

Development and psychometric validation of the student mathematical commitment scale

Retchelle P. Sangco¹, Leorence C. Tandog², Jonald L. Pimentel²

¹Department of Teacher Education, University of Mindanao Digos College, Digos City, Philippines

²Department of Mathematics and Statistics, University of Southern Mindanao, Cotabato, Philippines

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ABSTRACT

Commitment plays a significant role in shaping engagement and self-regulation in learning, yet no standard tool exists to measure students' learning commitment, especially in mathematics. This study aimed to develop the first validated scale for mathematical commitment. Using an exploratory-sequential mixed methods design, the study began with qualitative in-depth interviews (IDIs) to create the first version of the student mathematical commitment scale (SMCS) with 79 items. The quantitative phase employed exploratory and confirmatory factor analyses to establish the scale's validity and reliability, resulting in a refined 24-item version, with four confirmed dimensions. These dimensions: strategic learning engagement (SLE), affective learning engagement (ALE), learning engagement resilience (LER), and positive learning mindset (PLM) provide a holistic view of mathematical commitment, encompassing the cognitive, emotional, and psychological aspects of students' learning behavior. The findings provide a foundational understanding of mathematical commitment, suggesting the practical use of the scale in curriculum design, interventions, and student support with the goal of improving student learning outcomes.

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Corresponding Author:

Retchelle P. Sangco

Department of Teacher Education, University of Mindanao Digos College

Roxas Extension Street, Digos City, Philippines

Email: retchelle.sangco@umindanao.edu.ph

1. INTRODUCTION

Low mathematics performance among students remains a pressing global concern, especially after the COVID-19 pandemic. The 2022 Program for International Student Assessment (PISA) results revealed a significant decline in math scores among 15-year-olds across 81 countries, with an average drop of 15 points from 2018 [1]. This worldwide scenario is mirrored in the Philippine context, where mathematics performance remains critically low. In PISA 2022, Filipino students placed 77th out of 81 countries, reflecting only little to no progress from its 76th-place ranking in PISA 2018 [2]. Following this, it was reported that fewer than one-fourth of Filipino students reached the minimum proficiency level in mathematics despite post-pandemic reforms and test preparations [3].

While the pandemic contributed to the notable decline, the report suggests other underlying factors. These include student-related characteristics, pedagogical approaches, availability of teaching-learning resources, and the influence of family, community, and societal factors [4]. With student-related factors, it is important to consider willingness to learn, perceptions of mathematics, engagement with resources, relationships with teachers, and attentiveness [5]. Dispositional factors such as perseverance, persistence, and grit should also be taken into account, as they play a crucial role in students' ability to succeed in mathematics [6]. These factors can be collectively described as the students' commitment to learning mathematics.

Commitment reflects an individual's active and sustained engagement toward achieving goals, binding present intentions to future behaviors and promoting consistency in action [7]. Studies also show that learning commitment is shaped by various factors like metacognitive processes [8], teacher-student interactions [9], and evaluative beliefs about the self, the teacher, and the instruction [10]. Conceptually, learning commitment encompasses key elements of self-regulated learning such as grit, self-efficacy, and goal commitment [11], [12], with self-efficacy found to be closely associated with it [13]. However, empirical research focusing specifically on students' commitment in mathematics remains limited. Currently, there is no validated instrument designed to capture the underlying dimensions of mathematical commitment. Hence, this study sought to address these gaps.

The present study is mainly founded on the self-determination theory (SDT) [14] and expectancy-value theory (EVT) [15]. SDT reveals that people are self-motivated by the needs that are inherently psychological such as autonomy, competence, and relatedness. Once these needs are satisfied, individuals are more inclined to engage and become more committed to learning tasks [16]. Meanwhile, EVT establishes how individuals' expectations of success and value placement of learning goals influence commitment and engagement [17]. Based on this theory, students will engage in learning tasks if they think they will be successful in completing them (expectancy), and if they think the activities are beneficial to them (value). Both theories converge in explaining commitment as a function of learners' perceived capability and the meaning they assign to learning tasks. Empirical evidence further supports this integration, as self-efficacy and task value have been shown to positively predict learning persistence and sustained engagement [18]. Taken together, these theories provide a complementary theoretical basis for understanding commitment in mathematics learning and for informing motivational interventions in educational settings.

The current study intends to further explore the framework of learning commitment in the context of mathematics learning, building upon existing theories. It is also evident that commitment influences various aspects of educational experience, from motivation and engagement, to resilience and self-regulation. Commitment is a multifaceted construct with important implications in education. Hence, this research generally aimed to develop a standardized, valid, and reliable instrument to better understand the multidimensional construct of students' commitment to learning mathematics. Specifically, it sought to: i) determine the underlying dimensions of the student mathematical commitment scale (SMCS); ii) establish the convergent validity of the SMCS; and iii) establish the discriminant validity of the SMCS.

2. METHOD

2.1. Research design

This study employed mixed methods approach, specifically using an exploratory sequential research design. The study began with a qualitative phase to gather in-depth insights and personal perspectives from participants on the concept of mathematical commitment. Significant statements from this phase were used for initial development of the scale, ensuring that the instrument reflected authentic perspectives, and captured the multidimensionality of the construct. In the quantitative phase, exploratory factor analysis (EFA) was conducted to identify the underlying dimensions of the scale. From the results of EFA, a confirmatory factor analysis (CFA) was then carried out to statistically test whether the identified factor structure accurately reflects the data from the student sample.

2.2. Research participants/respondents

For the qualitative part of this study, participants were selected using purposive non-probability sampling. There were two sets of participants selected: senior high school students and mathematics teachers or administrators. The researchers also adhered to data saturation which served as the data adequacy point at which no new information can be acquired from participants [19]. In this study, data saturation was reached after the in-depth interviews (IDIs) of 16 participants consisting of eight senior high school students, and eight teachers or administrators.

For the quantitative phase, a total of 1,152 senior high school students participated across two stages using stratified random sampling, with proportional allocation across nine municipalities in Davao del Sur. The province was selected as the research locale because of its accessibility and economic considerations. However, the researchers acknowledge its limitation to generalizability of research findings. Moreover, in the first stage, 546 students were selected for EFA, adhering to the traditional guideline of five respondents per item [20], which was suitable for the 79-item draft scale. For CFA, the researchers collected data from 606 students, exceeding the recommendation of 300 participants for robust model validation [21]. After the refinement of the scale, the data obtained from the same sample were subjected to reliability tests.

2.3. Research instrument

The development of the SMCS began with item construction based on the significant statements extracted from the qualitative phase. The questions for the semi-structured interview guide were crafted based on the theoretical underpinning that commitment reflects a self-regulatory process in which evaluative beliefs about the self, the teacher, and instructional practices guide students' intentions and planned learning behaviors [10]. The questions were then initially grouped into those related to the self, teacher, and instruction which were also translated into local language for contextualization and relatability.

Using an inductive approach and from the qualitative content analysis, the researchers formulated 79 items to capture various dimensions of the construct. The items were consolidated for the survey and presented in a 5-point Likert scale (1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree, 5=strongly agree), which was treated as interval or ratio type of data to reflect increasing levels of commitment. To ensure face and content validity, the instrument was reviewed by three experts: one with master's degree in psychology, and two with PhDs in mathematics education. Their feedback on the point-scale used, construction of item statements, and psychological considerations were taken into account in the revision and refinement of the scale. The refined SMCS was then pilot-tested to 61 senior high school students which yielded a very high level of reliability, indicating that it should proceed to EFA. The scale was made available in both printed and electronic formats during the quantitative data gathering phase.

2.4. Data gathering procedure

The data gathering procedure followed a multiple-stage approach to ensure ethical and efficient data collection. For the qualitative phase, informed consent was obtained prior to data collection. Participants were given the option to choose between online interviews (via Google Meet, Zoom, or Messenger) or face-to-face interviews, both conducted with strict adherence to privacy and ethical guidelines. Semi-structured IDIs were used, guided by validated probing questions to ensure depth and clarity of responses, and interview settings were chosen based on participant convenience.

The quantitative data collection process began once the initial survey questionnaire was crafted and validated by experts. Pilot testing was conducted right after the revision and approval of experts to determine the initial reliability score of the instrument. After ensuring that the scale achieved an acceptable degree of consistency, it was then administered to the target respondents in-person (face to face) or online (Google Forms). Lastly, the study strictly adhered to ethical standards so that the identity of the respondents, and the data collected throughout the research process are protected.

2.5. Data analysis procedure

For the qualitative part of this study, the data collected and organized were subjected to content analysis. In this method, interview transcripts underwent the following processes: i) identification and translation of significant statements; ii) interpretation and formulation of meanings; and iii) crafting of items for the scale. Table 1 presents the sample analysis and coding of the interview transcripts.

Table 1. Sample analysis of the interview transcripts

Transcript	Significant statement with translation	Formulated meaning	Item for the scale
<p><i>“kanang ano sir pag naa syay activity nga ihatag for example, pag naay ihatag nga activity ang among mga teachers kanang makuan niya dayun, like kanang dili siya tapulan...”</i></p> <p>(Participant 2 – Lines 88-90)</p> <p>Translation: “Sir, whenever there is an activity given—for example, when our teachers give an activity, he/she completes it right away, like he’s/she’s not lazy...”</p> <p>(Participant 2, Lines 88-90)</p>	<p>Significant statement: <i>“pag naay ihatag nga activity ang among mga teachers kanang makuan niya dayun, like kanang dili siya tapulan.”</i></p> <p>Translation: “When there’s an activity given, for example, when our teachers give an activity, he/she completes it right away, like he’s/she’s not lazy.”</p>	<p>Committed students dive into tasks immediately, making the most of their time.</p>	<p>I get into math tasks promptly, making the most of my time.</p>

For the quantitative part, multiple assessment of the data's suitability for principal axis factoring (PAF) and oblique rotations were conducted before proceeding to EFA. This included initial reliability analysis and verification of assumptions using Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure. A significant Bartlett's test ($p < .05$) and a KMO value between .60 and .90 indicate that the data is appropriate for factor analysis [22]. PAF was then performed on the dataset, with factor loadings

of .40 or higher are considered meaningful [23]. The factor rotation method employed in the analysis was direct oblimin due to the assumption that the extracted factors may be correlated. Additionally, to determine the optimal number of factors to retain, a parallel analysis was conducted, which is a more reliable method for deciding how many factors should be retained for rotation [23].

To determine the underlying factor structure, initial factors were retrieved from the matrix post-rotation, which involved separating each variable's common or shared variance from its unique and error variance [23]. The factors were then named based on the content of the items associated with each factor. Reliability analysis was then conducted on each derived factor and the overall scale, ensuring that the SMCS demonstrated acceptable reliability after factor extraction.

CFA was performed to examine whether the resulting factor structure identified through EFA was present within a different sample of senior high school students. Several fit indices were used to assess model fitness. The Chi-square fit index evaluates overall model fit, though it is sensitive to large sample sizes, prompting the use of the normed Chi-square (χ^2/df) ratio, where values ≤ 2 suggest good fit, and values ≤ 3 are acceptable [24]. The comparative fit index (CFI) and Tucker Lewis index (TLI) were used to assess model-data correspondence, with values $\geq .95$ indicating a good fit [24]. Additionally, the standardized root mean square residual (SRMR) and root mean square error of approximation (RMSEA) were employed to evaluate residuals and approximation error, with values $\leq .08$ for SRMR and $\leq .06$ for RMSEA signifying good model fit [24].

The final questionnaire underwent validity and reliability testing using several statistical measures. Convergent validity was assessed through average variance extracted (AVE), where values above .50 indicate that a latent construct explains more than half of the variance in its indicators [25]. Discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT), where values below .85 confirm discriminant validity [26]. Lastly, composite reliability (CR) and Cronbach's alpha (α) were used to assess the reliability of the Likert-scale items, with values $\geq .70$ considered acceptable for internal consistency [25].

3. RESULTS AND DISCUSSION

3.1. Dimensions of the student mathematical commitment scale

Before conducting the EFA, an initial reliability test yielded a very high Cronbach's alpha of $\alpha=.993$, suggesting that the scale should proceed with EFA. Following this, Table 2 shows the results of the KMO test and Bartlett's test of sphericity, revealing a KMO value of .969 and a significant Bartlett's test (Chi-square=23335.51, $p<.001$) which are indicative of suitable conditions for conducting factor analysis.

Table 2. KMO test and Bartlett's test of sphericity		
KMO test for sampling adequacy		.969
Bartlett's test of sphericity	Chi-Square	23335.51
	df	3081
	Sig.	<.001

After ensuring that the created factors were suitable, the next step was to employ PAF and oblique (direct oblimin) rotation to evaluate the appropriateness of the dataset. Additionally, it was recommended to set a minimum factor loading of .30, with a preference for .40 or higher to ensure that only variables that meaningfully contribute to a factor are retained [23]. Consequently, items with factor loadings below .40 were removed. To determine the number of factors, parallel analysis was employed because it is less prone to over-extraction of factors [27].

After completing all the necessary analyses, the researchers considered the recommendation of removing factors with fewer than three items [23]. As a result, six factors were retained as shown in Table 3. Each of the identified dimension was then examined in light of existing literature highlighting its role in shaping students' mathematical commitment.

3.1.1. Strategic learning engagement (SLE)

It is an important dimension of mathematical commitment, emphasizing the deliberate use of cognitive and metacognitive strategies to achieve learning goals. Accordingly, strategic learning involves students' metacognitive processes and adaptive mindsets which enable them to become self-directed learners who are capable of effectively navigating diverse educational environments [28]. This factor aligns with SDT because students who actively plan, monitor, and regulate their learning demonstrate autonomy and competence. It is likewise supported by EVT as the deliberate use of strategies reflects an expectancy of success and the perceived value of achieving their learning goals.

Table 3. Rotated factor matrix

SMCS items	Factor					
	1	2	3	4	5	6
76. I communicate my ideas and thoughts in math class.	.571					
78. I take advantage of the guidance and feedback of my teacher to improve my math learning.	.553					
77. I strive to understand and follow the instructions and guidelines for math activities and discussions.	.535					
72. I adapt my learning strategies to different types of math activities and assessment.	.531					
73. I actively collaborate with my classmates and teacher during math activities.	.521					
69. I stay dedicated to learning math regardless of my teacher's classroom management.	.514					
71. I actively seek to connect math concepts to real-world situation to deepen my understanding.	.456					
66. I take the initiative to seek help with math when needed even beyond school hours.	.445					
62. I take advantage of the assistance and support provided by my teacher to enhance my math learning.	.440					
74. I utilize varied learning materials and technology during math activities to improve my learning.	.426					
75. I set high standards and goals for myself during math activities and discussions.	.424					
65. I communicate my needs and questions effectively to my teacher to facilitate my math learning.	.404					
37. I am competitive when it comes to learning math.		.589				
31. I actively participate in activities in my math class.		.568				
45. I have a strong passion, interest, and inclination in math.		.558				
23. I am confident with my ability to solve math problems.		.543				
33. I enjoy learning math concepts.		.520				
32. I consistently perform to the best of my ability in math.		.505				
34. I can see myself engaging with math in the future.		.481				
27. I stay focused and not easily distracted when learning math.		.454				
52. I strive to maintain focus on learning math even when faced with personal and family problems.			.569			
58. I stay dedicated to learning math even when I do not feel mentally ready.			.541			
57. I remain dedicated to learning math regardless of classroom atmosphere.			.523			
59. I remain dedicated to learning math even with limited family support.			.480			
56. I stay dedicated to learning math even if I plan to pursue an unrelated career in the future.			.437			
51. I strive to engage in math class regardless of teacher's personality.			.432			
40. I find ways to engage in learning math even if the learning environment is not ideal.			.418			
55. I remain dedicated to learning math even with limited financial and material resources.			.410			
50. I am not distracted by phones or social media when learning math.			.403			
19. I am dedicated to learning math, even if I am not good at it.				.643		
20. I am driven by curiosity to learn more and improve in math.				.452		
47. I stay dedicated to learning math even if I do not have good foundations in it.				.431		
18. I keep pushing myself to learn math even when it gets challenging.				.426		
12. I consistently put in effort to learn and get better at math.				.404		
22. My dedication to learning math is shaped by both success and failure in the subject.				.401		
2. I regularly practice, master, and update my skills and knowledge in mathematics.					.615	
3. I actively seek opportunities to learn and improve my mathematical skills.					.591	
1. I stay dedicated to learning mathematics even when I face challenges over time.					.476	
8. I have the confidence in learning math skills and concepts.					.415	
7. I am open to constructive criticism as this helps me improve my skills in math.						.613
42. I appreciate my teacher's dedication, support, and presence in helping me learn math.						.428
17. I understand the importance and relevance of learning math.						.428

3.1.2. Affective learning engagement (ALE)

Affective learning engagement (ALE), which reflects students' emotional involvement and attitudes to their learning experiences, plays a crucial role in shaping their learning commitment. Literature suggests that students who believe in their abilities (self-efficacy) are more engaged, and perform better, with emotional intelligence also playing a significant role [29]. From the theoretical perspective, this dimension reflects how students' positive emotions and confidence support autonomous motivation and competence (SDT), while their belief in their success and the value they attach to learning tasks (EVT) strengthens their sustained commitment and active participation in learning.

3.1.3. Learning engagement resilience (LER)

This dimension plays a crucial role in shaping mathematical commitment by enabling learners to stay motivated, engaged, and persistent despite academic challenges. It was also found that resilience and diligence significantly predict intellectual engagement, reinforcing the idea that students who persevere through difficulties are more likely to stay committed to their studies [30]. In relation to SDT and EVT, this

factor reflects students who actively persist through academic setbacks, and adapt strategies show self-motivation and confidence in their abilities (SDT), while their belief that these efforts will lead to meaningful learning outcomes reinforces sustained effort and long-term commitment to their studies (EVT).

3.1.4. Positive learning mindset (PLM)

It is increasingly recognized as a key dimension of learning commitment, emphasizing the role of attitudes and beliefs in fostering engagement and persistence in learning. It was found that a growth mindset fosters higher levels of grit, passion, and determination, all of which contribute to improved academic performance and sustained commitment to learning [31]. This factor is consistent with SDT, as students who embrace challenges and view effort as a path to growth demonstrate self-directed motivation and a sense of competence. It also reflects EVT, as confidence in mastering tasks and recognition of the personal importance of learning strengthen learning commitment.

3.1.5. Proactive perseverance

This factor refers to the sustained, strategic effort and time a learner invests in the learning journey by anticipating challenges, adapting strategies, and persistently overcoming obstacles. A study revealed how a proactive mindset and perseverance, combined with formal education, contribute to sustained commitment to learning and academic success [32]. Moreover, this dimension reflects SDT as students who take initiative to anticipate challenges and adapt strategies demonstrate autonomous engagement and a sense of mastery, while EVT is supported by their belief that these efforts will lead to meaningful outcomes which reinforces their sustained commitment and goal-directed behaviors.

3.1.6. Learning support appreciation

It reflects students' gratitude, and recognition of the people, resources, and environments that contribute to their learning process. External support, such as encouragement from teachers and peers, fosters self-regulation and cultivates a positive learning attitude, both of which contribute to sustained commitment and effort in learning [33]. This dimension reflects SDT by showing that when students recognize and appreciate external support, they are more likely to internalize motivation, feel capable of managing their own learning. Meanwhile, EVT is reflected when students perceive that leveraging these supports will help them succeed and achieve meaningful goals, which in turn reinforces sustained effort and commitment.

3.2. Convergent validity of the student mathematical commitment scale

To assess the suitability of items within the derived factors and the validity of the scale, a CFA was performed. Another sample of 606 respondents were randomly selected from nine public schools in Davao del Sur. Multiple fit indices were used to assess model fitness, including Chi-square fit index, normed Chi-square (≤ 3), CFI ($\geq .95$), TLI ($\geq .95$), SRMR ($\leq .08$), and RMSEA ($\leq .06$). Convergent and discriminant validity were also evaluated using the AVE ($AVE \geq .50$) and the HTMT ($HTMT \leq .85$).

Three models were tested to identify the best-fitting factor structure. Model 1 (6 dimensions, 42 items) served as the baseline from EFA. Model 2 (5 dimensions, 27 items) was an adjusted version of Model 1, and Model 3 (4 dimensions, 24 items) was a refinement of Model 2. These models were refined based on statistical and theoretical considerations. Items were removed from the models based on the modification indices, and their conceptual relevance to the factor to which they initially belonged. Based on the fit indices in Table 4, Model 2 demonstrated better fit model since it has satisfied all the necessary indices for the parameters being set: Normed Chi-square ($\chi^2/df=2.051$), CFI=.975, TLI=.972, SRMR=.034, and RMSEA=.042. However, Table 5 shows that learning support appreciation factor in Model 2 had an AVE of .437 which falls below the acceptable threshold of $\geq .50$, indicating the need for further refinement. Items that seem to overlap with other factors and conceptually not related to the dimension were removed. After item reduction, the factor was left with only two items, prompting its removal in accordance with standard psychometric guidelines. The CFA was subsequently re-run without this dimension.

Table 4. Tests for exact fit

	Standard	Model 1	Model 2	Model 3
χ^2		1980.41	644.14	519.81
df	Low χ^2 relative to df	804	314	246
χ^2/df ratio	≤ 3	2.463	2.051	2.113
CFI	$\geq .95$.941	.975	.977
TLI	$\geq .95$.937	.972	.974
SRMR	$\leq .08$.045	.034	.032
RMSEA	$\leq .06$.049	.042	.043

Furthermore, Tables 4 and 5 both reveal that Model 3 fits the data very well ($\chi^2=519.81$, $df=246$, $p<.001$). It satisfies the necessary fit indices, with a Normed Chi-Square ($\chi^2/df=2.113$), CFI=.977, TLI=.974, SRMR=.032, and RMSEA=.043. All factors have also achieved an AVE greater than .50 indicating strong convergent validity. With its established goodness of fit, Model 3 was adopted as the final and most appropriate structure for the SMCS.

Table 5. Summary of AVE for the three models

Factors	Model 1	Model 2	Model 3
SLE	.496	.517	.517
ALE	.506	.529	.529
LER	.471	.502	.503
PLM	.532	.513	.513
Proactive perseverance	.489	-	-
Learning support appreciation	.437	.437	-

3.3. Discriminant validity of the student mathematical commitment scale

To establish discriminant validity, HTMT analysis was performed, with all values falling below the .85 threshold, as shown in Table 6, indicating that the factors are distinct. Thus, the SMCS demonstrates strong discriminant validity. To further ensure the reliability of the scale, both CR and Cronbach’s alpha indices were computed. As shown in Table 6, the reliability values for all factors exceeded the acceptable threshold of .70, indicating good internal consistency. Figure 1 illustrates the final factor structure of the SMCS, which includes the four dimensions: SLE, ALE, LER, and PLM. Each dimension reflects a distinct aspect of students’ commitment to learning mathematics, with the corresponding items clearly mapped to their respective factors, providing a robust framework for assessing the various dimensions of students’ mathematical commitment.

Table 6. Summary table for discriminant validity and reliability tests

	SLE	ALE	LER	PLM	Overall
HTMT among factors					
SLE	1.00				
ALE	.811	1.00			
LER	.842	.810	1.00		
PLM	.840	.779	.722	1.00	
Reliability coefficients					
CR	.882	.870	.876	.807	.859
Cronbach’s alpha (α)	.856	.844	.826	.775	.940

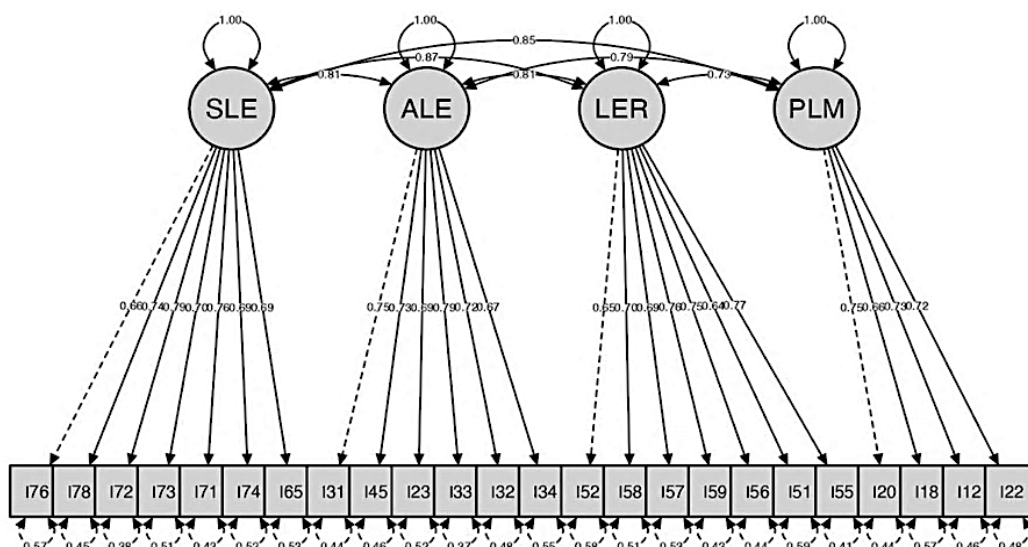


Figure 1. Factor structure of the final SMCS

Based on the rigorous analyses, the final version of the SMCS was developed. This scale demonstrates an optimal factor structure, with confirmed convergent and discriminant validity, and well-established reliability. The final scale comprises four factors and a total of 24 items as shown in Table 7.

The present study conceptualizes mathematical commitment as a multidimensional construct that is related to, yet distinct from, existing scales such as grit, self-efficacy, academic resilience, and engagement. Grit scales emphasize perseverance, passion, and resilience toward long-term goals [34], [35], whereas the SMCS extends beyond persistence by integrating strategic, affective, resilient, and mindset-oriented dimensions specific to mathematics learning. Similarly, self-regulated learning instruments like the motivated strategies for learning questionnaire (MSLQ) assess motivation and learning strategies across domains [36] but do not capture students' sustained commitment to mathematics as a subject. Academic resilience scales focus primarily on students' capacity to cope with adversity [37], while the SMCS positions resilience as one component within a broader framework of engagement and positive learning orientation. Engagement measures, although multidimensional (behavioral, emotional, and cognitive), primarily reflect participation rather than enduring psychological investment [38]. Collectively, the SMCS offers a holistic and domain-specific measure that complements existing constructs while addressing a distinct gap in assessing students' commitment to learning mathematics.

Table 7. Final SMCS

Dimension	Statements
SLE	I communicate my ideas and thoughts in math class.
	I take advantage of the guidance and feedback of my teacher to improve my math learning.
	I adapt my learning strategies to different types of math activities and assessment.
	I actively collaborate with my classmates and teacher during math activities.
	I actively seek to connect math concepts to real-world situation to deepen my understanding.
	I utilize varied learning materials and technology during math activities to improve my learning.
ALE	I communicate my needs and questions effectively to my teacher to facilitate my math learning.
	I actively participate in activities in my math class.
	I have a strong passion, interest, and inclination in math.
	I am confident with my ability to solve math problems.
	I enjoy learning math concepts.
LER	I consistently perform to the best of my ability in math.
	I can see myself engaging with math in the future.
	I strive to maintain focus on learning math even when faced with personal and family problems.
	I stay dedicated to learning math even when I do not feel mentally ready.
	I remain dedicated to learning math regardless of classroom atmosphere.
	I remain dedicated to learning math even with limited family support.
PLM	I stay dedicated to learning math even if I plan to pursue an unrelated career in the future.
	I strive to engage in math class regardless of teacher's personality.
	I remain dedicated to learning math even with limited financial and material resources.
	I am driven by curiosity to learn more and improve in math.
	I keep pushing myself to learn math even when it gets challenging.
	I consistently put in effort to learn and get better at math.
	My dedication to learning math is shaped by both success and failure in the subject.

4. CONCLUSION

The SMCS has undergone a comprehensive statistical data reduction process, reducing its original 79 items to a refined set of 24 items, with four identified and confirmed dimensions. This rigorous process has ensured reliability, as well as convergent and discriminant validity of the scale. With four dimensions: SLE, ALE, LER, and PLM, the SMCS provides a holistic view of mathematical commitment by examining the cognitive, emotional, psychological, and motivational aspects of students' learning behavior. Each dimension of the SMCS strengthens the overall construct of mathematical commitment, making it a valuable instrument that is also practical to use by teachers, school administrators, psychologists, and future researchers. Beyond classroom use, the SMCS has wider implications for educational practice and policy by informing teacher training through targeted motivational strategies, supporting school initiatives with evidence-based indicators for curriculum, and strengthening family engagement in fostering students' sustained commitment to learning mathematics. By measuring and understanding mathematical commitment, the SMCS offers the potential to transform the culture of math learning in the Philippines, cultivating students who are not only competent but also motivated, resilient, and confident in their mathematical journey.

Despite its strengths, the study has limitations which include a regional sample that is constrained only to Davao del Sur, reliance on self-report of the respondents, and the absence of longitudinal data. Future research should address these gaps by replicating the scale in other regions and grade levels, evaluating its

predictive validity (e.g., whether commitment predicts achievement over time), and integrating qualitative approaches to capture nuanced student experiences. These steps will enhance the scale's generalizability and deepen understanding of mathematical commitment in different contexts.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Retchelle P. Sangco	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Leurence C. Tandog		✓		✓	✓	✓		✓	✓	✓	✓	✓		
Jonald L. Pimentel		✓		✓	✓			✓	✓	✓	✓	✓		

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors affirm that they have no known financial, personal, or professional relationships that could be perceived as influencing the work reported in this paper. No political, religious, ideological, academic, or intellectual competing interests are associated with this study. The authors state no conflict of interest in the conduct of this research.

INFORMED CONSENT

The authors confirm that informed consent was obtained from all individuals who participated in this study. Participants were fully informed about the purpose, procedures, and use of their data, and written consent was secured prior to their inclusion. All efforts were made to protect participants' privacy and confidentiality throughout the research process.

ETHICAL APPROVAL

The authors confirm that this research complied with all relevant national regulations and institutional policies, in full accordance with the principles outlined in the Helsinki Declaration. Approval to conduct the study was granted by the University Research Ethics Committee, ensuring the safety, dignity, and rights of all human respondents. Should verification be required, the official certificate granting permission to conduct the research is available for review upon request.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [RPS]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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BIOGRAPHIES OF AUTHORS






Retchelle P. Sangco    is an associate professor of the Department of Teacher Education at the University of Mindanao Digos College in Digos City, Philippines. He obtained his PhD in Mathematics Education from the University of Southern Mindanao in Kabacan, Cotabato, Philippines. He has been serving the Research and Publication Center of UM Digos College as Research Associate since 2024, and is also a member of Asian Association for Academic Integrity whose vision is to promote academic integrity in research and publication centers of colleges and universities. He has published research articles on education and mathematics teaching, and collaborated with researchers both locally and internationally. With established experience and background in mathematics education, his research interests lie not only in improving mathematics literacy and skills of students both in basic and higher education, but students' quality education in general. He can be contacted at email: retchelle.sangco@umindanao.edu.ph.



Leorence C. Tandog    is a Professor VI of Department of Mathematics and Statistics of University of Southern Mindanao in Kabacan, Cotabato, Philippines. She earned her PhD in Science Education, major in Mathematics, from the University of the Philippines–Diliman, Quezon City, Philippines. Her academic journey reflects a strong commitment to advancing mathematics teaching and learning, particularly in contexts where resources and opportunities are limited. Her research interests include representation-based approaches, learner-centered pedagogies, and the integration of innovative materials to strengthen both numeracy and literacy. She has actively leveraged her training and research to expand access to quality education, especially among underserved populations, through extension projects and teacher professional development initiatives. She can be contacted at email: lectandog@usm.edu.ph.



Jonald L. Pimentel    is the 8th President of the University of Southern Mindanao in Kabacan, Cotabato, Philippines, with over 31 years of service in higher education. He has held key leadership roles as Professor VI, Dean of the College of Arts and Sciences, founding Dean of the College of Science and Mathematics, and President of the Faculty Association. He earned his PhD in Psychometrics from the University of Twente (Netherlands), a Master's in Biostatistics from Hasselt University (Belgium), and degrees in Mathematics from MSU–Iligan Institute of Technology. A prolific researcher with over 20 publications in local and international journals, including Scopus- and WoS-indexed papers, he is dedicated to inclusive and transformative education. He can be contacted at email: jlpmintel@usm.edu.ph.