Development and Psychometric Validation of the Mathematical Mindset Scale (MMS) for High School Students

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Abstract: Despite the expanding literature on mindset, domain-specific instruments that assess students' mindsets about mathematical intelligence remain limited. This study aimed to develop and validate the Mathematical Mindset Scale (MMS) for high school students. The data were collected from a total of 820 students, with one independent subsample used for exploratory factor analysis (EFA; n = 470) and another for confirmatory factor analysis (CFA; n = 350). The EFA results revealed a two-factor structure consisting of Growth Mathematical Mindset and Fixed Mathematical Mindset. These factors demonstrated acceptable internal consistency. The two-factor model was subsequently supported by CFA, indicating satisfactory model fit and providing evidence for construct validity. The findings suggest that the MMS is a psychometrically sound and practical instrument for assessing students' mathematical mindset profiles. The scale has the potential to support research on mindset development and to inform instructional practices aimed at fostering a growth mathematical mindset.

Keyword: Mathematical Mindset

Introduction

Beliefs about the nature of intelligence form the fundamental framework through which individuals understand their own cognitive capacities. According to Dweck's (1999) Implicit Theories of Intelligence, individuals hold initial assumptions about whether intelligence is a fixed trait or a quality that can be developed. Mindset refers to an individual's beliefs about their capacity to develop their potential (Haimovitz & Dweck, 2017) and reflects how they interpret their abilities (Pyper, 2018). These beliefs influence motivation and behaviour (Dweck & Yeager, 2019) and contribute to the formation of meaning systems (Molden & Dweck, 2006).

Beliefs about intelligence are commonly conceptualized as two mindsets (Dweck, 2006). Individuals who view intelligence as malleable hold a growth mindset, whereas those who believe intelligence cannot be changed endorse a fixed mindset (Boaler, 2016). These beliefs shape students' interpretations of learning situations, academic strategies, and responses to setbacks (Plaks et al., 2009; Blackwell et al., 2007), influencing learning outcomes (Boaler, 2016; Haimovitz & Dweck, 2017; Yeager & Dweck, 2012). Students' mindsets have been linked to motivation, learning, and academic performance over time (Blackwell et al., 2007; Burnette et al., 2013). However, meta-analytic evidence indicates that the association between mindsets and achievement can be weak and heterogeneous (Burnette et al., 2013; Sisk et al., 2018), suggesting that findings may depend on contextual factors and on how mindsets are operationalised and measured (Costa & Faria, 2018). A domain-specific perspective is therefore argued to provide deeper insight and stronger predictive power (De Castella & Byrne, 2015). General mindset scales may fail to capture independent beliefs across academic domains, making domain-specific investigation theoretically necessary (Laurell et al., 2025). Although growth mindset has often been associated with higher achievement (Burnette et al., 2013; Dweck et al., 1995a), mindset theory remains the subject of conceptual and empirical debate, highlighting the importance of precise construct definition and

measurement (Yan & Schuetze, 2023). Improving measurement precision is therefore essential for clarifying when and how mindset beliefs relate to educational outcomes (Boyd & Ash, 2018). Recent research has shifted from variable-centered to person-centered analyses, showing that students may display complex latent profiles rather than simple growth-fixed categories (Yu & McLellan, 2020). Identifying these profiles is critical for understanding how mindset beliefs relate to diverse academic outcomes

Mathematical mindset

Mathematical Mindset perspective emphasizes that mathematical ability is a dynamic, developable construct that grows through reasoning, exploration, and sustained effort rather than being innate and unchangeable. Mathematics is recognized as a domain where the innate ability myth is highly prevalent and where beliefs about malleability become especially salient in predicting success (Boaler, 2016). An individual's thinking about mathematical abilities and skills reflects their mathematical mindset (Pyper, 2018). Students often hold negative beliefs about mathematics, viewing ability as something one either has or does not have. Developing a growth mathematical mindset can help students move beyond these harmful beliefs (Boaler, 2016). Students may believe that success depends on innate ability (fixed mathematical mindset) or that ability can be developed through study and practice (growth mathematical mindset) (Daly et al., 2019). Although these beliefs are often presented as opposing tendencies, emerging perspectives suggest that growth- and fixed-oriented beliefs may coexist within individuals rather than representing opposite ends of a single continuum (Anderson et al., 2018; Karwowski, 2014; Orbach & Fritz, 2022).

Fixed beliefs may reinforce avoidance behaviours and reduce long-term engagement with mathematics (Boaler, 2016). Messages suggesting that mathematical ability is fixed from birth, particularly those implying that females are less likely to possess this ability, negatively affect females' sense of belonging in mathematics (Good et al., 2012). Fixed mindset beliefs are associated with higher mathematics anxiety and emotional cost, which can reduce working memory capacity and impair performance during complex tasks (Samuel & Warner, 2021). In addition, a fixed mindset toward intelligence has been shown to negatively affect middle school students' mathematics scores (Zhao & Wang, 2014). Longitudinal studies indicate that fixed mindset beliefs may increase during the transition from elementary to middle school, negatively influencing engagement and achievement (Kim & Park, 2021). In contrast, growth mathematical mindset emphasises that mathematics is learnable and that learners develop understanding through engagement with ideas (Boaler, 2016). Students who believe abilities can be developed tend to show higher achievement and greater completion of challenging mathematics courses (Yeager & Dweck, 2012). Growth mindset has also been linked to valuing mathematics more highly and to better performance outcomes, including among female students (Degol et al., 2018). In elementary school students, stronger growth mindset was associated with higher mathematics achievement, whereas stronger fixed mindset related to lower achievement (Park et al., 2016). Transforming mathematical mindsets therefore requires more than motivational messages; it involves creating classroom cultures that value mistakes, promote open-ended tasks, and support resilience and self-efficacy (Samuel & Warner, 2021).

Draft form of the MMS

Based on research on mindset theory and brain plasticity, Boaler (2016) introduced the concept of mathematical mindset, emphasizing that mathematical achievement is a developable process rather than an innate fixed ability. Her perspective helps explain why cultivating a growth mathematical mindset can reduce mathematics anxiety,

increase students' willingness to engage with challenging tasks, and support equitable participation in mathematics learning. In developing the items for the preliminary draft of the scale, Boaler's (2016) recommendations on *Positive Norms to Encourage in Math Class* were first examined, as these norms emphasize key principles of a growth-oriented mathematical mindset such as the belief that everyone can learn mathematics, that mistakes are valuable learning opportunities, and that mathematical thinking involves creativity, sense-making, and deep, reflective engagement rather than speed or innate talent. However, because these norms predominantly emphasize growth-oriented beliefs, additional sources were needed to incorporate fixed-mindset indicators. To achieve this conceptual balance, items from the Dweck's Mindset Scale (Dweck, 1999, 2006), which operationalize implicit theories of intelligence, were reviewed to identify statements reflecting fixed and malleable views of ability.

Furthermore, to ensure that the item pool was grounded in both theoretical and empirical evidence, several highly cited studies in the mindset literature (e.g., Bostwick et al., 2017; Burnette et al., 2013; Dweck & Yeager, 2019; Haimovitz & Dweck, 2017) were systematically examined. Insights from this literature informed refinements to item wording, the representation of both mindset dimensions, and the conceptual clarity of the scale. Integrating the theoretical and empirical insights obtained from the literature review, a preliminary scale consisting of thirteen items was subsequently developed. Two academicians with doctorates in mathematics education and two mathematics teachers provided feedback on the draft form. Following the expert's suggestions, specific sentences were revised to enhance clarity. Subsequently, the 13-item draft scale form was moved to Google Forms, where data were collected online. The scale is a Likert type (5 = strongly agree, 1 = strongly disagree).

The present study

Mindsets can be general (e.g., intelligence), domain-specific (e.g., mathematics), and independent (Furnham, 2014). Someone with a growth mindset in one domain may hold a fixed mindset in another (Dweck et al., 1995b). Emerging evidence suggests that growth- and fixed-oriented beliefs may function as related but relatively distinct dimensions, with implications for how mindset constructs are measured and interpreted (Karwowski, 2014; Petscher et al., 2021). Examining mindsets in a domain-specific manner can provide different perspectives on their structure (Costa & Faria, 2018). General mindset scales may fail to capture domain-specific nuances, making domain-specific measurement theoretically necessary. Mathematics, in particular, is frequently recognised as a domain where the innate ability myth is prevalent, leading students to hold subject-specific fixed beliefs even when they endorse a general growth mindset (Boaler, 2016). Consequently, domain-specific measures may provide stronger predictive power for academic outcomes than general instruments (Costa & Faria, 2018).

Findings regarding the mindset–achievement relationship are mixed. Some studies report positive effects of growth mindset and negative effects of fixed mindset on achievement (e.g., Cury et al., 2006; Gouëdard, 2021), whereas others report weak associations (e.g., Burnette et al., 2013; Costa & Faria, 2018; Sisk et al., 2018). These inconsistencies may partly reflect differences in how mindset constructs are operationalised and measured (Yan & Schuetze, 2023). Thus, improving measurement has been identified as a key research need (Yan & Schuetze, 2023). The Dweck's Mindset Scale (Dweck, 1999, 2006) and the Implicit Theories of Intelligence Scale for Children (Blackwell et al., 2007) are widely used; however, domain-specific scales are needed to better examine mindset structure (Boyd & Ash, 2018; Costa & Faria, 2018). Domain-specific mindset scales have been developed in areas such as reading, science, foreign language learning, and creativity (Chen & Tutwiler, 2017; Karwowski, 2014; Lou

& Noels, 2019; Petscher et al., 2017), demonstrating that beliefs about malleability differ across domains.

Attempts to develop mathematical mindset scales remain limited (Im & Park, 2023). Although this work represents an important contribution, it focused on middle school populations and included only growth-oriented items derived from positive norms, without indicators of fixed mathematical mindset. Accordingly, there is a need for a domain-specific and culturally adaptable instrument incorporating both fixed and growth-oriented beliefs. Developing such a measure may clarify the multidimensional nature of mathematical mindset and support more consistent interpretation of findings. In line with this need, the present study aims to develop and validate a Mathematical Mindset Scale (MMS) for high school students in Türkiye, incorporating both positive and negative norms to capture the full range of students' mathematical mindset beliefs.

Method

Participants

The participants were selected through convenience sampling and consisted of high school students enrolled in public schools under the Ministry of National Education in Ankara during the fall semester of 2025-2026. The research included two independent samples: one for exploratory factor analysis (EFA; n = 470) and another for confirmatory factor analysis (CFA; n = 350), resulting in a total of 820 participants. In the EFA sample, 250 (53.2%) students were female and 220 (46.8%) were male. The distribution across grade levels was as follows: 129 (27.4%) ninth graders, 154 (32.8%) tenth graders, 101 (21.5%) eleventh graders, and 86 (18.3%) twelfth graders. Participants' ages ranged from 14 to 18 years (M = 15.35, SD = 1.08). In the CFA sample, 181 (51.7%) students were female and 169 (48.3%) were male. The grade-level distribution was relatively balanced, with 91 ninth graders (26%), 86 tenth graders (24.6%), 87 eleventh graders (24.9%), and 86 twelfth graders (24.6%). Ages also ranged from 14 to 18 years (M = 15.51, SD = 1.13).

Data collection

Data were collected separately for the EFA and CFA stages. Before participation, all students were provided with clear and comprehensive information regarding the purpose of the study, the procedures involved, and the management of their personal data. Participation was entirely voluntary, and students were informed that they could withdraw from the study at any time without any consequences. Written informed consent was obtained electronically through Google Forms, and parental consent was secured for all underage participants. No personally identifiable information was collected, ensuring complete anonymity throughout the process. All data were stored securely and used exclusively for research purposes. Ethical approval for the study was obtained from Kütahya Dumlupınar University Social and Human Sciences Scientific Research and Publication Ethics Committee (Approval number: 2024/08), confirming adherence to institutional and national ethical regulations.

Data analysis

EFA was used to identify the underlying factor structure of the scale. In evaluating the suitability of the data for EFA, the sample size was first examined. Sample adequacy was evaluated using established guidelines recommending at least five to ten participants per item (Pallant, 2016; Tabachnick & Fidell, 2013). Sampling adequacy was further assessed using the Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of

Sphericity. KMO values of .60, .70, and .80 correspond to mediocre, middling, and meritorious sampling adequacy, respectively (Hair et al., 2019), and a significant Bartlett test (Bartlett, 1950) indicated that the data were suitable for factor analysis.

Next, decisions regarding factor extraction and rotation were made within a unified framework. Although numerous extraction techniques exist, the literature indicates limited consensus on the optimal approach for varying factor structures and sample sizes (De Winter & Dodou, 2012). Employing multiple criteria minimizes the risk of over- or under-extracting factors and increases the robustness of the solution. The number of factors can be identified if the computed eigenvalue is greater than 1. An alternative approach would be to determine the optimal number of factors based on the flattening point of the scree plot. Another method would be to count the number of factors based on the variance ratio explained by each component. When there is no discernible increase in variance, factors may be removed from the model (Finch et al., 2016).

Although researchers in various disciplines have discussed the total variance percentage criterion and proposed different thresholds, no universally accepted cut-off exists (Williams et al., 2010). In the social sciences, where constructs are often complex and measurement precision is relatively lower, solutions accounting for around 50% of the total variance are generally considered satisfactory, and in some cases lower values may also be acceptable (Hair et al., 2019). Accordingly, these complementary criteria were employed in the present study.

Given these criteria, Principal Axis Factoring (PAF) was selected because it isolates the shared variance among items and does not rely on strict assumptions of multivariate normality (Costello & Osborne, 2005). Additionally, PAF performs reliably when factor loadings are uneven, when the number of indicators per factor is limited, and when sample sizes are modest; it is also more capable of retrieving weaker latent dimensions compared to many alternative estimation techniques (Grieder & Steiner, 2022). This methodological justification aligns with recommendations for psychological and educational measurement contexts, where latent constructs rarely meet strict normality assumptions. Because factors are typically expected to correlate, an oblique rotation (Direct Oblimin) was employed to obtain a more realistic and interpretable factor structure (Hair et al., 2019; Tabachnick & Fidell, 2013).

Each item was evaluated based on its factor loading value when determining the items included in each factor. Items with a factor loading value of .32 or higher are often regarded as loaded on a factor (Tabachnick & Fidell, 2013), although values of .30 may be regarded as minimally acceptable (Hair et al., 2019). The normal distribution of the data was examined using skewness and kurtosis values.

Various ways exist to calculate the scale's reliability. The most accurate estimates of reliability are Cronbach's α and McDonald's ω (Edwards et al., 2021). ω was reported because it provides more accurate reliability estimates when factor loadings differ across items. Thus, α and ω values were considered to determine the scale's reliability. Coefficients above the .70 benchmark are generally regarded as evidence of adequate internal consistency (DeVellis & Thorpe, 2021), although a .60 level can be used in exploratory research (Hair et al., 2019). The difference between the 27% upper group and lower group mean scores was calculated with an independent samples t-test to determine the discrimination of the scale items.

The scale's factor structure was verified using CFA. The model identified through EFA was subsequently tested in CFA (Kline, 2016). The goodness of fit indices were calculated and interpreted using CFA. Although different indices are emphasized across

studies, the present study adhered to widely accepted benchmark values, including χ^2/df < 5, CFI, NFI, and TLI > .90, and SRMR and RMSEA < .08 (Byrne, 2016; Kline, 2016). All EFA were conducted using SPSS 25, and all CFA were performed using Mplus 8.3. The CFA model was estimated using the Maximum Likelihood Robust (MLR) estimator, which provides standard errors and fit statistics that are robust to non-normality (Muthén & Muthén, 2017).

Results

The normality of the data was examined using skewness and kurtosis values. The skewness coefficients ranged from -1.97 to 1.18, and the kurtosis coefficients ranged from -.98 to 1.47. According to the criterion suggesting that the absolute values of skewness and kurtosis should not exceed 2 (Hair et al., 2019), the data were considered to exhibit an approximately normal distribution.

The KMO value was calculated as .70. Bartlett's Test of Sphericity was significant, $\chi^2_{(45)} = 626.23$, $p < .001$. The results indicated that the scale is appropriate for factorization. Figure 1 illustrates the eigenvalue graph of the MMS.

Figure 1.
Eigenvalue graph of the MMS.

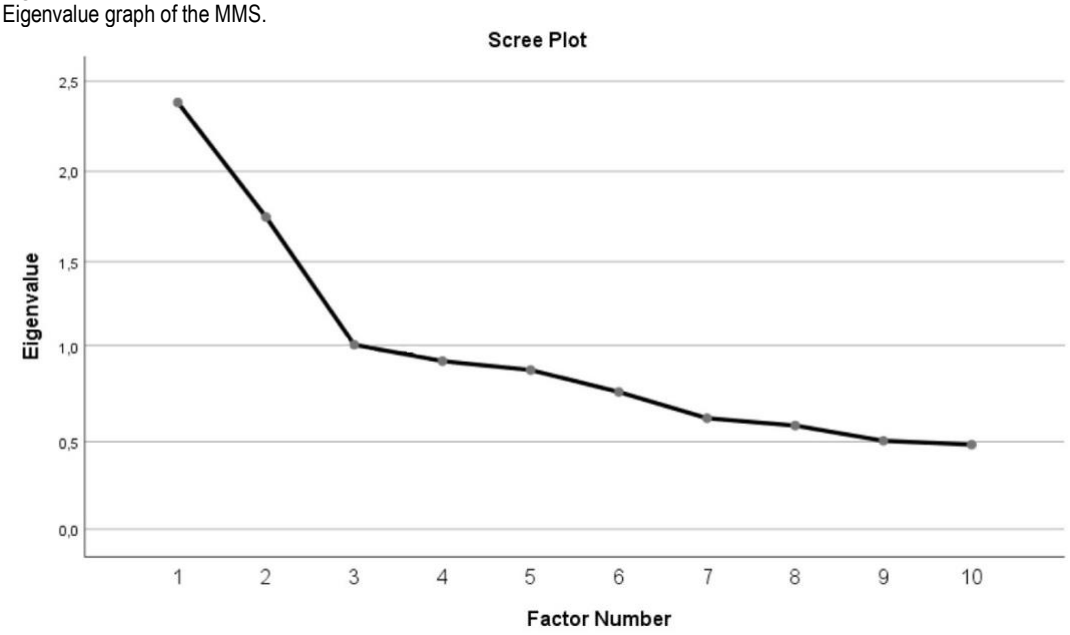


Figure 1 shows that the eigenvalues begin to level off after the second factor and only the first two factors have eigenvalues greater than one, indicating that a two-factor solution is optimal. In addition, the incremental variance explained after the second factor is minimal. Therefore, the scale was determined to have two factors. The variance explained by the first of these factors is 23.83%, and the second is 17.47%, totalling 41.30%.

When determining which items to include in the scale, the factor loading of each item was examined, and items with a factor loading of .32 or higher were considered to be loaded on a factor. The analysis revealed that the factor loadings of items 7, 12, and 13 were below the threshold. Therefore, these items were excluded from the scale. The item numbers, factor loadings, means, standard deviations of the items, and Cronbach's α and McDonald's ω values of the factors in the MMS are presented in Table 1.

Table 1.
Descriptive statistics of the MMS items

Factor	Item No	Factor Load	M	SD	α	ω
First Factor	i9	.72	4.14	.85	.71	.70
	i8	.70	3.83	1.04		
	i4	.65	4.20	.93		
	i1	.49	4.45	.77		
	i6	.45	2.58	1.31		
	i11	.41	3.61	.99		
Second Factor	i2	.79	2.34	1.11	.72	.72
	i3	.77	3.21	1.07		
	i5	.76	2.17	1.08		
	i10	.47	1.88	.98		

Table 1 shows that the factor loadings range from .41 to .79, indicating acceptable to strong item-factor relationships. The first factor consists of six items (i1, i4, i6, i8, i9, i11), while the second factor consists of four items (i2, i3, i5, i10). The descriptive statistics (*M* and *SD*) indicate that item responses exhibit adequate variability across participants. Internal consistency analyses yielded Cronbach's α coefficients of .71 for the first factor and .72 for the second factor. Similarly, McDonald's ω coefficients were .70 and .72, respectively, suggesting acceptable levels of internal consistency for both subscales. Table 2 shows the item numbers, item expressions, and factor names.

Table 2.
Item numbers, item expressions, and factor names.

Factor Name	Item No	Item Expressions
Growth Mathematical Mindset	i9	Mathematics requires thinking, making sense, and making connections between ideas.
	i8	Persistence should be maintained in performing mathematical tasks, even difficult ones.
	i4	Studying mathematics and learning new things enhances one's intelligence.
	i1	Learning mathematics requires struggle and time.
	i6	Mistakes made in mathematics enhance one's motivation to learn.
	i11	In mathematics, understanding is more important than being fast.
Fixed Mathematical Mindset	i2	Only intelligent people can be successful in mathematics.
	i3	Mathematical intelligence is innate.
	i5	If a person lacks mathematical intelligence, it is impossible to change it.
	i10	Mathematics consists merely of memorizing rules and procedures.

Note. i7, i12, and i13 were excluded from the scale.

Table 2 shows the distribution of scale items across the factors. The first factor was labelled *Growth Mathematical Mindset*, and the second was labelled *Fixed Mathematical Mindset*, considering the meaning relationship between the items. The Pearson correlation coefficients for factors are shown in Table 3.

Table 3.
Inter-correlation between the factors.

Factors	1.	2.
1. Growth Mathematical Mindset	-	
2. Fixed Mathematical Mindset	-.25**	-

** $p < .001$

Table 3 shows a weak, negative, and significant correlation between the factors of the MMS (r = -.25, p < .001). The discrimination of the scale items was evaluated by computing the mean score difference between the upper 27% and lower 27% groups using a *t*-test for independent groups, and the results are presented in Table 4.

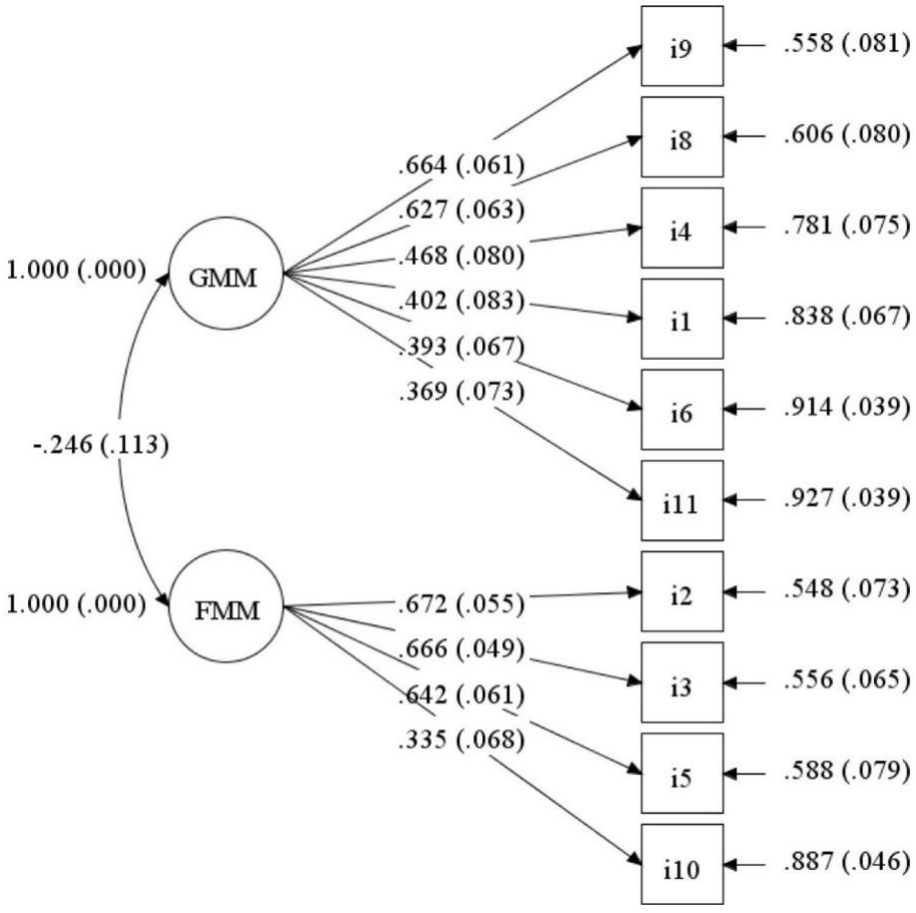
Table 4.
Item discrimination t-test results.

Factors	Groups	n	M	SD	df	t	p
FMM	Lower	127	6.24	2.16	252	-32.67	< .001
	Upper	127	13.38	1.19			
GMM	Lower	127	18.71	2.35	252	-32.59	< .001
	Upper	127	26.84	1.55			

Table 4 shows statistically significant mean differences between the upper and lower 27% groups for both FMM ($t_{(252)}$ = -32.67, p < .001) and GMM ($t_{(252)}$ = -32.59, p < .001). These results suggest that both subscales can differentiate between participants with relatively lower and higher scores on the respective constructs.

A first-level multifactor CFA model was employed to validate the MMS two-factor structure, illustrated in Figure 2.

Figure 2.
First-level multi-factor CFA model of the MMS.



Note. i = item; GMM = growth mathematical mindset; FMM = fixed mathematical mindset.

As a result of the analysis, fit indices were calculated as χ^2 = 61.882, df = 34, χ^2/df = 1.82, p < .01, RMSEA = .048, SRMR = .050, CFI = .91, TLI = .90. These indices indicate that the proposed two-factor model provides an acceptable representation of the data.

Discussion and Conclusion

The current study developed and validated the MMS. EFA results showed that the MMS had two factors containing ten items, and CFA results confirmed this two-factor structure. Notably, the CFA model demonstrated good fit without any correlated residuals or

modification indices, providing a parsimonious representation of the MMS structure. Higher scores on each factor reflect a stronger endorsement of the corresponding mindset dimension. This two-factor structure is consistent with recent work suggesting that mindsets do not operate as a single, uniform construct, but instead reflect multiple, coexisting patterns of beliefs that may vary across individuals and contexts (Altikulaç et al., 2024; Laurell et al., 2025; Orbach & Fritz, 2022). Importantly, the weak negative association observed between the two factors suggests that growth and fixed mathematical mindsets should not be interpreted as strict opposites positioned on a single continuum. Rather, the findings support the interpretation that students may simultaneously endorse both growth- and fixed-oriented beliefs to varying degrees, reflecting the multidimensional nature of mindset constructs. This interpretation aligns with emerging perspectives emphasizing that mindset beliefs can coexist within individuals depending on context, prior experiences, or task characteristics. Person-centered analyses further show that students may display complex mindset profiles rather than simple polarization (Yu & McLellan, 2020). Together, these findings suggest that the MMS captures mathematically relevant belief patterns that extend beyond a simple growth-fixed dichotomy, supporting the interpretation of mathematical mindset as a multidimensional construct.

The first factor of the MMS is called the Growth Mathematical Mindset. The items in this factor convey the mindset that mathematics can be learned through patient study and effort, and that mathematical skills and abilities can be developed. The literature indicates that interventions that promote a growth mindset can lead to increased student achievement over time (e.g., Blackwell et al., 2007; Paunesku et al., 2015; Yeager et al., 2016). Claro et al. (2016) found that students with a growth mindset scored better on national tests. Huang et al. (2019) determined that having a growth mindset in male students was associated with higher mathematics self-efficacy and career interests in mathematics and science. Samuel and Warner (2021) found that a growth mindset-based intervention increased students' mathematics proficiency and reduced their mathematics anxiety. Boaler et al. (2018) determined that when students were given education appropriate to the growth mathematical mindset, they engaged better in mathematics and showed higher mathematical performance. In contrast, Thibert-Dagenais and Ratelle (2024) found a negative association between growth mindset and mathematics achievement in elementary school. Some studies have also reported weak or inconsistent associations between mindset and achievement (Burnette et al., 2013; Costa & Faria, 2018; Sisk et al., 2018). More broadly, prior research has shown that students who endorse growth-oriented beliefs tend to display greater perseverance, more adaptive learning strategies, and higher confidence when encountering academic challenges (Aronson et al., 2002; Blackwell et al., 2007). Such students are more likely to view effort as a meaningful component of learning and to interpret mistakes as opportunities for improvement rather than as indicators of low ability. These findings support the relevance of the MMS Growth Mathematical Mindset factor and underscore its potential utility in identifying students who may benefit from instructional practices that promote resilience and productive engagement with mathematics. Importantly, the present findings position growth mathematical mindset not merely as a motivational orientation but as a belief structure potentially linked to adaptive learning processes in mathematics.

The second factor of the MMS is called the Fixed Mathematical Mindset. The items in this factor express the mindset that mathematical intelligence is inherent and cannot be improved later. Those with a fixed mindset do not view failure as an opportunity to learn, as they fear appearing inadequate (Dweck, 2006). Students with a fixed mindset view mistakes as failures and strive for performance-oriented goals (Rattan et al., 2012). Blackwell et al. (2007) found that students with a fixed mindset tended to exhibit declining mathematics achievement over a two-year period. Park et al. (2016) found a negative

correlation between a fixed mindset and mathematics achievement in elementary school, with low achievement predicting a more entrenched fixed mindset (and vice versa). Thibert-Dagenais and Ratelle (2024) found that elementary school students who perceive themselves as skilled in mathematics are more likely to reject a fixed mathematical mindset. Additionally, a negative relationship was found between a fixed mindset and mathematics achievement. These findings collectively indicate that fixed mindset beliefs may function as a risk factor for maladaptive academic patterns. In line with these findings, fixed ability beliefs have also been associated with avoidance behaviours, heightened sensitivity to failure, and a tendency to disengage from challenging tasks (Dweck & Yeager, 2019; Rattan et al., 2012). Studies further suggest that fixed mindsets may be linked to negative affective responses such as test anxiety and mathematics anxiety (Lee et al., 2025; Wijaya et al., 2025). These patterns highlight the importance of the MMS Fixed Mathematical Mindset factor as a domain-specific tool for identifying students who may be at risk for maladaptive learning trajectories and mathematics-related difficulties. From this perspective, the fixed mindset dimension may function as an early indicator of students who are vulnerable to disengagement or negative emotional experiences in mathematics learning environments.

Although many studies have examined the link between mindset and achievement, findings remain inconsistent, with some reporting positive effects and others showing weak or negligible associations (Burgoyne et al., 2020; Sisk et al., 2018). These mixed results underscore the need for domain-specific and psychometrically robust instruments that can capture nuanced belief patterns. The MMS directly addresses this need by providing a mathematics-focused measure that distinguishes growth- and fixed-oriented beliefs within a single framework. Valid measurement tools are essential for identifying students' mindset profiles and monitoring the impact of instructional interventions. Given that growth mindset interventions can support motivation, performance, and equity (Blackwell et al., 2007; Paunesku et al., 2015), the MMS offers researchers and practitioners a practical tool for guiding and evaluating such efforts.

Implications for Practice

Research has shown that mindsets toward intelligence can be taught in school settings and can influence students' academic behaviours (e.g., Aronson et al., 2002; Good et al., 2003). Even a single message or learning experience may substantially shape students' beliefs (Cohen & Garcia, 2014). Students' mindsets regarding their abilities guide their motivation, learning strategies, and responses to academic challenges (Burnette et al., 2013). Cultivating a growth mathematical mindset is therefore considered an important pedagogical goal for reducing negative beliefs about mathematics and supporting productive learning dispositions (Boaler, 2016). Identifying and interpreting students' mathematical mindsets is a complex but essential step for designing instruction that can effectively support mindset development. In this regard, the MMS developed in this study provides a practical and psychometrically sound tool for assessing students' mathematical mindset profiles.

Limitations and Suggestions for Future Research

The findings of the present study should be interpreted in light of several limitations related to measurement, sampling, and item functioning. Inspection of the CFA results indicated relatively high residual variances for several items (particularly i6, i10, and i11), suggesting that these items may capture aspects of students' mathematical mindset beliefs that are not fully explained by the latent factors. Although these items met acceptable loading criteria and were theoretically retained to preserve conceptual breadth, their elevated error terms indicate that future studies may benefit from refining

item wording or further examining item functioning across different samples. Accordingly, subsequent validation studies may consider alternative phrasings or additional indicators to strengthen the precision of factor representation. Another limitation of the present study is the absence of explicit evidence for convergent and discriminant validity. Although the scale development process was supported by theoretical and factorial evidence, future research should examine relationships with theoretically related and distinct constructs to provide stronger evidence for the scale's construct validity.

The data were obtained through convenience sampling from schools within a single metropolitan area, which may limit the sample's representativeness of the broader high school population and reduce the generalisability of the findings. Voluntary participation may also introduce selection bias. Additionally, the lack of sociodemographic information limits the sample's contextual diversity. Although convenience sampling is common in scale development research, future research using more diverse and representative samples would enhance the scale's external validity. Three items representing GMM (i7 = Even knowledgeable individuals may struggle with mathematics; i12 = Everyone is capable of learning mathematics; i13 = females and males have the same level of mathematical ability) were excluded from the MMS. Item 7 may require a more abstract understanding of the relationship between intelligence and mathematical struggle, which younger respondents may interpret inconsistently. Item 12 may have been influenced by social desirability or ceiling effects, reducing its discriminative capacity. Item 13, which addresses gender-related beliefs about mathematical ability, may reflect culturally shaped stereotype perceptions rather than the mathematical mindset itself, thereby compromising construct validity. Future research may consider revising and re-evaluating these items in culturally diverse and developmentally appropriate samples.

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