

Frequently Cited but Seldomly Actually Measured: The Mathematical Cast of Mind

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Supplementary Materials: Code, Data [see [Index of Supplementary Materials](#)]



Abstract

Understanding the sources of individual differences in mathematical abilities is considered essential by both researchers and society alike. Almost 50 years ago, the Russian psychologist V.A. Krutetskii proposed the concept of a mathematical cast of mind (MCOM), which he described as a predisposition to perceive the world through ‘mathematical eyes’. This MCOM should be particularly evident in gifted individuals, enabling them to acquire mathematical knowledge more rapidly and to achieve higher levels of mathematical performance. Although Krutetskii’s concept is often referred to in models of mathematical giftedness, empirical attempts to measure it have been limited. The aim of this study is to identify specific tasks that capture aspects of the MCOM and to determine whether these tasks contribute to an MCOM factor that is associated with mathematical achievement above and beyond verbal and figural intelligence. To this end, 82 university students worked on tasks that measure the MCOM components of obtaining mathematical information, processing of mathematical information, and motivational tendencies. The results of an exploratory factor analysis showed a three-factor structure in line with theoretical components of MCOM but not a single factor of MCOM. From the three components, only motivational tendencies was a significant predictor of mathematical achievement. Obtaining mathematical information, in contrast, showed negative correlations with the other two factors and did not significantly predict individual differences in mathematical competence. These findings provide further insights into the concept of MCOM and if it can be measured reliably to eventually predict individual differences in mathematics.



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Keywords

mathematical cast of mind, individual differences, mathematical achievement

Researchers and modern societies regard an in-depth understanding of the sources of individual differences in mathematics achievement as essential. High mathematical achievement is not only a central goal of school instruction but also a cornerstone for constructive and reflective citizenship in society (OECD, 2024). In 1968, Russian Psychologist V.A. Krutetskii published his book ‘The Psychology of Mathematical Abilities in Schoolchildren’ (English translation 1976), in which he examined the mathematical abilities of about 200 students aged 6 to 17 over a ten-year period. Based on his qualitative and quantitative assessments, he proposed a framework for understanding the structure of mathematical abilities. The gist of Krutetskii’s work is the assumption of a ‘mathematical cast of mind’ (MCOM), which he described as the tendency to interpret the world mathematically. Mathematically gifted individuals would literally ‘see the world through mathematical eyes’ (Krutetskii, 1976, p. 302); that is, they perceive and interpret their environment through the lens of logical and mathematical categories. Krutetskii postulated that MCOM is composed of different components that ‘are closely interrelated, influencing one another and forming in their aggregate a single integral system’ (Krutetskii, 1976, p. 351). Although Krutetskii’s work has often been cited and praised for its high relevance for research (e.g., Campos Ferreira & Moreira, 2024; Vilkomir & O’Donoghue, 2009) and has been incorporated into theoretical models of (mathematical) giftedness (e.g., Subotnik et al., 2009), attempts to empirically validate it have been rare. This is likely due to the unresolved question which tasks can objectively and reliably capture the different components of MCOM. Furthermore, it remains unclear whether the different components contribute to an overarching MCOM factor associated with mathematical achievement, independent of other important predictors such as verbal and figural intelligence. The general aim of the present study is to address these questions, drawing not only on Krutetskii’s seminal work but also on more recent findings from research in mathematical cognition.

Obtaining Mathematical Information

The first component postulated in Krutetskii’s model is *obtaining mathematical information*, which involves the ability to formally perceive mathematical material. This component most closely aligns with the notion that mathematically gifted children ‘see the world through mathematical eyes’. This component appears similar to two concepts studied in the domain of mathematical cognition: spontaneous focusing on numerosity (SFON) and attention to numbers (ATN). SFON is characterized by an individual’s tendency to recognize and focus on numerical features without explicit instruction to do so (McMullen et al., 2019). ATN refers to an automatic attentional process that supports the

recognition and discrimination of numbers (Chan & Mazzocco, 2017). Although the definitions of both concepts are similar, the tasks typically used to measure each differ. SFON is primarily assessed in children using behavioral (e.g., imitating an action demonstrated by an experimenter like feeding a parrot a certain number of berries and observing whether the child feeds the same number of berries without being explicitly told to focus on numbers) and verbal tasks (e.g., children describe a picture and it is observed whether the child gives numerical responses such as there are four ducks in the pond; Li et al., 2025). The main task to assess ATN is a picture matching task in which one must select the picture that best matches a target based on visual features such as color, shape, location, and number. A match solely based on number is considered an indication of ATN. Therefore, ATN is sometimes argued to be a ‘pure’ laboratory-based indicator of SFON tendencies (Mazzocco et al., 2020). However, although differences in children’s SFON have been reliably associated with mathematics learning and performance (for a review, see McMullen et al., 2019), the relationship between ATN and mathematical achievement is less clear: some studies report a positive relationship while others do not (Mazzocco et al., 2020). In the present study, we aim to assess Krutetskii’s MCOM component of *obtaining mathematical information* by tasks rooted in both SFON and ATN.

Processing of Mathematical Information

The second proposed component, *processing of mathematical information*, comprises six subfacets (Krutetskii, 1976, p. 350): a) Logic: Engaging in logical thought regarding quantitative and spatial relationships, as well as number and letter symbols; this includes the ability to think in mathematical symbols. b) Generalization: Rapidly and broadly generalizing mathematical objects, relations, and operations. c) Curtailment: Shortening the process of mathematical reasoning and the corresponding system of operations. d) Flexibility: Switching between different mental operations during mathematical activities. e) Elegance of solutions: Striving for clarity, simplicity, economy, and rationality in solutions. f) Reversibility: Rapidly and freely reconstructing the direction of a mental process, switching from a direct to a reverse train of thought in mathematical reasoning.

Based on recent literature in mathematical cognition we consider flexibility to be the most important subfacet of this component. Krutetskii (1976) defined flexibility of thought as the ability to switch between mental operations, approach problem-solving from multiple perspectives, and break free from conventional thinking, allowing for adaptive problem-solving. He assessed it using tasks that allowed for multiple solutions, whereby a problem could be solved in different ways. This is consistent with current definitions of mathematical creativity and corresponding assessment tasks. Mathematical creativity has been defined as the process that results in unusual or novel as well as useful solutions to a given mathematical problem (Sipahi & Bahar, 2025; Sriraman et al., 2013) and is commonly measured using divergent thinking tasks that require individuals

to generate multiple potential solutions to mathematical problems (Sipahi & Bahar, 2025; Suherman & Vidákovich, 2022). Similar to creativity in other domains, mathematical creativity is typically characterized by three core components: fluency, flexibility, and originality. Fluency refers to the ability to produce a large number of ideas, flexibility to the ability to generate ideas across different categories or solution strategies, and originality to the ability to generate unusual or unique ideas. Performance in mathematical creativity tasks has been consistently linked to mathematical achievement both in children and adolescents (e.g., Bicer et al., 2021) as well as in adults (e.g., Meier et al., 2021). Additionally, mathematical creativity has been considered the essence of mathematics (Elgrably & Leikin, 2021; Kozłowski et al., 2019) and is inherently connected with mathematical giftedness (Leikin, 2021; Singer, 2018; Sriraman et al., 2013). Against this background, in this study we assess *processing of mathematical information* with flexibility, fluency, and originality derived from two mathematical divergent thinking tasks.

Motivational Aspects

While not explicitly included in Krutetskii's model, motivational aspects are frequently acknowledged in his book as important for mathematical abilities and giftedness. By interviewing professional mathematicians, Krutetskii identified general personality traits that contribute to success in mathematics. These traits include a focused interest in mathematics, persistence, a drive for mathematical knowledge, and a need to engage in mathematics. Based on these interviews, Krutetskii concluded that a strong level of interest in mathematics is particularly important for high mathematical achievement. In a more recent model of mathematical giftedness, it was reported that professional mathematicians emphasized the link between MCOM and the intrinsic motivation to learn (Subotnik et al., 2009). These factors can drive students to attempt more challenging forms of mathematics. A related concept in current personality research is the need for cognition (NFC), defined as 'the intrinsic motivation to engage in and enjoy effortful analytic activity' (Cacioppo & Petty, 1982, p. 116). This concept has significant implications for academic performance, as a recent meta-analysis demonstrated a positive relationship between NFC and academic achievement ($r = .20$; Liu & Nesbit, 2024). Although the authors defined academic achievement very broadly (e.g., course grades, grade point averages) and did not examine specific subjects, such as mathematics, separately, they reported a significant correlation of $r = .17$ between NFC and academic achievement in the natural sciences. Given the significant role that motivational aspects play in achieving high levels in mathematics (e.g., Breit et al., 2025; Myers et al., 2017), we aim to capture *motivational tendencies* as part of MCOM by assessing interest, self-concept, and NFC.

Previous Research

To our knowledge, there is only one study that aimed to measure MCOM using tasks from current mathematical cognition research. Bakker et al. (2022) examined the characteristics of high achievers in mathematics by comparing 81 high achievers and 81 average achievers among 10- to 12-year-old children. The ATN task mentioned above was used as a measure of MCOM. Additionally, the researchers administered the adaptive number task. In this task, children had to reach a target number using four to five given numbers along with the four arithmetic operations (McMullen et al., 2016). They also performed the variability on demand task. In this task, children were required to solve complex multidigit arithmetic operations. They were then asked to explain their solution strategy and whether they knew other solution strategies (Torbeyns et al., 2009). Both of those tasks were intended to measure flexibility, with the latter also assessing the striving for elegance. Furthermore, NFC, spatial visualization ability, and working memory were tested. The results of this study demonstrated that high achievers outperformed the average achievers on all tasks except for the ATN task. The authors argued that the ATN task may not have been sensitive enough to detect subtle differences in children's MCOM. However, two important points should be noted here. First, the study viewed MCOM and flexibility as separate constructs. In our study, we will examine the structure of the MCOM and hypothesize that flexibility is nested within MCOM. Second, the authors did not include verbal and figural intelligence as control variables.

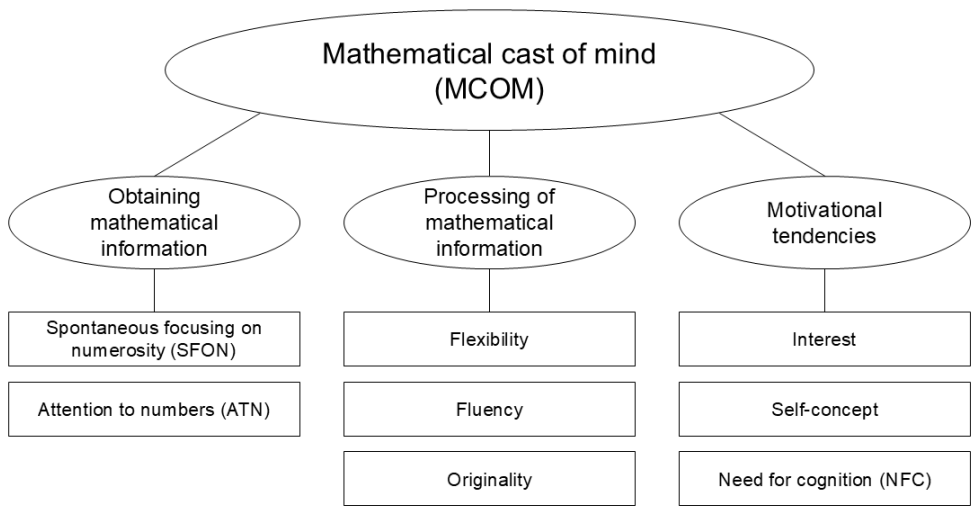
This is particularly crucial because a recent meta-analysis of the role of learner characteristics in mathematical achievement (Breit et al., 2025) showed that particularly the verbal and figural components of intelligence are highly important predictors of mathematical achievement. Verbal intelligence is important because language skills facilitate learning in mathematics, and mathematics requires receptive and productive linguistic comprehension. Figural intelligence, incorporating spatial abilities, is important because spatial representations are used as a cognitive strategy to understand and solve many mathematical problems, and mathematics comprises several spatial areas, such as geometry.

The Present Study

The main goal of the present study was to examine the structure of MCOM in a sample of adults with varying levels of mathematical achievement. The first research objective was to test whether individuals' performance on selected tasks are positively correlated with one another and form an overarching factor that represents MCOM (see Figure 1). We operationalized *obtaining mathematical information* using a SFON task and an ATN task. *Processing of mathematical information* was assessed via flexibility, fluency, and originality in two well-established mathematical creativity tasks drawing on divergent thinking. *Motivational tendencies* were measured using questionnaires on

interest, self-concept, and NFC in mathematics. The second research objective was to determine whether MCOM, as an overarching factor or as separate components, is significantly associated with mathematical achievement beyond verbal and figural intelligence. Mathematical achievement was assessed at both a more fundamental arithmetic and a more knowledge-based level.

Figure 1
Visualization of the MCOM Model in This Study



Method

Participants

The sample comprised 82 young adults (52 female, 30 male), aged between 18-37 years ($M = 23.23$, $SD = 3.41$). Of these, 63 individuals (77%) were university students. 50 (60%) participants studied psychology and the remainder were enrolled in various other subjects (e.g., mathematics, law, German philology). The remaining 19 participants were employed across diverse industries, and roughly half had completed tertiary education. All participants were native German speakers and reported no learning disabilities such as dyslexia or dyscalculia. Two participants reported a diagnosis of Attention-Deficit-Hyperactivity-Disorder; however, as their performance on most tasks fell within the normal range, they were not excluded. For an exploratory factor analysis with eight variables, a ratio of cases per variable between 4 to 1 and 20 to 1 is recommended, resulting in 32 to 160 participants for our study (Lorenzo-Seva & Ferrando, 2024). A post-hoc sensitivity analysis using G-power (Faul et al., 2007) indicated that for single regression coefficients

in a linear multiple regression with six predictors, effect sizes of $f^2 = .10$ and larger can be detected with a power of .80 using the present sample size. Recruitment involved sending an e-mail to all students at the local university and personal outreach to friends and acquaintances by the researchers. Written informed consent was obtained from all participants, and the local ethics committee approved the study.

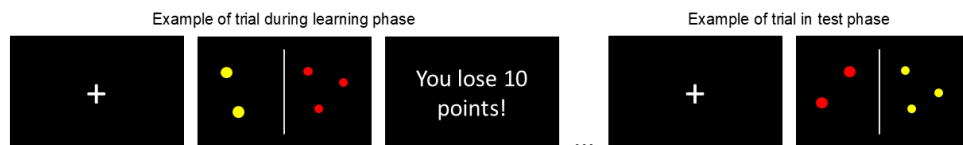
Material

Obtaining Mathematical Information

Spontaneous Focusing on Numerosity (SFON) — We used the numerosity bias task (Ben-Shachar et al., 2020) to assess the tendency of adults to spontaneously focus on numerosity. While the majority of SFON research has been conducted with children, this task was specifically designed for adults. During this computerized forced-choice task, participants were presented with two stimuli side by side, separated by a gray line—for example, two yellow dots versus three red dots (see Figure 2). They were instructed to choose one of the configurations by pressing the arrow key corresponding to the side where their chosen stimulus was displayed. After making their choice, participants received feedback indicating whether they had gained or lost points—for example, selecting the three red dots could earn points, while choosing the two yellow dots could result in a loss of points. Unbeknownst to the participants, each block of the task comprised two phases: a learning phase (consisting of 8 to 11 trials) and a test phase (the final trial).

Figure 2

Visualization of the Spontaneous Focusing on Numerosity (SFON) Task

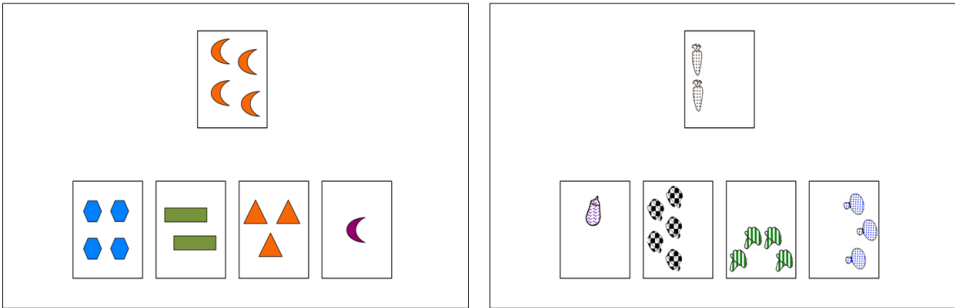


During the learning phase, color and numerosity were consistently paired together (e.g., three red dots). In contrast, the test phase presented a reversal of these two dimensions (e.g., two red dots versus three yellow dots), thus requiring participants to base their last choice either on numerosity (believing that ‘the three dots will earn me points’) or on color (believing that ‘the red dots will earn me points’). No feedback was provided during the test phase regarding point gains or losses. In total, there were 24 blocks in this task, and the stimuli consisted of different combinations of the number of objects (from one to four) and colors (red, green, blue, or yellow). A sum score of the test phase (the last trial in each block, ranging from 0 to a maximum of 24) was calculated to determine how often participants made a numerosity-based choice. Using the Spearman-Brown

split-half (odd-even) reliability coefficient, Ben-Shachar et al. (2020) reported a very good reliability ($r = .97$) for this task. Using the same method with the sample from this study, we found a very good split-half reliability ($r = .95$). To account for the possibility that individual differences in sensitivity to the salience of the color dimension (i.e., spontaneous focusing on color) could influence the SFON measure, an additional eight "Shape vs. Color" control blocks were included (Ben-Shachar et al., 2020). The principle of the task remained the same; however, instead of the number of objects, different shapes were used (rectangles, circles, triangles). The sum score of the test phase (ranging from 0 to a maximum of 8) was included as a control variable in the regression analyses performed.

Attention to Number (ATN) — We used the computer-based ATN as an additional measure to capture individual differences in the perception of numerical material (Chan & Mazzocco, 2017). Participants were shown 32 target pictures and had to decide which of four presented pictures best matched each target picture (Mazzocco et al., 2020). The stimuli included geometric shapes and line drawings of fruits and vegetables, which varied in number, color, shape, and location (see Figure 3).

Figure 3
Example Item With Numerical Match (Left) and Without Numerical Match (Right) of the Attention to Number (ATN) Task



The response options either matched the target picture in one of these features or were completely different. Although there was no normatively ‘correct’ response, participants had to decide which of the four response options best matched the target image. A numerosity match was possible for only 16 of the 32 items. After the first round, participants were shown all 32 items again with the question: "Is there another response option that you think would also be a good match?" The answer selected in the first round was marked to prevent participants from choosing it again. This approach aimed to determine whether participants ever recognized numerosity as a feature, even if it

was not their preferred match. There was no time limit for viewing the images, but participants were instructed to decide as quickly as possible.

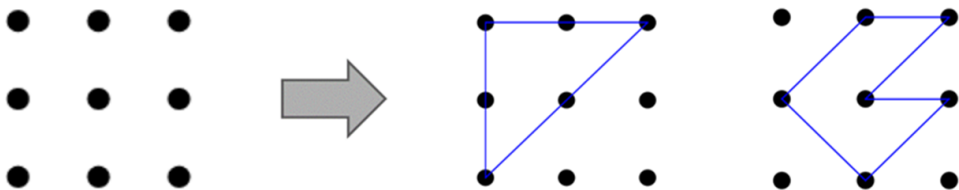
To score this task, we counted the number of times a participant selected the numerosity-based match in both rounds. However, unlike the original study, which combined the total frequency of numerosity choices across both rounds, we opted for a weighted scoring approach. Selecting numerosity as the best match in the first round should be weighted more heavily than selecting it in the second round, where participants had to select the next best match. Our weighted score was calculated using the following formula: $ATN = (\text{numerosity-based matches in the first round} \times 1) + (\text{numerosity-based matches in the second round} \times 0.5)$. Thus, participants could achieve a maximum score of 16 points. Because the original studies (Chan & Mazzocco, 2017; Mazzocco et al., 2020) did not explicitly report reliability, we estimated it in our sample using the split-half (odd-even) method with the Spearman-Brown adjustment. The reliability of the weighted ATN score was good ($r = .84$).

Processing of Mathematical Information

Mathematical Creativity — We measured mathematical creativity and its components flexibility, fluency, and originality using a paper-and-pencil test consisting of two divergent-thinking, open-ended problem-solving items. The first item involved figural content (Figural Generate, adapted from Haylock, 1997), in which participants had to form shapes measuring exactly 2 cm^2 within given 4 cm^2 squares (represented by nine dots spaced 1 cm apart) by connecting the dots with lines (see Figure 4).

Figure 4

Visualization of the (a) Figural Generate Item, Along With One Less Creative and One More Creative Example Solution



The second item involved numerical content (Numerical Generate, Kattou et al., 2013), in which participants had to create equations using only the digits 1, 2, 3, 4, 5, and 6 and the mathematical symbols (+, -, ×, ÷, ()) to fill in the blanks on either side of an equal sign. Participants were instructed to generate both as many and as creative answers as possible. A less creative example solution would be: “ $1 + 1 = 2$ ”. A more creative solution would be: “ $1 \times (5 - 4) = 6 / (2 \times 3)$ ”. Although these items were originally designed for

children and adolescents, they have been successfully administered to adults and even mathematics experts (Meier et al., 2021, 2023).

Prior to each item, participants received written instructions to generate as many creative solutions as possible to a given problem within a three-minute time limit. Both mathematical creativity items were scored for flexibility (number of categorically different answers), fluency (number of mathematically correct answers), and originality (evaluated by five independent raters and adjusted for fluency bias by dividing by fluency; see Forthmann et al., 2020 for more information on fluency bias). The inter-rater reliability for originality, assessed using the intraclass correlation coefficient (ICC) at the response level, was good for all tasks (Figural Generate: ICC = .87; Numerical Generate: ICC = .87). For the analyses, we first aggregated the flexibility scores into a general flexibility score, both fluency scores into a general fluency score, and both originality scores into a general originality score.

Motivational Tendencies

Interest in Mathematics — Interest in mathematics refers to an individual's inclination, curiosity, and enjoyment in engaging with mathematical concepts, problems, and activities (Heinze et al., 2005). We used four items previously employed in the PISA studies (OECD, 2013), with participants responding on a scale from 1 ("does not apply") to 4 ("applies"). An example item measuring interest in mathematics is: "When I engage with mathematics, I sometimes forget everything around me.". The four items demonstrated good internal consistency in our sample (Cronbach's $\alpha = .84$). For the analyses, we calculated individual scores for each participant by averaging the response to the four items.

Self-Concept in Mathematics — Domain-specific self-concept reflects a student's self-beliefs about their competence in a specific academic domain or ability, in this case, mathematics (Arens et al., 2022). We used four items, and participants responded on a scale from 1 ("does not apply") to 4 ("applies"). An example item for self-concept is: "Mathematics is one of my best subjects". The four items demonstrated good internal consistency in our sample (Cronbach's $\alpha = .92$). For the analyses, we calculated individual scores for each participant by averaging the response to the four items.

Need for Cognition (NFC) — Need for cognition (NFC) is an individual's tendency to engage in and enjoy activities that require thinking, analysis, and mental effort (Cacioppo & Petty, 1982). As research shows that assessing NFC in a domain-specific manner can predict mathematical achievement beyond domain-general NFC (Keller et al., 2019), we adapted items from the German short version of the NFC scale (Bless et al., 1994) to the domain of mathematics. This adaptation resulted in a total of 16 items, which participants answered on a 7-point Likert scale ranging from 1 ("does not

apply at all") to 7 ("applies perfectly"). An example is: "I really enjoy the task of finding new solutions to mathematical problems". After reverse-scoring the respective items, an overall mean was calculated for further analysis. Our adapted NFC scale showed a good internal consistency in our sample (Cronbach's $\alpha = .91$).

Dependent Variables and Control Variables

Arithmetic Fluency — We measured arithmetic fluency using two subtasks of a paper-and-pencil arithmetic competency measure (Vogel et al., 2017). The first subtask consisted of 128 simple one-digit multiplication problems, which are typically solved by retrieving the answer from long-term memory (Hinault & Lemaire, 2016). Participants were given 90 seconds to solve as many problems as possible. The second subtask consisted of 60 complex subtraction problems, each with two two-digit operands, which are typically solved using a calculation procedure (Hinault & Lemaire, 2016). Participants were given 120 seconds to solve as many problems as possible. The number of correctly solved problems was counted for each subtask. As the two scores were highly correlated in our sample ($r = .72$, $p < .001$), they were combined to create an overall arithmetic fluency score (0-188).

Mathematical Achievement — We used the official short version of the Mathematics Test for Personnel Selection (MPA; Jasper & Wagener, 2013) to measure mathematical achievement. This test consists of 31 mathematical problems covering topics such as fractions, unit conversion, exponentiation, division involving decimals, algebra, geometry, roots, and logarithms. Participants have a maximum of 15 minutes to answer these open-ended and multiple-choice questions. Individual's mathematical achievement score was calculated by summing the correct answers, resulting in a raw score ranging from 0 to 31. The short version of the test has been shown to have a high correlation with the long version ($r = .93$) and strong reliability in a large ($N = 1,948$) and representative sample (Cronbach's $\alpha = .89$; Jasper & Wagener, 2013).

Intelligence — We measured intelligence using three tasks from the Intelligence Structure Test (I-S-T 2000 R; Liepmann et al., 2007) in paper-and-pencil format. In the verbal task (similarities), six words were presented, but only two of them could be described by a common generic term. Participants had to identify which two these were. In the numerical task (number series), participants had to continue a series of seven numbers. In the figural task (cubes), participants were presented with five different three-dimensional cubes, each with distinct patterns on their sides. Each item displayed one of the five cubes in a different position, and participants had to determine which one it was. Each task consisted of 20 items of increasing difficulty, and participants had 7 minutes (verbal), 10 minutes (numerical), and 9 minutes (figural) to solve these items. The reliability of the tasks has been shown to be good in a large ($N = 3,484$) and representative sample

(Cronbach's $\alpha = .76, .91, .80$, respectively; [Liepmann et al., 2007](#)). For further analysis, we used the raw scores by summing all the correct answers for the subscales.

Procedure

The data were collected in the laboratory, either individually or in groups, with a maximum of four participants per session. Participants were first informed about the purpose and procedure of the study. After signing the informed consent form, they created a participation code to match the data from each task. The first task was the SFON task (15 minutes), followed by the ATN task (15 minutes). Both tasks were presented on the computer using PsychoPy ([Peirce et al., 2022](#)). After completing these computerized tasks, participants were asked to complete the paper-and-pencil arithmetic fluency task (4 minutes), followed by a demographic data questionnaire and the motivational tendencies questionnaires (5 minutes). After a brief five-minute break, participants continued with the paper-and-pencil mathematical achievement test (15 minutes), the intelligence test (26 minutes), and the mathematical creativity tasks (7 minutes). The total duration of the study was 90 minutes.

Results

All analyses were performed using the open-source statistical software R (version 4.5.0; [R Core Team, 2025](#)). All data as well as the analysis script are openly available in the [OSF project](#).

We used exploratory factor analysis to test the structure of the MCOM model. The Kaiser-Meyer-Olkin (KMO) criterion indicates whether the variables are sufficiently intercorrelated for an exploratory factor analysis. Values greater than .50 are considered acceptable, while values greater than .70 are desirable ([Watkins, 2018](#)). In our study, the KMO criterion yielded a value of .62, exceeding the minimum required threshold. A closer look at the Pearson's correlations between all variables in the MCOM model (see [Table A1](#) in the Appendix) showed that the two subcomponents of obtaining mathematical information, SFON and ATN, were not significantly correlated with each other ($r = .20, p = .072$). Flexibility correlated with both fluency ($r = .44, p < .001$) and originality ($r = .60, p < .001$), but fluency and originality did not correlate with each other ($r = .20, p = .079$). In contrast, the three subcomponents of motivational tendencies, interest, self-concept, and NFC were highly correlated with each other ($r = .61, .71, .73$, all $p < .001$). In addition to the KMO criterion, the Bartlett test of sphericity was significant (Bartlett test: $\chi^2 = 200.40, df = 28, p < .001$), supporting the suitability of the data for factor analysis.

Originally, principal axis factor analysis was chosen as the extraction method because we assumed that the measured variables were influenced by the same underlying latent construct and principal axis estimation outperforms other estimation methods when the

relationships between measured variables and factors are relatively weak ($\leq .40$) and the sample size is relatively small (≤ 300) (Watkins, 2018). However, as the principal axis factoring produced a Haywood Case, indicated by a negative residual variance, we switched to regularized common factor analysis (RCFA), developed by Jung and Takane (2008). RCFA is particularly well-suited for factor analysis in small samples and has been shown to prevent Heywood cases and accurately recover EFA model parameters (Cooperman & Waller, 2022). Unfortunately, the RCFA approach does not evaluate or test the statistical fit of the model.

The number of factors was determined through parallel analysis and visual inspection of the scree plot, resulting in the selection of three factors. An oblique rotation (promax) was employed to allow for intercorrelations among the factors. Contrary to our expectations, the exploratory factor analysis did not reveal a single MCOM factor; instead, it identified three distinct factors (see Table 1). The tasks for obtaining mathematical information (ATN and SFON) loaded onto one latent factor, while the three measures of mathematical information processing (flexibility, fluency, and originality) loaded onto another factor. The measures of motivational tendencies (interest, self-concept, and NFC) loaded onto a third latent factor. Although a single unifying factor was not identified and our first hypothesis must be rejected, the present findings support the theoretically proposed structure of three latent factors.

Table 1
Factor Loadings of the MCOM Model (Promax Rotated Pattern Matrix)

Variable	Factor			Communality estimates
	1 Obtaining mathematical information	2 Processing of mathematical information	3 Motivational tendencies	
SFON	0.46			0.24
ATN	0.49			0.29
Flexibility		0.84		0.70
Fluency		0.41		0.33
Originality		0.70		0.46
Interest			0.82	0.76
Self-concept			0.79	0.66
Need for cognition			0.82	0.63
Eigenvalue	1.26	1.57	2.76	

Note. Factor loadings below 0.30 are not shown to improve clarity.

In our second research question, we examined whether MCOM can predict arithmetic fluency and mathematical achievement beyond verbal and figural intelligence. To investigate this, we conducted two hierarchical multiple linear regressions for these dependent variables (the zero-order correlations can be found in Table A1 in the Appendix). In the first step, verbal and figural intelligence and spontaneous focusing on color were entered as control variables, while in the second step, the three MCOM factors were added. The three latent factor scores of the MCOM model were estimated using the tenBerge method, as this finds weights such that the correlation between factors for an oblique solution is preserved. The assumptions for regression analysis were met: there was no autocorrelation, multicollinearity, or heteroscedasticity, and the residuals were normally distributed.

For arithmetic fluency, figural intelligence was a significant predictor in the first step, with the overall model explaining 13% of the variance (see Table 2). After including the three MCOM factors, significantly more variance was explained (i.e., 20%); figural intelligence remained a significant predictor and motivational aspects could also significantly predict arithmetic fluency. Processing of mathematical information showed also a medium-sized regression coefficient but did not reach significance.

Table 2
Multiple Linear Hierarchical Regression Model for Arithmetic Fluency Predicted From the Control Variables (Verbal Intelligence, Figural Intelligence, Spontaneous Focusing on Color) and MCOM (Obtaining, Processing, Motivation)

Variable	β	p
Arithmetic fluency		
Model 0: Adj. $R^2 = .13$, $F(3, 78) = 5.03$, $p = .003$		
Verbal intelligence	.12	.271
Figural intelligence	.34	.002
Spontaneous focusing on color	-.10	.322
Model 1: Adj. $R^2 = .20$, $F(6, 75) = 4.28$, $p < .001$, $R^2_{\text{Change}} = .09$, $p = .030$		
Verbal intelligence	.02	.844
Figural intelligence	.22	.042
Spontaneous focusing on color	-.09	.434
Obtaining mathematical information	.02	.876
Processing of mathematical information	.19	.090
Motivational tendencies	.23	.047

Note. Significant results are highlighted in bold.

For mathematical achievement, both verbal and figural intelligence were significant predictors in the first step, explaining 38% of the variance (see Table 3). When the three MCOM factors were included in the second step, both verbal intelligence and figural

intelligence remained significant predictors. Additionally, motivational tendencies also reached significance, whereas processing of mathematical information did not, together explaining 58% of the variance.

Table 3

Multiple Linear Hierarchical Regression Model for Mathematical Achievement Predicted From the Control Variables (Verbal Intelligence, Figural Intelligence, Spontaneous Focusing on Color) and MCOM (Obtaining, Processing, Motivation)

Variable	β	p
Mathematical achievement		
Model 0, $Adj. R^2 = .38, F(3, 78) = 17.40, p < .001$		
Verbal intelligence	.49	< .001
Figural intelligence	.31	< .001
Spontaneous focusing on color	-.05	.602
Model 1, $Adj. R^2 = .57, F(6, 75) = 18.74, p < .001, R^2_{Change} = .20, p < .001$		
Verbal intelligence	.36	< .001
Figural intelligence	.16	.044
Spontaneous focusing on color	-.06	.499
Obtaining mathematical information	.04	.641
Processing of mathematical information	.14	.090
Motivational tendencies	.42	< .001

Note. Significant results are highlighted in bold.

Discussion

In the present study, we reviewed and empirically tested the concept of the mathematical cast of mind (MCOM), proposed by Krutetskii over 50 years ago, as a core characteristic of mathematical achievement. First, we tested whether adults’ performances on tasks conceptually linked to MCOM are positively correlated and form a single factor. In an exploratory factor analysis, we did not find such a factor but observed the three theoretically proposed components: obtaining mathematical information, processing of mathematical information, and motivational tendencies. Second, we examined whether these three components are associated with mathematical abilities beyond verbal and figural intelligence. Hierarchical multiple linear regressions revealed a differentiated picture for arithmetic fluency and mathematical achievement. Only motivational tendencies significantly predicted arithmetic fluency and mathematical achievement; processing of mathematical information did not reach significance even though showing small effects. Obtaining mathematical information did not have any influence on arithmetic fluency or mathematical achievement.

Structure of MCOM

There are several potential reasons why, contrary to our initial predictions, we did not find one general factor of MCOM. One possible explanation relates to the way we interpreted the theoretical model. We chose to see MCOM as a general, overarching factor. But there are also interpretations of Krutetskii's work that could lead to different conclusions. Krutetskii outlined the structure of mathematical abilities by identifying four main aspects: 'obtaining mathematical information' as the first aspect, 'processing mathematical information' as the second, 'retaining mathematical information' as the third, and a 'general synthetic component: mathematical cast of mind'. This framework allows for the interpretation of MCOM as an independent factor rather than a general overarching factor including the three other components. This alternative interpretation has been adopted by Bakker et al. (2022), who operationalized MCOM solely through the ATN task. Krutetskii (1976, p. 351), however, also emphasized that 'these components are closely interrelated, influencing one another and forming in their aggregate a single integral system, a distinctive syndrome of mathematical giftedness, the mathematical cast of mind'. This assertion supports our decision to consider MCOM as a general factor, as it highlights the interconnectedness of the components within the structure of giftedness.

Another reason for the lack of an overarching factor of MCOM could be that we did not assess all components of Krutetskii's model. As noted above, another component in Krutetskii's model is 'retention of mathematical information', which occurs after the information has been obtained and processed. However, retaining mathematical information is not merely a matter of memorizing symbols and numbers, rather it involves a generalized memory for mathematical relations, types of properties, argument schemes, proofs, and methods of problem solving. For now, this aspect has not been included because there is very little empirical evidence that the concept of retaining mathematical information, as defined by Krutetskii, is important for achievement in mathematics. Most studies on memory in mathematics focus on the conceptually different working memory or short-term memory (see Breit et al., 2025, for a review). Furthermore, it is debatable whether how mathematical information is stored can be considered a predictor of achievement in mathematics or whether it should be considered a criterion of mathematical knowledge. Nevertheless, future studies should attempt to operationalize this component and include it in the full MCOM model.

Our operationalization of the first component of MCOM may provide another explanation for our findings. Compared to the other two factors, the factor obtaining mathematical information performed rather badly. First, SFON and ATN had low sampling adequacy (MSA) values (.36 and .39, respectively), whereas all other variables had MSA values above .50. Typically, variables with MSA values lower than .50 are excluded from factor analysis, as low values may indicate that the variables do not represent the same construct (Lorenzo-Seva & Ferrando, 2021). However, because one of our primary aims

was to examine which variables in our model capture shared variance, we retained SFON and ATN in the analysis (results excluding SFON and ATN can be found in the OSF project). Second, this concern is further reflected in the non-significant correlation between SFON and ATN ($r = .20$) and their relatively low factor loadings. Third, neither SFON nor ATN correlated significantly with any of the other variables (see [Table A1](#) in the Appendix). The factor representing the ability to obtain mathematical information correlated negatively, albeit non-significant, with motivational aspects ($r = -.06$) and processing of mathematical information ($r = -.13$). These points should be considered when interpreting findings related to this factor. Additionally, our measurements of obtaining mathematical information may have captured only a limited aspect of a potentially broader spectrum. While the literature on spontaneous focusing tendencies originally centered on numerosity, more recent research has extended this to include a focus on numerical order and quantitative relationships ([Harju et al., 2024](#); [McMullen et al., 2019](#)). Furthermore, the literature on mathematical experts highlights that recognizing patterns in various contexts, not just in terms of numerosity, is an essential component of high achievement ([Mehta et al., 2016](#); [Meier et al., 2023](#)). Therefore, future studies should consider expanding the concept of obtaining mathematical information beyond numerosity to include other aspects of mathematics, such as the recognition of patterns, which are often describe as fundamental for mathematical thinking and learning ([Fyfe et al., 2017](#); [Vogel, 2005](#)).

Furthermore, future studies should aim to select tasks that theoretically cover all subcomponents and that use different assessment modes within each subcomponent, as this is a limitation of the current study. SFON and ATN are both forced-choice tasks, while flexibility, fluency, and originality are based on open-ended tasks, and motivational tendencies are based on Likert rating scales. Therefore, tasks within each factor share a common method, while the methods vary systematically across factors. Consequently, the factors may be construed not only because they reflect a shared theoretical or cognitive construct, but also because they share common assessment methods. However, this common method bias can lead to biased estimates of the reliability and validity of latent variables. Unfortunately, post hoc statistical methods to control for common method bias are not yet promising ([Podsakoff et al., 2024](#)). This highlights the importance of taking common method bias into account when selecting tasks for future studies.

Finally, as this study is the first attempt to measure MCOM in adults, we focused on a general student population. It should be noted, however, that while a few participants were from STEM fields, the majority were Psychology students. Additionally, relative to the overall adult population, our sample was highly educated and likely underrepresented the lowest-performing and the highest-performing individuals of mathematical ability, given that participants did not have a math-focused background. Future studies should aim to include larger and more diverse samples. Additionally, since the concept of MCOM was designed to explain high achievement in mathematics, our originally

proposed model may hold true if restricted to gifted individuals. Thus, future research should investigate MCOM using different populations. This could include individuals from a broader range of backgrounds, from those with dyscalculia to gifted students. Furthermore, many Fields Medal laureates, who are considered the mathematical equivalent of Nobel Prize winners, describe mathematics as omnipresent and a constant, intuitive facet of their lives (Mehta et al., 2016). This could be interpreted as seeing the world through mathematical eyes and having a MCOM. Therefore, an empirical comparison between mathematics experts and experts in non-mathematical subjects along dimensions of MCOM would be desirable.

Predictive Value of MCOM

Based on the results from the EFA we examined how the three factors, obtaining mathematical information, processing of mathematical information, and motivational tendencies, predicted arithmetic fluency and mathematical achievement, with verbal and figural intelligence included as control variable. Our analysis revealed a differentiated picture for arithmetic fluency and mathematical achievement. Overall, the model explained 20% of the variance in arithmetic fluency and 57% of the variance in mathematical achievement. This is consistent with the MCOM model, which aims to explain mathematical giftedness—a construct characterized by high mathematical achievement but not necessarily high arithmetic fluency (Sipahi & Bahar, 2024). Additionally, intelligence is known to be more strongly related to more complex mathematical tasks (Peng et al., 2019), which aligns with the observed pattern of explained variance, as the items used in our mathematical achievement questionnaire are more complex compared to the arithmetic fluency task. The MCOM factors accounted for an additional 20% of the variance in mathematical achievement, but only 9% in arithmetic fluency, further supporting these theoretical considerations. Notably, only motivational tendencies significantly predicted both arithmetic fluency and mathematical achievement, whereas the factors representing the obtaining and processing of mathematical information did not.

Contrary to our expectations, the first factor, obtaining mathematical information could not predict either arithmetic fluency or mathematical achievement. This is regardless whether one uses the latent factor, or the two manifest variables SFON and ATN (this can be also found in the OSF project). This contrasts with findings of both Ben-Shachar et al. (2020) and Mazzocco et al. (2020). Ben-Shachar and colleagues (2020) examined data from 77 undergraduate students and assessed participants' mathematical performance by having them report their quantitative reasoning scores from their college entrance exam. This exam measures an individual's ability to use numbers and mathematical knowledge to solve quantitative problems presented in both verbal and visual (e.g., tables, graphs) formats. A logistic regression analysis demonstrated that individuals with higher mathematical ability were more likely to focus on the numerosity of the stimuli in the SFON task. Mazzocco et al. (2020) examined the relationship between the

ATN task and measures of math performance in a sample of 90 undergraduate students. Participants completed an arithmetic fluency task, and the authors collected data from a standardized college entrance exam measuring mathematical problem-solving. While they found a positive association with mathematical achievement ($r = .25$), no significant correlation emerged for arithmetic skills ($r = -.03$). In contrast, Bakker et al. (2022) compared high-achieving children in mathematics with average achievers in the ATN task and found no difference in performance between both groups. Additionally, the ATN was not correlated with performance in two other mathematics-specific tasks. However, it is important to consider that when comparing our findings to those from children and adolescents, SFON and ATN may be subject to developmental changes. While a meta-analysis examining the relationship between SFON and mathematical performance (Li et al., 2025) found this association to be stronger in older children and adolescents, no studies involving adults were included. Thus, it is challenging to draw firm connections to our work.

Surprisingly, we did not find a significant positive relationship between the second factor, processing of mathematical information, where we used divergent thinking tasks as a proxy, and mathematical achievement. A substantial body of evidence demonstrates that mathematical creativity is linked to mathematical achievement in both children and adults. A meta-analysis by Bicer et al. (2021) reported a positive correlation between mathematical creativity and mathematical achievement in children and adolescents, studies involving adults have shown similar results (e.g., Meier et al., 2021). Furthermore, creativity is often intrinsically linked to giftedness in both domain-general and domain-specific models of giftedness (Kaufman & Sternberg, 2019; Sriraman et al., 2013). Empirical evidence has also shown that mathematically gifted children often outperform their typically developing peers in mathematical creativity tasks (Kroesbergen & Schoevers, 2017). Despite finding small effects ($\beta = .19$ and $.14$), they were not significant in our multiple regressions. While our regression analysis included only the combined creativity score (flexibility, fluency, and originality), flexibility had the strongest factor loading. This pattern, in which flexibility shows stronger loadings on an overarching factor of mathematical creativity compared to fluency and originality, has also been reported by others (e.g., Kattou et al., 2013). It aligns with the research of Bakker et al. (2022), which demonstrated that high-achieving children scored higher on tasks assessing flexibility in mathematical processing compared to average-achieving children. Furthermore, this finding aligns with our expectations regarding the significance of flexibility, as supported by literature emphasizing the importance of mathematical flexibility for mathematics (Hickendorff et al., 2022; Newton et al., 2020). Additionally, when examining the full correlation matrix (see Table A1 in the Appendix), flexibility correlated more strongly with mathematical achievement ($r = .42$) compared to fluency ($r = .27$) and originality ($r = .21$).

While we have chosen to consider flexibility, fluency and originality, assessed with divergent thinking tasks as one aspect of how individuals process mathematical information, [Krutetskii \(1976\)](#) proposed several other aspects. Among these, he discusses the reversibility of mental processes in mathematical reasoning, which allows individuals to switch from a direct to a reverse train of thought, an ability that, in our opinion, also requires flexibility. Another aspect worth investigating in future studies is the elegance of solutions, characterized by the pursuit of clarity, simplicity, economy, and rationality of solutions. This quality has not only been identified as a characteristic of high-achieving children ([Bakker et al., 2022](#)), but professional mathematicians also cite aesthetic aspirations and striving for mathematical beauty as driving force for their work ([Mehta et al., 2016](#); [Sa et al., 2024](#)). Thus, future studies on MCOM should broaden the ways in which the processing of mathematical information is assessed.

The third factor, motivational tendencies, was the strongest predictor of arithmetic fluency and mathematical achievement, even when verbal and figural intelligence and the two other factors of the MCOM were included. [Krutetskii \(1976\)](#) emphasized the importance of personality factors, such as motivation, attitudes, and interest, for mathematical performance. These aspects were addressed in our questionnaires on interest in mathematics, mathematical self-concept, and domain-specific need for cognition. Our findings are consistent with empirical studies that link motivational aspects and mathematical achievement ([Schukajlow et al., 2023](#); [Strobel et al., 2024](#)). [Breit et al. \(2025\)](#) conducted an extensive review of meta-analyses that summarized the extent to which various learner characteristics influence mathematical achievement. In addition to knowledge, skills, and aptitude, the authors examined personality traits, such as non-cognitive personality traits, attitudes, and emotional and motivational variables. Mathematical self-concept had the strongest effect size of all personality variables ($r = .43$), even having a larger effect on mathematical achievement than many cognitive abilities. This strong influence is assumed to be caused by the reciprocal relationship between achievement and self-concept. High levels of achievement foster a more positive self-concept, which encourages greater engagement with the subject and results in higher achievement. But also enjoyment of mathematics ($r = .31$) and attitudes toward mathematics ($r = .12$) were positively associated with mathematical achievement ([Breit et al., 2025](#)). As shown in [Table A1](#) in the Appendix, in our study self-concept, interest, and NFC all showed strong relationships with arithmetic fluency ($r = .31 - .38$) and mathematical achievement ($r = .52 - .57$).

It is worth mentioning that among the control variables, figural intelligence was a significant predictor of both arithmetic fluency and mathematical achievement. This link has been consistently reported throughout the literature (e.g., [Breit et al., 2025](#)), probably reflecting the role of visual-spatial skills in mathematical problem-solving and the ability to manipulate abstract concepts ([Atit et al., 2022](#)). Verbal intelligence also contributed to mathematical achievement, likely due to the task demands. Unlike the arithmetic

fluency task, the mathematical achievement task involved a variety of mathematical problems, many of which were presented in a verbal format. Previous studies have also demonstrated the role of verbal intelligence in higher mathematical achievement (e.g., Berkowitz & Stern, 2018). However, it should be noted that, due to time constraints, we only used one task to assess verbal and figural intelligence instead of the three tasks stated in the manual. Therefore, our scores only provide a rough estimate of verbal and figural intelligence, and future studies should aim to assess verbal and figural intelligence more comprehensively.

Conclusion

In conclusion, while this study does not provide evidence for a general MCOM factor in our adult sample, it underscores the significance of factors such as motivation and cognitive flexibility, in contributing to mathematical achievement beyond verbal and figural intelligence. Further research is needed to explore whether these findings hold true in samples of high-achievers and gifted individuals, as proposed by Krutetskii. Nevertheless, the current work provides a solid starting point to empirically test the model of MCOM and to critically evaluate whether it is a reliable construct that can predict high mathematical achievement or merely a term used to describe mathematically gifted individuals.

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Data Availability: All data as well as the analysis script are openly available in the OSF project (<https://osf.io/gc9wy/>). The material will be made available upon request.

Supplementary Materials

The Supplementary Materials contain all data as well as the analysis script (see Meier, 2025S).

Index of Supplementary Materials

Meier, M. A. (2025S). *Frequently cited but seldomly actually measured: The mathematical cast of mind* [Research data and analysis script]. OSF. <https://osf.io/gc9wy/>

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Appendix

Table A1
Pearson Correlations for All Measurements Without Correction for Multiple Comparisons

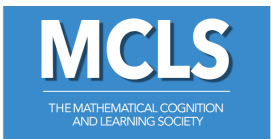
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. SFON	—																
2. ATN	.20	—															
3. Obtaining mathematical information	.69***		—														
4. Flexibility	-.21	.25*	-.15	—													
5. Fluency	-.13	-.05	-.54***	.44***	—												
6. Originality	-.04	.16	.10	.60***	.20	—											
7. Processing of mathematical information	-.19	.29*	-.13	.95***	.53***	.76***	—										
8. Interest	-.05	.11	-.05	.23*	.20	.15	.30**	—									
9. Self-concept	-.11	.11	-.16	.23*	.26*	.18	.35***	.73***	—								
10. Need for cognition	.01	.07	.09	.17	.05	.19	.18	.71***	.61***	—							
11. Motivational tendencies	-.07	.13	-.06	.29**	.23*	.18	.36**	.94***	.87***	.85***	—						
12. Arithmetic fluency	.10	.16	.04	.32**	.22*	.22*	.36**	.31**	.37***	.31**	.38***	—					
13. Mathematical achievement	-.01	.21	-.01	.42***	.27*	.21	.44***	.56***	.57***	.52***	.63***	.52***	—				
14. Numerical intelligence	-.07	.15	-.09	.42***	.30**	.18	.43***	.54***	.52***	.47***	.59***	.56***	.64***	—			
15. Verbal intelligence	.01	.17	.08	.24*	.05	.18	.25*	.21	.30**	.29**	.29**	.18	.55***	.32**	—		
16. Figural intelligence	.22*	.21	.13	.26*	.27*	.19	.30**	.24*	.28**	.30**	.31**	.37***	.40***	.34**	.18	—	
17. Spontaneous focusing on color	-.59***	-.19	-.41***	-.01	-.02	-.20	-.08	-.04	-.05	-.01	-.04	-.14	-.10	-.05	-.06	-.08	—

Note. Latent factors variables are italicized.

Table A2
Descriptive Statistics for All Variables

Variable	M	SD	Range
Spontaneous focusing on number	7.01	6.96	0 – 23
Attention to numbers	5.02	3.19	0.5 – 16
<i>Obtaining mathematical information</i>	0	1.00	-2.11 – 2.58
Flexibility	4.03	1.10	1 – 6.5
Fluency	12.54	5.34	1 – 31
Originality	1.50	0.29	0.6 – 2.23
<i>Processing of mathematical information</i>	0	1.00	-3.23 – 2.28
Interest	2.47	0.76	1 – 4
Self-concept	2.79	0.94	1 – 4
Need for Cognition	4.17	1.14	1.62 – 6.44
<i>Motivational tendencies</i>	0	1.00	-2.26 – 1.95
Arithmetic fluency	62.57	25.13	12 – 122
Mathematical achievement	18.93	7.21	5 – 31
Numerical intelligence	14.71	4.84	3 – 20
Verbal intelligence	11.26	3.10	3 – 17
Figural intelligence	11.22	4.56	1 – 20
Spontaneous focusing on color	4.56	2.65	0 – 8

Note. Latent factors variables are italicized.



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