environment) and SDL (motivation, perseverance, competence, pedagogy, interaction), all significantly impacted by AI.

4.7 Model validation through multiple linear regression analysis

Reliability assessment using Cronbach's alpha. The internal consistency of the measurement scales employed in this study was evaluated using Cronbach's alpha. This statistical technique is widely accepted for assessing the reliability of multi-item constructs. The analysis results indicate that all initial scales demonstrated satisfactory reliability, exceeding the commonly accepted threshold ($\alpha > 0.70$). For instance, the scale measuring perceptions of FA yielded the following reliability coefficient:

Table 1. Reliability statistics

Cronbach's Alpha	No. of Items
.886	4

The reliability coefficient for the scale "Perceptions of Formative Assessment," as measured by Cronbach's alpha, was 0.886, indicating a high level of internal consistency and excellent reliability (see Table 1).

Table 2. Item-total statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BA1	11.84	4.477	.766	.848
BA2	11.79	4.240	.746	.855
BA3	11.69	4.558	.753	.853
BA4	11.95	4.207	.744	.856

The coefficients in the 'Corrected Item-Total Correlation' column meet the required condition (>= 0.7); therefore, all four items BA1, BA2, BA3, and BA4 are retained (see Table 2). Similarly, reliability tests were conducted for the BB, BC, BD, and BE scales. All five scales demonstrate high reliability, with Cronbach's alpha values ranging from 0.8 to 0.95 (> 0.7), as presented in the Table 3.

Table 3. Cronbach's alpha analysis

No.	Scale	Number of Items Removed	Cronbach's Alpha	Conclusion
1	BA	None	0.886	Good quality
2	BB	None	0.908	Good quality
3	BC	None	0.920	Good quality
4	BD	None	0.932	Good quality
5	BE	None	0.924	Good quality
6	B (Formative Assessment)	None	0.843	Good quality

Exploratory factor analysis. Following the Cronbach's alpha reliability analysis, five independent variables and one dependent variable comprising a total of 20 observed items were subjected to exploratory factor analysis (EFA). The independent variables were analyzed simultaneously, while the dependent variable, "Formative Assessment", was analyzed separately. The factor extraction method employed was Principal Component Analysis with orthogonal varimax rotation, and factors were retained based on eigenvalues greater than 1.

EFA for independent variables. The independent variables—BA, BB, BC, BD, and BE—consisted of 20 observed items: B1, B2, B3, B4, B5; C1, C2, C3, C4, C5; D1, D2, D3, D4, D5; and E1, E2, E3, E4, E5. Among these, three observed variables exhibited total factor loadings greater than 1, with a cumulative variance explained of 74.085%. The remaining items, which had total factor loadings less than 1, were included in the EFA. The extraction method used was Principal Axis Factoring with Varimax rotation. The detailed results of the factor analysis are presented in Table 4.

Table 4. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.955
Bartlett's Test of Sphericity	Approx. Chi-Square	8169.794
	df	231
	Sig.	.000

The KMO coefficient (0.955) and Bartlett's Test (Sig. = 0.000) confirm the suitability of the dataset for factor analysis. The cumulative variance explained reaches 74.085%, with eigenvalues of the first three components greater than 1, indicating strong explanatory power. After rotation, the initial five-factor model converges into three distinct factors: X1 (teacher support and learning environment), X2 (students' perceptions, beliefs, and attitudes), and X3 (skills in conducting process assessment). Factor loadings are satisfactory, ensuring clear differentiation among factors. This new structure demonstrates strong convergence of variables within each factor, as detailed in Table 5.

Table 5. Rotated component matrix[a]

	Component				Component		
	X1	X2	X3		X1	X2	X3
BD3	.797			BB2		.770	
BD2	.793			BA3		.769	
BD4	.765			BA1		.693	
BE2	.741			BB4		.626	
BE3	.731			BA4		.590	
BD1	.726			BB3		.581	
BE1	.713			BC3			.822
BE4	.704			BC2			.821
BD5	.540			BC5			.765
BA2		.793		BC1			.749
BB1		.781		BC4			.749
BC4			.749				

- Cognition (BA1–BA4)
- Beliefs and Attitudes (BB1–BB4)
- Skills (BC1–BC5)
- Instructor Support (BD1–BD5)
- Learning Environment (BE1–BE4)

EFA for the dependent variable "formative assessment". The dependent variable "Process Assessment" (ĐGQT) was measured using five observed items: B1, B2, B3, B4, and B5. The results of the exploratory factor analysis (EFA) for this variable are summarized in Table 6.

Table 6. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	741.423
	df	10
	Sig.	.000

The KMO coefficient is 0.838, indicating a good level of sampling adequacy and confirming the appropriateness of conducting factor analysis. Bartlett's Test of Sphericity yielded a significance value of 0.000, suggesting that the variables are correlated and suitable for factor extraction. The total variance explained (Cumulative %) is 61.763%, which is considered satisfactory.

The analysis results show that one factor was extracted with an eigenvalue of 3.088 (>1), accounting for 61.763% of the total variance among the five observed variables included in the EFA. Moreover, all observed variables have factor loadings greater than 0.6, indicating strong associations with the extracted factor.

Table 7. Component matrix[a]

	Component		
	1	B2	.777
B4	.857	B1	.697
B5	.804		
B3	.787		

Regression analysis. The independent variables (BA, BB, BC, BD, BE) and the dependent variable (Formative Assessment – ĐGQT) were entered into the regression model using the Enter method (simultaneous entry), as the hypothesis posits that all factors—BA, BB, BC, BD, and BE—positively influence ĐGQT in the context of mathematics self-study among pre-service teachers. The results of the multiple regression analysis are presented in Table 8.

Results of the multiple regression model analysis.

Table 8. Model summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.760[a]	.577	.574	.65293655	1.966

Notes: a. Predictors: (Constant), X1, X2, X3; b. Dependent Variable: B.

Table 9. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	217.554	3	72.518	170.100	.000[b]
	Residual	159.446	374	.426		
	Total	377.000	377			

Notes: a. Dependent Variable: B; b. Predictors: (Constant), X1, X2, X3.

Table 10. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	–5.740E-017	.034		.000	1.000		
	X1	.463	.034	.463	13.762	.000	1.000	1.000
	X2	.522	.034	.522	15.512	.000	1.000	1.000
	X3	.301	.034	.301	8.960	.000	1.000	1.000

Note: a. Dependent Variable: B.

The correlation coefficient is $r = 0.760$, indicating a relatively strong relationship, with Sig. = 0.000 < 0.05, confirming statistical significance. All standardized regression coefficients for X1, X2, and X3 are positive, which supports the hypothesized positive influences.

Standardized regression equation.

$$B \text{ (Formative Assessment)} = 0.463 \cdot X1 + 0.522 \cdot X2 + 0.301 \cdot X3$$

Based on this equation, the degree of influence of the three newly constructed factors on FA is ranked as follows:

- The strongest influence is from the factor related to students' perceptions, beliefs, and attitudes toward formative assessment (coefficient = 0.522).
- The second strongest influence comes from teacher support and the learning environment, including the role of AI (coefficient = 0.463).
- The third is the factor concerning formative assessment skills (coefficient = 0.301).

4.8 Mathematics self-study among pre-service teachers

Reliability testing using Cronbach's alpha. The scales presented in the study were tested for internal consistency using Cronbach's alpha. The results indicate that all initial scales met the reliability threshold. For example, the scale measuring "Motivation for Mathematics Self-Study" yielded the following results (refer to Table 11).

Table 11. Reliability statistics

Cronbach's Alpha	N of Items
.814	4

The reliability of the scale measuring "Motivation for Mathematics Self-Study" is confirmed by a Cronbach's alpha coefficient of 0.814, indicating a high level of internal consistency.

Table 12. Item-total statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CA1	11.93	4.231	.551	.818
CA2	11.41	4.869	.594	.785
CA3	11.57	4.325	.764	.708
CA4	11.79	4.417	.661	.753

The coefficients in the Corrected Item-Total Correlation column meet the required threshold (>= 0.3); therefore, all four items—CA1, CA2, CA3, and CA4—are retained. Similarly, reliability testing was conducted for the CB, CC, CD, CE, and CF scales. All five scales demonstrated high reliability, with Cronbach's alpha values ranging from 0.8 to 0.95, as presented in Table 13.

Table 13. Reliability analysis of the scales

No.	Scale	Number of Items Removed	Cronbach's Alpha	Conclusion
1	CA	None	0.814	Good quality
2	CB	None	0.919	Good quality
3	CC	None	0.901	Good quality
4	CD	None	0.941	Good quality
5	CE	None	0.916	Good quality
6	CF	None	0.887	Good quality
7	B (Self-Study)	None	0.884	Good quality

Exploratory factor analysis. Following the Cronbach's alpha reliability analysis, six independent variables and one dependent variable (Self-Study) comprising a total of 24 observed items were subjected to EFA. The independent variables were analyzed simultaneously, while the dependent variable B (Self-Study) was analyzed separately. In the factor analysis, the Principal Component extraction method was employed with orthogonal rotation (Varimax), and factors were retained based on eigenvalues greater than 1.

EFA for independent variables. The independent variables—CA, CB, CC, CD, CE, and CF—consisted of 24 observed items, which were entered into the EFA. The Principal Axis Factoring extraction method with Varimax rotation was used to analyze the factor structure of the independent variable scales. The results of the factor analysis are presented in Table 14.

Table 14. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.952
Bartlett's Test of Sphericity	Approx. Chi-Square	8740.757
	df	276
	Sig.	.000

The KMO coefficient is 0.952, indicating excellent sampling adequacy and confirming that the factor analysis being conducted is appropriate for the dataset. Bartlett's Test of Sphericity has a significance value of 0.000, suggesting that the variables are significantly correlated and suitable for factor extraction. The total variance explained (Cumulative %) is 70.025%, which is considered quite satisfactory.

The total eigenvalues for the first three components are all greater than 1, which meets the standard requirement. The factor loadings are adequate and demonstrate sufficient differentiation; however, there is a deviation from the initial model. While the original model proposed five factors, the rotated solution converged into six factors (represented by three columns, excluding the first column containing variable names).

Notably, three variables—CA2, CC3, and CF4—have cross-loadings greater than 0.5 on two separate factors. Therefore, these variables were removed from the dataset, and EFA was conducted again.

Table 15. Rotated component matrix[a]

	Component				Component		
	1	2	3		1	2	3
CB3	.816			CD4		.778	
CB4	.767			CD1		.774	
CB2	.762			CD2		.736	
CA3	.726			CE1		.710	
CB1	.709			CE2		.675	
CC2	.682			CE3		.667	
CC1	.644			CF3		.615	
CA2	.618	.541		CE4		.597	
CA4	.602			CF1			.709
CC4	.598			CF2			.708
CA1				CC3	.541		.596
CD3		.844		CF4		.528	.566

Motivation for Self-Study (CA1–CA4); Beliefs, Willpower, and Persistence (CB1–CB4); Personal Competence (CC1–CC4); Instructor's Teaching Methods (CD1–CD4); Peer Interaction (CE1–CE4)

After removing the variables CA2, CC3, and CF4 and conducting the EFA, the following results were obtained:

Table 16. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.950
Bartlett's Test of Sphericity	Approx. Chi-Square	7500.900
	df	210
	Sig.	.000

- After removing CA2, CC3, and CF4, the re-conducted EFA produced strong results: KMO = 0.950 (excellent sampling adequacy), Bartlett's test p = 0.000 (significant correlations), and total variance explained = 67.146% (satisfactory). Two representative factors were identified: Y1 (CA1, CA3, CA4, CB1–CB4, CC1, CC2, CC4), capturing students' intrinsic motivation, beliefs, perseverance, and self-learning capacity; and Y2 (CD1–CD4, CE1–CE4, CF1–CF3), reflecting teacher instructional methods, peer interaction, and supportive learning environments.

Table 17. Rotated component matrix[a] after removing the 3 items

	Component				
	1	2		1	2
CB3	.851		CD3		.871
CB4	.811		CD1		.818
CB2	.786		CD4		.813
CA3	.756		CD2		.799
CB1	.730		CE1		.704
CA4	.704		CE3		.704
CC2	.704		CF3		.698
CC1	.681		CE2		.690
CC4	.670		CE4		.641
CA1	.598		CF2		.628
			CF1		.516

EFA for the dependent variable "B (Self-Study)". The dependent variable "B (Self-Study)" was measured through six independent variables and 24 observed items. The results of the EFA for this variable are summarized in Table 18.

Table 18. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.873
Bartlett's Test of Sphericity	Approx. Chi-Square	1043.453
	df	10
	Sig.	.000

The KMO coefficient was 0.873, indicating a good level of sampling adequacy, thus confirming the appropriateness of conducting EFA. The Bartlett's test of sphericity was significant (Sig = 0.000), suggesting that the observed variables are sufficiently correlated to warrant factor analysis. One factor was extracted at an eigenvalue of 3.482 > 1, explaining 69.632% of the total variance among the five observed variables included in the analysis. All factor loadings were above 0.7, indicating a strong relationship between the observed variables and the extracted factor.

The independent variables (CA, CB, CC, CE, CD, CF) and the dependent variable B(TH) were included in the regression model using the Enter method, as the hypothesis proposed that all six factors have a positive influence on B(TH), which represents the Mathematics self-study effectiveness of pre-service teachers. The regression results show a correlation coefficient (r) of 0.765, indicating a strong relationship, with a significance level of 0.000 < 0.05. The coefficients for both extracted factors (Y1 and Y2) were positive, which supports the hypothesis.

Standardized regression equation.

$$B(TH) = 0.694 \cdot Y1 + 0.321 \cdot Y2$$

Results of the multiple regression model analysis.

Table 19. Model summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.765[a]	.585	.583	.64580594	1.890

Notes: a. Predictors: (Constant), Y1, Y2; b. Dependent Variable: B(TH).

Table 20. ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	220.601	2	110.300	264.468	.000[b]
	Residual	156.399	375	.417		
	Total	377.000	377			

Notes: a. Dependent Variable: B(TH); b. Predictors: (Constant), Y1, Y2.

Table 21. Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	−2.589E-017	.033		.000	1.000		
	Y1	.694	.033	.694	20.877	.000	1.000	1.000
	Y2	.321	.033	.321	9.649	.000	1.000	1.000

Note: a. Dependent Variable: B(TH).

Regression analysis. The correlation coefficient is r = 0.765, indicating a relatively strong relationship, with Sig. = 0.000 < 0.05, confirming statistical significance. The standardized regression coefficients for Y1 and Y2 are positive, which supports the hypothesized positive effects.

Standardized regression equation.

$$B\ (\text{Self-Study}) = 0.694 \cdot Y1 + 0.321 \cdot Y2$$

The standardized regression equation indicates that the self-directed learning of Mathematics among pre-service teachers is influenced by two key factors. The strongest predictor (β = 0.694) is Y1, which represents students' motivation for self-study, including their beliefs, willpower, perseverance, and self-regulated learning capacity. The second factor, Y2 (β = 0.321), encompasses instructional methods that foster self-study, peer interaction in Mathematics learning, and supportive learning environments, including the integration of AI tools.

5 CONCLUSION AND RECOMMENDATIONS

The structural analysis of the formative assessment model for mathematics self-study among pre-service teachers, supported by AI, clarifies the relationships between independent, dependent, and observed variables across three core components. SPSS results yielded two regression equations showing that, among 44 observed variables, the most influential factors are students' perceptions, beliefs, and attitudes toward process assessment, alongside intrinsic motivation, willpower, and persistence. While some items aligned with established theories, their statistical divergence reflects variability in students' valuation of self-study, often shaped by limited instructional practices and a narrow focus on procedural learning. The SEM results confirm that metacognitive competence and self-assessment skills significantly affect learning outcomes, with AI tools, online platforms, and lecturer guidance serving as mediators. Despite challenges—such as reliance on instructors, inconsistent motivation, and uneven digital integration—the proposed model demonstrates a feasible and contextually relevant pathway to strengthen mathematics self-study competence. Its application can enhance teacher education quality and contribute to building an adaptive, innovative, and sustainable educational ecosystem."

6 REFERENCES

[1] H. Andrade and G. J. Cizek, Eds., *Handbook of Formative Assessment*. New York, NY: Routledge. https://doi.org/10.4324/9780203874851

[2] T. Baker Smith and N. Anissa, "Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges," nesta, 2019. https://www.nesta.org.uk/report/education-rebooted/

[3] P. Black and D. Wiliam, "Assessment and classroom learning," *Assessment in Education: Principles, Policy & Practice*, vol. 5, no. 1, pp. 7–74, 1998. https://doi.org/10.1080/0969595980050102

[4] P. Black and D. Wiliam, "Developing the theory of formative assessment," *Educational Assessment, Evaluation and Accountability*, vol. 21, no. 1, pp. 5–31, 2009. https://doi.org/10.1007/s11092-008-9068-5

[5] L. A. Bragg, "Learning through guided play: A mathematical journey," *Australian Primary Mathematics Classroom*, vol. 20, no. 3, pp. 30–35, 2015.

[6] P. C. Candy, *Self-Direction for Lifelong Learning: A Comprehensive Guide to Theory and Practice*. San Francisco, CA: Jossey-Bass, 2000.

[7] B. Cowie and B. Bell, "A model of formative assessment in science education," *Assessment in Education: Principles, Policy & Practice*, vol. 6, no. 1, pp. 101–116, 1999. https://doi.org/10.1080/09695949993026

[8] D. R. Garrison and N. D. Vaughan, *Blended Learning in Higher Education: Framework, Principles, and Guidelines*. San Francisco, CA: Jossey-Bass, 2008. https://doi.org/10.1002/9781118269558

[9] A. Hakim and R. Firmansyah, "Pedagogical competencies and their impact on student achievement in mathematics," *Journal of Teacher Education Research*, vol. 18, no. 1, pp. 22–34, 2024.

[10] W. Holmes, M. Bialik, and C. Fadel, "Artificial intelligence in education: Promises and implications for teaching and learning," Center for Curriculum Redesign, 2019.

[11] D. Ifenthaler and J. Y. K. Yau, "Utilising learning analytics to support study success in higher education: A systematic review," *Educational Technology Research and Development*, vol. 68, pp. 1961–1990, 2020. https://doi.org/10.1007/s11423-020-09788-z

[12] R. Ibrahim, “Self-regulated learning strategies and student performance in mathematics teacher education,” *Asia-Pacific Journal of Educational Research*, vol. 16, no. 2, pp. 35–49, 2024.
[13] M. S. Knowles, “Self-directed learning: A guide for learners and teachers,” 1975.
[14] P. Q. Lê, “Developing self-assessment competency in mathematics education,” *Vietnam Journal of Education Studies*, vol. 2, no. 15, pp. 44–55, 2020.
[15] T. H. Lê, “Năng lực tự đánh giá trong học tập của sinh viên Việt Nam: Thực trạng và khuyến nghị,” *Tạp chí Khoa học Giáo dục Việt Nam*, vol. 17, no. 3, pp. 45–53, 2020. (In Vietnamese)
[16] Q. V. Lê and T. T. Phạm, “Assessment of critical thinking in self-directed learning among pre-service teachers,” *Vietnam Journal of Educational Innovation*, vol. 4, no. 1, pp. 65–78, 2022.
[17] T. H. Lê and Q. T. Phạm, “Đánh giá quá trình và vai trò trong việc phát triển năng lực tư duy phản biện cho sinh viên sư phạm,” *Tạp chí Giáo dục và Xã hội*, vol. 78, no. 1, pp. 21–28, 2022.
[18] R. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, *Intelligence Unleashed: An Argument for AI in Education*. London: Pearson. 2016. https://www.pearson.com/content/dam/one-dot-com/one-dot-com/global/Files/about-pearson/innovation/open-ideas/Intelligence_Unleashed_Pub_2016.pdf
[19] N. Makhova, “Competency-based and activity-based learning in mathematics education,” *International Journal of Instructional Pedagogy*, vol. 12, no. 1, pp. 14–28, 2024.
[20] H. T. Ngô and V. Q. Đỗ, “Enhancing assessment design competency among university lecturers,” *Vietnam Educational Review*, vol. 3, no. 10, pp. 22–29, 2019.
[21] M. T. Ngô and P. V. Đỗ, “Những hạn chế trong đánh giá quá trình ở các trường sư phạm hiện nay,” *Tạp chí Khoa học Giáo dục Việt Nam*, vol. 14, no. 2, pp. 67–73, 2019. (In Vietnamese)
[22] T. H. Nguyễn, “Phát triển năng lực học tập suốt đời cho sinh viên trong bối cảnh giáo dục hiện đại,” *Tạp chí Khoa học Giáo dục*, vol. 19, no. 4, pp. 30–39, 2021. (In Vietnamese)
[23] T. H. Nguyễn, “Assessment for lifelong learning in teacher training in the context of innovation,” *Journal of Educational Reform and Development*, vol. 12, no. 4, pp. 35–42, 2021.
[24] T. H. Nguyễn, “Trí tuệ nhân tạo trong giáo dục: Tiềm năng và định hướng triển khai tại Việt Nam,” *Tạp chí Công nghệ Giáo dục*, vol. 8, no. 2, pp. 14–22, 2021. (In Vietnamese)
[25] T. H. Nguyễn and M. T. Trần, “Formative assessment in Vietnamese higher education: Current practices and solutions,” *Vietnam Journal of Educational Research*, vol. 29, no. 6, pp. 55–67, 2021.
[26] V. H. Nguyễn and M. Q. Trần, “Đánh giá quá trình trong dạy học toán: Từ lý luận đến thực tiễn,” *Tạp chí Giáo dục*, vol. 489, pp. 58–62, 2021. (In Vietnamese)
[27] R. Octariani, “The effect of self-regulated learning on students’ mathematics achievement,” *International Journal of Learning and Teaching*, vol. 3, no. 3, pp. 197–201, 2017.
[28] T. M. Phạm and T. L. Nguyễn, “Ứng dụng công nghệ trong đánh giá quá trình môn Toán ở trường đại học: Cơ hội và thách thức,” *Tạp chí Khoa học và Công nghệ*, vol. 60, no. 3, pp. 45–52, 2022. (In Vietnamese)
[29] T. T. Phạm and L. T. Nguyễn, “Technology application in formative assessment for math learning,” *Vietnam Education Technology Journal*, vol. 8, no. 3, pp. 45–58, 2022.
[30] T. T. N. Phạm and H. M. Nguyễn, “AI-based formative assessment in mathematics education: Potentials and practices,” *Vietnam Journal of Mathematics and Pedagogy*, vol. 5, no. 2, pp. 91–102, 2022.
[31] D. R. Sadler, “Formative assessment and the design of instructional systems,” *Instructional Science*, vol. 18, pp. 119–144, 1989. https://doi.org/10.1007/BF00117714
[32] S. Schuck and L. Pereira, “What counts in mathematics teacher education? Self-directed learning and identity,” *Australian Journal of Teacher Education*, vol. 36, no. 7, pp. 1–15, 2011. https://doi.org/10.1007/978-94-007-0461-9_1

[33] V. J. Shute and M. Ventura, *Stealth Assessment: Measuring and Supporting Learning in Video Games*. Cambridge, MA: MIT Press, 2013. https://doi.org/10.7551/mitpress/9589.001.0001
[34] R. Smith, "Narrative inquiry and reflective practice in teacher education," *Reflective Practice*, vol. 7, no. 3, pp. 327–341, 2006.
[35] M. T. Trần and T. H. Nguyễn, "The role of formative assessment in learning motivation," *Vietnam Journal of Educational Psychology*, vol. 15, no. 2, pp. 72–85, 2020.
[36] M. Q. Trần and V. H. Nguyễn, "Đánh giá quá trình và động lực học tập: Một số vấn đề lý luận và thực tiễn," *Tạp chí Khoa học Giáo dục*, vol. 18, no. 2, pp. 54–61, 2020. (In Vietnamese)
[37] T. H. Vũ, "The challenge of performative teaching in contemporary Vietnamese education," *Vietnam Journal of Teacher Education Studies*, vol. 6, no. 1, pp. 33–48, 2019.
[38] T. N. Vũ, "Từ giáo viên trình diễn đến nhà giáo dục sáng tạo: Vấn đề năng lực sư phạm hiện nay," *Tạp chí Nghiên cứu Giáo dục*, vol. 24, no. 6, pp. 40–47, 2019. (In Vietnamese)
[39] B. Williamson and R. Eynon, "Historical threads, missing links, and future directions in AI and education," *Learning, Media and Technology*, vol. 45, no. 3, pp. 223–236, 2020. https://doi.org/10.1080/17439884.2020.1798995
[40] Z. Wenxiao, "Assessment for learning in China: A review of policy and practice," *Assessment in Education: Principles, Policy & Practice*, vol. 24, no. 3, pp. 331–346, 2017.
[41] B. P. Woolf, *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing e-Learning*. New York, NY: Morgan Kaufmann, 2010.
[42] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education – where are the educators?" *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, p. 39, 2019. https://doi.org/10.1186/s41239-019-0171-0
[43] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," *Theory into Practice*, vol. 41, no. 2, pp. 64–70, 2002. https://doi.org/10.1207/s15430421tip4102_2
[44] V. Rattanawiboonsom, H. Sikandar, U. Thatsaringkharnsakun, and N. Khan, "The role of mobile technologies in tracking cyberbullying trends and social adaptation among teenagers," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 19, no. 1, pp. 171–186, 2025. https://doi.org/10.3991/ijim.v19i01.52747
[45] V. Rattanawiboonsom and N. Khan, "Blockchain technology in mobile payments: A systematic review of security enhancements in mobile commerce," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 21, pp. 134–148, 2024. https://doi.org/10.3991/ijim.v18i21.52099
[46] N. Khan, M. I. Qureshi, M. Falahat, H. Sikandar, and R. Bt Sham, "Navigating the renewable energy transition: A systematic review of economic and policy strategies for grid integration, stability, and viability," *International Journal of Energy Economics and Policy*, vol. 15, no. 4, pp. 709–723, 2025. https://doi.org/10.32479/ijeep.20348
[47] V. Q. Chung, N. T. Van, N. T. Thanh, and N. M. Thuong, "The flipped classroom model and the impact of perseverance on developing mathematics self-learning competency in Vietnam," *Communications on Applied Nonlinear Analysis*, vol. 32, no. 10s, pp. 816–837, 2025. https://doi.org/10.52783/cana.v32.4871

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