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Task Features Change the Relation Between Math Anxiety and Number Line Estimation Performance With Rational Numbers: Two Large-Scale Online Studies

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Math performance is negatively related to math anxiety (MA), though MA may impact certain math skills more than others. We investigated whether the relation between MA and math performance is affected by task features, such as number type (e.g., fractions, whole numbers, percentages), number format (symbolic vs. nonsymbolic), and ratio component size (small vs. large). Across two large-scale studies (combined $n = 3,822$), the MA-performance relation was strongest for large whole numbers and fractions, and stronger for symbolic than nonsymbolic fractions. The MA-performance relation was also stronger for smaller relative to larger components, and MA relating to specific number types may be a better predictor of performance than general MA for certain tasks. The relation between MA and estimation performance changes depending on task features, which suggests that MA may relate to certain math skills more than others, which may have implications for how people reason with numerical information and may inform future interventions.

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The study design, hypotheses, and analytic plan were preregistered on OSF (https://osf.io/zygk8) and have not been disseminated prior to this manuscript. The data and materials for the parent studies are available on OSF (https://osf.io/e6pgh), as is the code for analyses.

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Public Significance Statement

Math anxiety is a well-documented obstacle to math achievement. The extent to which math anxiety relates to performance on tasks assessing the understanding of numerical magnitude may change depending on task features. Across two pre-registered studies, the relation between math anxiety and performance was strongest for large whole numbers and fractions compared to other rational number types, stronger for symbolic than nonsymbolic fractions, and stronger for small-relative to large-component fractions. These findings contribute to a more nuanced understanding of the relation between math anxiety and different aspects of numerical magnitude understanding. Math anxiety may relate to certain aspects of numerical magnitude understanding more than others, which has implications for developing more targeted educational interventions and for designing accurate assessments of mathematical understanding.

Keywords: math anxiety, rational numbers, number-line estimation, nonsymbolic comparison

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Adults use mathematics constantly in their everyday lives. As with young children, math performance in adulthood encompasses a wide range of skills with different complexity levels, ranging from being able to choose the most efficient line in a grocery store (weighing the relative number of people in each line and the approximate number of items in their carts) to accurately finding a place in line according to an assigned number (as when lining up to board a plane), to being able to quickly compute a tip after a meal. Unsurprisingly, there are large individual differences among adults in math performance (Dowker, 2019a). These individual differences are related to not only variability in practice, strategy use, and cognitive skills, but also to affective processes (Batchelor et al., 2019), such as math anxiety (MA)—the feeling of tension, fear, or apprehension toward mathematics.

Math Anxiety

Math performance and MA are negatively related (Dowker, 2019b; Mammarella et al., 2019; Richardson & Suinn, 1972; see meta-analyses by Hembree, 1990; Ma & Kishor, 1997; Namkung et al., 2019). A recent meta-analysis found a small-to-moderate, but statistically reliable, correlation between MA and math performance ($r = -.28$, Barroso et al., 2021). In general, people with higher math anxiety have, or are at risk of having, lower math performance (Barroso et al., 2021; Soltanlou et al., 2019); however, the direction of association remains unclear because it is difficult to disentangle whether high MA causes lower math performance or vice versa.

Over the past 40 years, several accounts of the directionality of the relation and the mechanism underlying the relation between MA and math performance have been proposed (Ashcraft, 2019; Barroso et al., 2021; Ramirez et al., 2018). According to the Disruption Account, math anxiety leads to worry and anxious ruminations that reduce available resources of the working memory system that can be allocated toward the math task (Eysenck & Calvo, 1992; see also Ashcraft & Kirk, 2001; Beilock & DeCaro, 2007; Eysenck, 1997, 2013; Hopko et al., 1998; Lee & Cho, 2018; LeFevre et al., 2005). According to the Reduced Competency Account, MA relates to, and possibly results from, a deficiency of basic as well as advanced math skills (Maloney et al., 2010; see also: Maloney & Beilock, 2012; Maloney et al., 2011; Nuñez-Peña & Suárez-Pellicioni, 2014). Finally, the Interpretation Account proposes that it is an individual's appraisal of previous math experiences as indicators of lack of math ability that leads to math anxiety (Ramirez et al., 2018; see also Jamieson et al., 2016; Meece et al., 1990; Park et al., 2014). There is empirical evidence supporting each theory, and they are not necessarily mutually exclusive (Ashcraft, 2019); the goal of this research is not to take a stand in favor of any theory, specifically. However, in the discussion, we return to these theories to aid in the interpretation of our findings.

There is some evidence that MA may be more strongly related to particular aspects of mathematics, such as specific subdomains or components of math, or specific math tasks or difficulty level of the math task (Dowker, 2019b). For example, there is some evidence to suggest math anxiety mostly arises in the context of complex or unfamiliar math tasks (Maloney & Beilock, 2012). Existing research on MA and math performance has primarily focused on numerical aspects of mathematics (Dowker, 2019b); yet, it remains unclear whether the association between math anxiety and math task performance varies depending on task features, such as number type (e.g., fractions, whole numbers, percentages; Mielicki, Fitzsimmons, et al., 2022; Sidney et al., 2021), component size (e.g., large [15/30] vs. small [½]; Fitzsimmons et al., 2020a; Fitzsimmons & Thompson, 2022), and number format (e.g., symbolic vs. nonsymbolic; Fazio et al., 2014). Here, we investigate the extent to which the relation between math anxiety and math performance is modulated by numerical task features.

Numerical Task Features Impact Affective Responses to Math

Specific features of numbers in a given math task, such as number type (e.g., fractions, whole numbers, etc.) and component size (e.g., 1/5 is a small-component fraction relative to the large-component fraction, 60/300) may relate to adults' feelings of anxiety when solving a problem. Prior studies have demonstrated that manipulating features of tasks that make problems seemingly more complex (e.g., by using fractions rather than whole numbers; using large-component fractions rather than smaller ones) elicits affective responses that are related to MA. For example, adults and children endorse liking whole numbers more than percentages and fractions (Mielicki, Schiller, et al., 2022; Sidney et al., 2021). Even educators with years of experience teaching fraction content report more anxiety about fractions than other math content (Mielicki et al., 2022). People also report lower confidence for large-component relative to

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small-component fractions and rate their familiarity higher for small-component relative to large-component fractions (Fitzsimmons et al., 2020b). The relation between MA, as an affective response to math, and types of numbers may follow a similar pattern and vary depending on number type, which may have implications for the link between MA and math performance. In the present study, we test how task features (number type, format, and component size) impact the relation between MA and performance on numerical tasks.

Numerical Task Features Impact Math Performance

Math is a complex, multidimensional skill, encompassing highly diverse subdomains. Investigating specific mathematical skills is essential to obtain a deeper, more nuanced understanding of the precise role of affective processes, such as MA, the association between MA and math performance, and the potential influence of numerical task features on this association. The current study focuses on the number-line estimation (NLE) task, which is the "gold standard" for assessing the understanding of the relative magnitude of rational numbers (Thompson, Sidney, et al., 2022). NLE performance is strongly associated with important math outcomes (Fazio et al., 2014; Siegler et al., 2011; Siegler & Pyke, 2013; Siegler & Thompson, 2014; Xing et al., 2021). In addition, adults' NLE performance has been shown to relate to their ability to solve health-related ratio problems, such as comparing COVID-19 to the common flu by considering deaths relative to cases for each disease (Fitzsimmons et al., 2022; Thompson et al., 2021), and being able to solve such problems may have implications for health cognition (Mielicki, Fitzsimmons, et al., 2022). Although performance on NLE tasks and MA are negatively correlated (Fitzsimmons & Thompson, 2022; Lau, Wilkey, et al., 2022; Maloney et al., 2011; Sidney et al., 2021; Sidney, Thalluri, et al., 2019; Thompson et al., 2021), the relation between NLE and MA has not been explored for magnitude understanding across different types of rational numbers.

NLE tasks have been used to assess rational number magnitude understanding across various numerical ranges for whole numbers (Fitzsimmons et al., 2021; Landy et al., 2013; Siegler & Booth, 2004; Siegler & Opfer, 2003; Siegler & Ramani, 2009; Thompson & Opfer, 2010; Thompson & Siegler, 2010; Wall et al., 2016) and fractions (Sidney et al., 2021; Sidney, Thalluri et al., 2019; Sidney, Thompson, & Opfer, 2019; Siegler et al., 2011; Siegler & Thompson, 2014; Thompson et al., 2021, 2022). Children are less accurate when placing fractions on number lines than when placing whole numbers (Fazio et al., 2014), and more accurate for both fractions and whole numbers up to 1,000 compared to whole numbers up to 100,000 (Fitzsimmons & Thompson, 2022). Adults with lower prior knowledge of equivalence (i.e., two magnitudes are equal) were less precise when estimating large-component relative to small-component equivalent fractions (Fitzsimmons et al., 2020a) than adults with higher prior equivalence knowledge. Overall, NLE performance varies depending on the type of number being estimated and the size of the components of rational numbers. However, no existing work has examined how these task features impact the relation between MA and performance on NLE tasks.

Number format, whether numbers are presented symbolically (i.e., as Arabic digits) or nonsymbolically (e.g., as ratios of dot arrays or line segments), has also been found to impact performance on other math tasks. For example, people take longer to compare pairs of symbolic fractions than pairs of nonsymbolic fractions (Kalra et al., 2020; Matthews & Chesney, 2015). Prior work has shown a stronger association between MA and symbolic number processing than nonsymbolic number processing (e.g., Braham & Libertus, 2018; Colomé, 2019; Dietrich et al., 2015; Starling-Alves et al., 2022). Thus, number format may also impact MA, if symbolic tasks recruit different working memory resources than nonsymbolic tasks (van't Noordende et al., 2021; Xenidou-Dervou et al., 2015), or if people perceive nonsymbolic tasks to be less "math-like" than symbolic tasks due to their lack of numbers.

The Current Study

Task features influence people's NLE precision (Fazio et al., 2014; Wall et al., 2016), confidence, attitudes, and sense of familiarity. Given that task features impact reasoning as well as affective responses, these features may also impact the relation between MA and math performance. In the current research, we investigate the extent to which task features change the relation between MA and number line estimation performance. Specifically, in two large-scale studies (combined $N = 3{,}822$), we investigated, on the one hand, the impact of three numerical task features (i.e., number type, number format, and component size) on the relation between MA and math performance, and, on the other hand, how adults' general math anxiety and anxiety about specific types of numbers was associated with performance on different number line estimation tasks. A more nuanced understanding of the specific impact of MA on different aspects of numerical magnitude understanding is critical because MA poses a significant obstacle to realizing the full potential of one's math skill development (Dowker et al., 2016).

We conducted preregistered secondary data analyses on two large samples of adults (Study 1: Lau, Wilkey, et al., 2022; Study 2: Thompson et al., 2021). In Studies 1 and 2, we investigated the following research questions: (RQ1) Does the relation between MA and performance vary by number type (e.g., fractions, whole numbers, percentages, etc.)? (RQ2) Does the relation between MA and performance vary for symbolic versus nonsymbolic fractions? And (RQ3) Does the relation between MA and performance on fraction estimation problems vary by component size? Additionally, in Study 2, we also investigated whether the relation between MA and NLE performance varied depending on whether the MA measure aligned with the behavioral measure (RQ4) by testing whether number-specific MA was a stronger predictor than general MA for whole-number and fraction NLE performance. This research question was motivated by prior work demonstrating that the relation between attitudes and specific behaviors is stronger when the attitude measure and the behavior are measured with similar specificity (e.g., Pajares, 1996).

Study 1

In Study 1, we performed a secondary data analysis on the dataset from Lau, Wilkey, et al. (2022) investigating the effects of mathematical understanding on attitudes and behaviors toward COVID-19.

Method

Transparency and Openness

The survey flow of all measures is included in the supplemental materials, which are available on the open science framework (OSF; https://osf.io/e6pgh), and question wording for all survey items is available on the OSF page for the project (see the author note). The data and analytic code are also available on the OSF page for the project.

Participants

A large dataset of adults ($N = 2{,}124$), recruited through Qualtrics panels, was used in the current secondary data analyses (Lau, Wilkey, et al., 2022). Participants from Canada, the United States, and the United Kingdom were recruited in December 2020 and were stratified by age, gender, and educational attainment (see Table A1 for demographic characteristics). After data cleaning according to preregistered exclusion criteria (for full details see "Exclusion Criteria and Outlier Identification" and "Missing Data" from Lau, Wilkey, et al., 2022), the final analytic sample was 2,032 participants. Participants were excluded when they (a) had multiple submissions, (b) indicated that they were not serious when completing the survey, (c) incorrectly answered more than one attention check question (e.g., "This is an attention check, please select answer 3 for this item;" Barends & de Vries, 2019), (d) had more than 25% missing data from selecting "prefer not to answer," or (e) indicated that they were vaccinated or participated in a COVID-19 vaccination trial. Additionally, poor responders on the number-line estimation tasks, defined as participants with a median absolute deviation of their estimates below 0.10, were excluded from the final analyses.

Tasks and Procedure

The online Qualtrics survey administered in Lau, Wilkey, et al. (2022) took approximately 20 min to complete and included four sections: demographics, basic numeracy, COVID-19 health numeracy, and COVID-19 health-related attitudes and behaviors. First, participants completed the consent form followed by a section about demographics and other cultural variables. Then, they completed the basic numeracy, COVID-19 health numeracy, and COVID-19 health-related attitudes and behaviors sections. The order of these three sections was randomized across participants. Details of sampling and data collection procedures are available on OSF: https://osf.io/xj874/ . For the purpose of the current study, only the demographics and basic numeracy sections were analyzed. Below, we discuss only the measures used to test our specific research questions.

Demographics. Participants reported their anxiety from 1 = *not anxious* to 10 = *very anxious* for two items pertaining to trait anxiety, and MA. The one-item MA measure has been shown to be strongly correlated with longer MA scales (Ashcraft, 2002; Hart & Ganley, 2019; Núñez-Peña et al., 2014). The primary predictor of interest, MA, was assessed with the question: "How anxious do you feel when you are expected to do math?" Trait anxiety was assessed with the question: "How anxious were you in general, before the COVID-19 pandemic?" Participants indicated their gender by selecting one of the following options: male, female, nonbinary, prefer not to disclose, or prefer to self-describe. If participants selected to self-describe, they were prompted to do so in a separate text box. Participants also indicated their age, level of education ("How many years of schooling have you completed? (Including grade 1/Year 1 and onwards)," and country of residence (United States, U.K., or Canada).

Number Line Estimation Tasks. All participants completed the following number line estimation tasks: (a) nonsymbolic fractions, (b) large whole numbers (with 1,000 and 1,000,000,000 as endpoints), (c) percentages (with 0%–5% as endpoints), (d) fractions (with 0 and 5 as endpoints), and (e) whole-number frequencies (with 0 in 100 and 100 in 100 as endpoints). All tasks had acceptable internal consistency (Cronbach's α: whole number frequencies = .61, fractions = .75, whole numbers = .70, percentages = .60, and nonsymbolic fractions = .58). The number line estimation task types were presented in randomized blocks and individual items were randomized within those blocks across participants. The number-line estimation tasks featuring fractions and whole-number frequencies included items with either small (e.g., 1/9) or large (e.g., 63/45) numerator and denominator components (e.g., Braithwaite & Siegler, 2018a; Fitzsimmons et al., 2020a). For all tasks, participants estimated the location of a value on a number line. Estimation precision was operationalized as percent absolute error (PAE), the distance of the estimate from the exact value adjusting for the range of possible values (Siegler & Booth, 2004). PAE = ((|estimate − true value|)/numerical range) × 100. PAE was calculated separately for each number type (large whole numbers, percentages, whole-number frequencies, fractions, and nonsymbolic ratios). For fractions and whole-number frequencies, we also calculated PAE separately for small and large components.

Results

As preregistered (https://osf.io/e6pgh/?view_only=fbabbf180aef4915a1ff6c1ffb82abe9), we fit several linear mixed-effects models for item-level PAE using the lme4 package (Bates et al., 2012) in R (version 4.1.1; R Core Team, 2021), and p values were estimated using the lmerTest package (Kuznetsova et al., 2017). Models were fit using restricted maximum likelihood estimation. For all mixed-effects models reported below, we followed an approach recommended by Barr (2013) to simplify the random-effects structure when necessary. We first ran each model with the maximal random structure, including random intercepts at the subject and item levels as well as subject-level random slopes for MA. If the model failed to converge, we first fixed the correlation between slopes and intercepts to zero, then eliminated any by-subject random slopes, and finally eliminated by-item random intercepts. Parameters are evaluated with t-tests (for individual contrasts) and Type III F-tests (for multi-degree-of-freedom tests of model comparisons) using Satterthwaite's method for estimating degrees of freedom. To further evaluate contrasts and test the simple slopes for each level of the factor of interest, we used the emtrends function in emmeans (Lenth, 2020), which reports t-tests associated with individual contrasts with Satterthwaite's method for estimating degrees of freedom.

In addition to the predictors of interest, all models included the following preregistered covariates: country, gender, education level, age, and trait anxiety. Gender was dummy-coded with nonmales (i.e., females and one nonbinary participant) as the reference group. Country was dummy-coded with the United States as the reference group. Education level was dichotomized, and dummy-coded with "13 years or less" as the reference group. Since all models included higher-level interactions with MA, it was grand mean-centered so that lower-level relations could be interpreted. Trait anxiety and age were standardized such that $M = 0$ and $SD = 1$. Descriptives and correlations among measures in Study 1 can be found in Table 1, and the number of participants in each cell by gender, country, and dichotomized education can be found in Table A2.

As preregistered, we first tested whether MA differed by country in a one-way ANOVA. Indeed, country differences in MA were present in this data set, $F(2, 2{,}018) = 32.01$, $p < .001$. Participants in the United States reported lower MA ($M = 3.16$, $SD = 2.46$) than participants in

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Table 1
Means, Standard Deviations, and Correlations for All Measures in Study 1

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. NLE-WNF	0.12	0.11							
2. NLE-F	0.21	0.14	.25** [0.21, 0.29]						
3. NLE-P	0.10	0.10	.38** [0.35, 0.42]	.26** [0.22, 0.30]					
4. NLE-WN	0.20	0.14	.42** [0.38, 0.45]	.35** [0.31, 0.39]	.31** [0.27, 0.35]				
5. NLE-NS	0.18	0.14	.27** [0.23, 0.31]	.29** [0.25, 0.33]	.26** [0.22, 0.30]	.31** [0.27, 0.35]			
6. MA	3.81	2.63	.23** [0.18, 0.27]	.26** [0.22, 0.30]	.16** [0.12, 0.21]	.23** [0.19, 0.27]	.17** [0.13, 0.21]		
7. Trait anxiety	3.70	2.42	.14** [0.09, 0.18]	.13** [0.09, 0.17]	.10** [0.06, 0.14]	.19** [0.14, 0.23]	.16** [0.12, 0.20]	.45** [0.41, 0.48]	
8. Age	59.75	14.44	−.07** [−0.12, −0.03]	−.15** [−0.19, −0.11]	−.03 [−0.07, 0.01]	−.09** [−0.13, −0.04]	−.15** [−0.19, −0.11]	−.22** [−0.26, −0.17]	−.30** [−0.34, −0.26]

Note. NLE-WNF: Percent absolute error (PAE) for number line estimation using whole-number frequencies (with 0 in 100 and 100 in 100 as endpoints), NLE-F: PAE for number line estimationusing fractions (with 0 and 5 as endpoints), NLE-P: PAE for number line estimation using percentages (with 0%–5% as endpoints), NLE-WN: PAE for number line estimationusing large whole numbers (with 1,000 and 1,000,000,000 as endpoints), NLE-NS: PAE for number line estimationusing nonsymbolic fractions, MA: math anxiety (1–10 scale), Trait Anxiety: sum score of trait anxiety. PAE is a measure of error and higher values reflect less accurate estimates. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014).
$^*p < .05$. $^{**}p < .01$.

the U.K. ($M = 4.12$, $SD = 2.69$) and Canada ($M = 4.16$, $SD = 2.61$), who did not differ. Thus, the country was included as a covariate in all models for Study 1 reported below.[1] Consistent with prior research (Else-Quest et al., 2010), we observed gender differences[2] in MA with nonmales reporting higher MA than males, $t(1{,}966) = 11.00$, $p < .001$, Cohen's $d = 0.49$.

Does the Relation Between MA and Performance Vary by Number Type?

To test this question, we predicted PAE (i.e., performance on the number-line estimation tasks) from MA, number type (large whole numbers, whole number frequencies, fractions, and percentages), and their interaction while controlling for the covariates described above. We followed up the interaction by testing whether the effect of anxiety was significant for each of the number types. Number type was dummy-coded with fractions as reference. The model with by-subject random slopes failed to converge, so the final model included only subject- and item-level intercepts.

The interaction between MA and number type was significant, $F(3, 38{,}213) = 22.20$, $p < .001$ (see Table 2). The relation between MA and PAE was significant for all number types (fractions: $b = 1.07$, 95% CI [0.89, 1.25], large whole numbers: $b = 0.92$, 95% CI [0.74, 1.11], whole number frequencies: $b = 0.59$, 95% CI [0.41, 0.77], percentages: $b = 0.33$, 95% CI [0.11, 0.54]), with higher MA associated with higher PAE (Figure 1). However, contrasts of the simple slope effects revealed that the relation between MA and PAE was stronger for fractions than for whole-number frequencies, $b = 0.48$, $SE = 0.06$, $t(38{,}210) = 5.62$, $p < .001$, and percentages, $b = 0.75$, $SE = 0.10$, $t(38{,}210) = 7.18$, $p < .001$. In addition, the relation was stronger for large whole numbers than whole-number frequencies, $b = 0.33$, $SE = 0.09$, $t(38{,}225) = 3.70$, $p = .001$, and percentages, $b = 0.60$, $SE = 0.11$, $t(38{,}203) = 5.57$, $p < .001$, and for whole-number frequencies than percentages, $b = 0.27$, $SE = 0.10$, $t(38{,}213) = 2.56$, $p = .049$. Surprisingly, the relation was similar for fractions and large whole numbers, $b = 0.15$, $SE = 0.09$, $t(38{,}213) = 1.67$, $p = .343$.

Does the Relation Between MA and Performance Vary for Symbolic Versus Nonsymbolic Fractions?

To test this question, we predicted PAE from MA, number format (symbolic vs. nonsymbolic), and their interaction while controlling for

[1] We also ran exploratory models (not preregistered) with three-way interactions with country to examine whether the effects of number type, symbolic versus nonsymbolic fraction format, and component size on the relationship between MA and performance varied by country (see Tables A3–A5 in the Appendix). The only model that featured a significant interaction by country was the model for component size (RQ3). The significant interaction suggests that the strength of the relation between MA and performance varied by component size for participants in the UK, but for participants in the United States and CA, the relation did not reach significance. None of the models revealed significant two-way interactions for country and MA.

[2] We also ran exploratory models (not preregistered) with three-way interactions with gender to examine whether the effects of number type, symbolic versus nonsymbolic fraction format, and component size on the relationship between MA and performance varied by gender (see Tables A6 to A8 in the Appendix). None of the models revealed significant three-way interactions with gender, suggesting that, despite gender differences in MA, the relation between MA and math task performance varies by aspects of the problem similarly for males and nonmales.

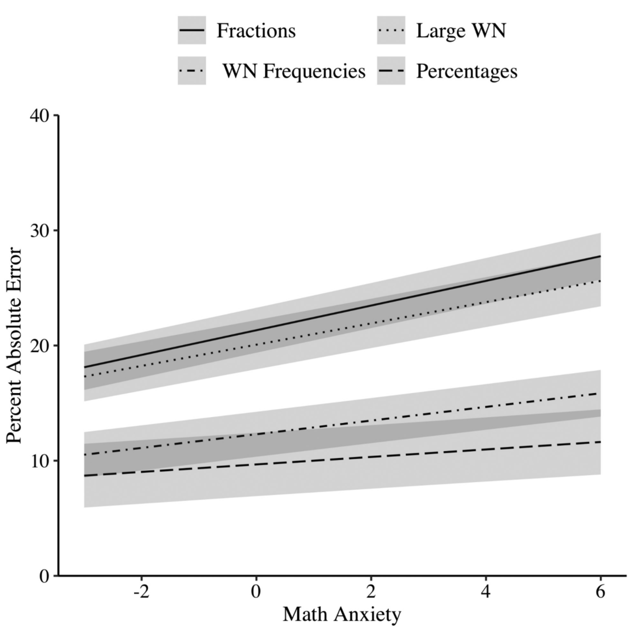
Table 2
Linear Mixed-Effects Models for Number Line Estimation With Different Number Types in Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	26.82 (2.00)	13.41***	18.09	Subject (intercept)	48.30
MA	1.07 (0.09)	11.60***	4,037.84	Item (intercept)	22.40
Type-WNF	−9.03 (2.74)	−3.29**	16.00	Residual	301.50
Type-P	−11.65 (3.36)	−3.47**	16.00		
Type-WN	−1.25 (2.88)	−0.44	16.00		
Gender	−3.83 (0.37)	−10.37***	2,011.19		
Country (CA)	1.94 (0.49)	3.98***	2,011.27		
Country (UK)	−1.04 (0.50)	−2.09*	2,010.53		
Education	−3.69 (0.40)	−9.31***	2,011.47		
Age	−0.71 (0.22)	−3.28**	2,011.34		
Trait anxiety	0.45 (0.20)	2.23*	2,011.82		
MA × Type-WNF	−0.48 (0.09)	−5.62***	38,210.24		
MA × Type-P	−0.75 (0.10)	−7.17***	38,209.83		
MA × Type-WN	−0.15 (0.09)	−1.66	38,212.76		

Note. Fractions, nonmales, the United States, and 13 years (of education) or less were the reference groups. MA = mean-centered math anxiety; Type-WNF = Main effect of whole-number frequencies (with 0 in 100 and 100 in 100 as endpoints) compared to fractions; Type-P = main effect of percentages (with 0%–5% as endpoints) compared to fractions; Type-WN = main effect of large whole numbers (with 1,000 and 1,000,000,000 as endpoints) compared to fractions; MA × Type-WNF = interaction of math anxiety and number type comparing whole-number frequencies to fractions; MA × Type-P = interaction of math anxiety and number type comparing percentages to fractions; MA × Type-WN = interaction of math anxiety and number type comparing large whole numbers to fractions.
*$p < .05$. **$p < .01$. ***$p < .001$.

the covariates described above. We followed up the interaction by testing whether the effect of anxiety was significant for each number format. Number format was coded with symbolic fractions as reference. The final model had maximal random structure with random slopes of format by subject as well as subject- and item-level intercepts.

Figure 1
Interaction Between MA and Different Types of Numbers (Fractions, Large Whole Numbers, Whole-Number Frequencies, and Percentages) in Study 1



Note. WN = whole numbers. Country, gender, education level, age, and trait anxiety were included as covariates. Math anxiety (MA) was grand-mean-centered. Error ribbons represent standard error of the effect.

The interaction between MA and number format was significant, $F(1, 2{,}002.54) = 7.42$, $p = .007$ (see Table 3). As can be seen in Figure 2, the relation between MA and number format was significant for both symbolic ($b = 1.04$, 95% CI [0.80, 1.27]) and nonsymbolic tasks ($b = 0.64$, 95% CI [0.38, 0.90]). However, the relation between MA and PAE was stronger for symbolic fractions than for nonsymbolic fractions, $b = 0.40$, $SE = 0.15$, $t(2{,}003) = 2.72$, $p = .007$).

Does the Relation Between MA and Performance on Whole-Number Frequency and Fraction Estimation Vary by Component Size?

In Study 1, whole number frequencies and fractions were presented with either small (e.g., “1 in 9” or 4/7) or large (e.g., “80 in 96” or 63/45) numerical components. To investigate whether the relation between MA and number line estimation performance varied by component size, we first fit a model that included the three-way interaction between MA, number type (whole number frequencies, fractions), and component size (small, large) as a predictor as well as all main effects. Both number type and component size were dummy-coded, and fractions and small components were reference groups. The model with by-subject random slopes failed to converge, so the final model included only subject- and item-level intercepts. The three-way interaction was not significant, so we reran the model collapsing across tasks (see Figure 3), with MA, component size, and their interaction as predictors, along with the covariates.

The model with maximal random structure failed to converge, so the final model included only subject- and item-level random intercepts. The interaction between MA and component size was significant (see Table 4), so we followed up the interaction by testing whether the effect of anxiety was significant for each component size. As can be seen in Figure 3, the relation between MA was significant for both small, $b = 0.98$, 95% CI [0.79, 1.16], and large components, $b = 0.74$, 95% CI [0.55, 0.93], with higher MA

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Table 3
Linear Mixed-Effects Models for Number Line Estimation With Symbolic and Nonsymbolic Fractions in Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	26.39 (1.81)	14.62***	9.38	Subject (intercept)	121.90
MA	1.04 (0.12)	8.53***	2,201.46	Format|Subject	147.60
Format	−1.77 (2.92)	−0.61	7.12	Item (intercept)	16.70
Gender	−2.75 (0.50)	−5.55***	2,003.61	Residual	284.50
Country (CA)	−1.51 (0.65)	−2.30*	2,001.08		
Country (UK)	−0.58 (0.67)	−0.86	1,997.33		
Education	−4.28 (0.53)	−8.06***	2,002.97		
Age	−1.67 (0.29)	−5.77***	1,995.35		
Trait anxiety	0.39 (0.27)	1.42	2,000.63		
MA × Format	−0.40 (0.15)	−2.72**	2,002.55		

Note. Symbolic fractions, nonmales, the United States, and 13 years (of education) or less were the reference groups; MA = mean-centered math anxiety.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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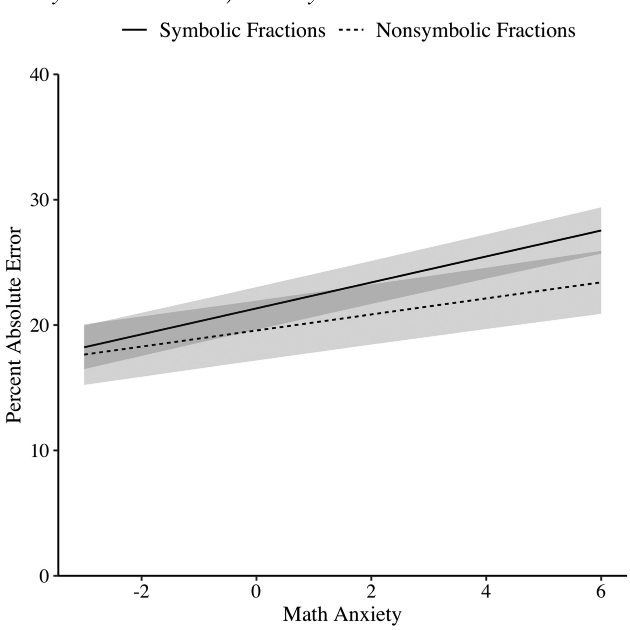
associated with higher PAE. However, the relation between MA and PAE was stronger for small compared to large components, $b = 0.23$, $SE = 0.09$, $t(22{,}098) = 2.68$, $p = .007$.

Study 2

In Study 2, we conducted a conceptual replication and extension of Study 1, using data from Thompson et al. (2021), who investigated whether an educational intervention that taught adults how to calculate case-fatality rates improved COVID-19 related math problem-solving. We again investigated whether the relation between MA and performance varied by type of number (RQ1) and whether the relation between MA and performance varied for symbolic versus nonsymbolic fractions (RQ2) with a different nonsymbolic task than that used in Study 1. In addition, we included number-specific MA items (e.g., specifically relating to anxiety about fractions) to address whether the relation between MA and NLE performance varies depending on whether the MA measure aligns with the behavioral measure (RQ4). In other words, whether number-specific MA measures are better predictors of performance on number-specific math tasks than general MA measures (e.g., MA related to whole numbers better predicts NLE performance with whole numbers). Finally, we explored which type of MA measure (general, whole-number-specific, or fraction-specific) was most predictive of nonsymbolic ratio comparison performance.

Figure 2
Interaction Between MA and Number Format (Symbolic vs. Nonsymbolic Fractions) in Study 1



Note. Country, gender, education level, age, and trait anxiety were included as covariates. Math anxiety (MA) was grand-mean-centered. Error ribbons represent standard error of the effect.

Method

Transparency and Openness

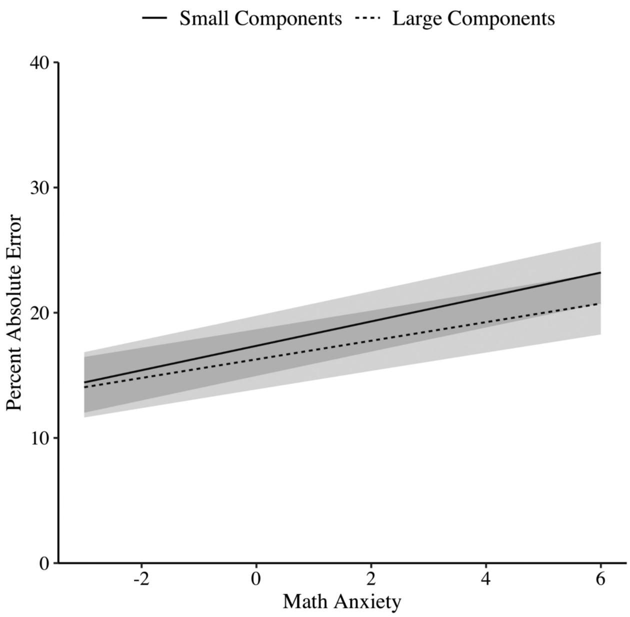
The survey flow of all measures is included in the supplemental materials, which are available on the OSF page (https://osf.io/e6pgh), and question wording for all survey items is available on the OSF page for the project (see the author note). The data and analytic code are also available on the OSF page for the project.

Participants

Thompson et al. (2021) sampled 2,000 American adults, who were deemed to have provided a "quality complete" survey by the Qualtrics data collection team. Sampling was stratified by age, gender, and educational attainment. A total of 1,820 participants met preregistered inclusion criteria (https://osf.io/97vda). Thompson et al. (2021) excluded participants who took the survey twice, who had participated in a prior survey that used many of the same measures, and who missed more than one of five attention checks embedded in the survey (Gilman et al., 2017). Furthermore, participants who showed random or inattentive responding on the math tasks were excluded as has been done in prior work (e.g., Sidney et al., 2021). Specifically, participants were excluded if they provided estimates that only varied within 10% of the line (i.e., the same location for each trial). Additionally, participants were excluded for consistently selecting either the left or right option for the nonsymbolic ratio comparison task. Finally, participants were excluded if they provided nonsensical responses to health-related math problem-solving items.

Figure 3

Interaction Between MA and Component Size (Small vs. Large) in Study 1



Note. Country, gender, education level, age, and trait anxiety were included as covariates. Math anxiety (MA) was grand-mean-centered. Error ribbons represent standard error of the effect.

Because both parent studies were conducted with a Qualtrics panel of participants at similar points in time, we excluded overlapping participants ($n = 30$) who took part in both Lau, Wilkey, et al. (2022) and Thompson et al. (2021) from our analyses in Study 2. Thus, the final sample used for the analyses reported below was $N = 1,790$ (see Table A1 for demographic characteristics).

Tasks and Procedure

Participants completed an approximately 45-min online survey via Qualtrics. After this baseline survey, participants had the opportunity to complete 10 days of follow-up daily diaries. The diary questionnaires took approximately 5 min to complete and primarily asked participants about their COVID-19 health cognitions and health-related behaviors.

Of relevance for these secondary data analyses, participants first completed a section on their sociodemographic characteristics. Prior to the educational intervention, participants also rated their MA for math in general as well as MA for specific number types (i.e., whole numbers, fractions, percentages, whole number frequencies), and they completed symbolic and nonsymbolic number magnitude tasks. Then, participants completed the educational intervention or a control task, described above, that was not related to the research questions for the current secondary data analyses. However, participants completed the fraction and large whole-number number line estimation tasks and the nonsymbolic ratio comparison task after the educational intervention. Thus, we tested whether there were condition differences on these variables (see Table A9 in the Appendix) and included condition in the models as a covariate.

Demographics

As in Study 1, the primary outcome measure was number-line estimation performance. In Thompson et al. (2021), participants estimated the location of large symbolic whole numbers up to 1 billion (Cronbach's $\alpha = .85$) and symbolic fractions within the 0–5 range on number lines (Cronbach's $\alpha = .74$). As in Study 1, estimation precision was operationalized as percent absolute error (PAE). Participants also completed a nonsymbolic ratio comparison task (Cronbach's $\alpha = .73$). For this measure, participants judged which pair of line segments had the larger ratio of white to black line segments (Matthews et al., 2016). Accuracy on this task was calculated as the proportion of correctly answered items out of 18 total items.

As in Study 1, MA was the primary predictor of interest. Participants completed five MA items; however, for the purposes of this study, we analyzed their ratings for three items. Each item included the prompt "On a scale of 1–10, with 10 being the most anxious" and then included specific text (italicized) for each MA measure (indicated in parentheses): *how math anxious are you?* (general), *how math anxious are you about whole numbers (numbers like 34 or 57)?* (whole number), *how math anxious are you about fractions (numbers like 3⁄4 or 5⁄7)?* (fraction).

We also included trait anxiety as a covariate. Thompson et al. (2021) administered the Trait Anxiety scale (Spielberger et al., 1970) before and after the intervention. For the current study, we

Table 4

Linear Mixed-Effects Models for Number Line Estimation With Small and Large Rational Number Components in Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	22.65 (2.45)	9.23***	11.03	Subject (intercept)	51.80
MA	0.97 (0.10)	10.14***	3,148.79	Item (intercept)	34.20
Component	−1.08 (3.39)	−0.32	10.00	Residual	311.70
Gender	−3.74 (0.41)	−9.13***	2,010.08		
Country (CA)	1.51 (0.54)	2.78**	2,009.13		
Country (UK)	−0.07 (0.55)	−0.13**	2,009.01		
Education	−4.15 (0.44)	−9.45***	2,010.63		
Age	−.085 (0.24)	−3.55***	2,009.65		
Trait anxiety	0.10 (0.23)	0.45	2,012.01		
MA × component	−0.23 (0.09)	−2.68**	22,097.91		

Note. Small components, nonmales, the United States, and 13 years (of education) or less were the reference groups; MA = mean-centered math anxiety.
$^{**}p < .01$. $^{***}p < .001$.

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analyzed participants' responses from the pre-intervention assessment. Participants indicated the extent to which statements like, "I am 'calm, cool, and collected' described themselves. The scale included 20 items with a scale of 1 = *almost never* to 4 = *almost always*. Nine of these items were reverse coded such that higher values indicated more anxiety. The sum score was used in the current analyses.

Finally, as in Study 1, we also included age, gender, and level of educational attainment (Less than high school diploma, high school diploma/GED, Some college (no degree), Associate's degree, Bachelor's degree, Graduate degree) as covariates in our statistical models. Participants indicated their gender by indicating which gender they MOST identified with (male, female, nonbinary, different identity). Participants also had the option to choose not to report this information.

Study 2 Results

As preregistered, we fit several mixed-effects models, including by-subject random slopes where possible. In addition to the predictors of interest, all models included the following covariates: gender, education, age, condition, and trait anxiety. We dummy-coded gender with nonmales as the reference group. We dummy-coded condition with control as the reference group. We dichotomized and dummy-coded education level with "No College" as the reference group compared to "Some College and Above." We grand mean-centered MA, and we standardized general anxiety and age such that $M = 0$ and $SD = 1$. As in Study 1, parameters are evaluated with t-tests (for individual contrasts) and Type III F-tests (for multi-degree-of-freedom tests of model comparisons) using Satterthwaite's method for estimating degrees of freedom. To address whether the relation between MA and NLE performance varies depending on whether the MA measure aligns with the behavioral measure (RQ4), we compared several linear regression models with the same covariates as those described for the mixed-effects models above. Correlations among measures in Study 2 can be found in Table 5.

As preregistered, we first tested whether MA differed by condition in an independent-samples t-test. There were no condition differences in whole number PAE, fraction PAE, nonsymbolic comparison accuracy, general MA, whole-number MA, or fraction MA (see Table A6). As in Study 1, and consistent with prior research (Else-Quest et al., 2010), we observed gender differences[3] in MA with nonmales reporting higher MA than males, $t(1,788) = 6.00$, $p < .001$, Cohen's $d = 0.27$.

Does the Relation Between MA and Performance Vary by Number Type?

To test this question, we fit a linear mixed-effects model predicting PAE from general MA, number type (large whole numbers and fractions), and their interaction with our covariates described above. Number type was dummy-coded with fractions as reference. The final model included random slope of number type by subject as well as subject- and item-level random intercepts.

The interaction between MA and number type was significant (see Table 6). As in Study 1, the relation between MA and PAE was significant for both fractions, $b = 1.00$, 95% CI [0.83, 1.17], and large whole numbers, $b = 1.53$, 95% CI [1.21, 1.86] (see Figure 4), with higher MA associated with higher PAE. However, in Study 2, this relation was stronger for large whole numbers than for fractions, $b = 0.54$, $SE = 0.16$, $t(1,788) = 3.38$, $p < .001$.

Does the Relation Between MA and Performance Vary for Symbolic Versus Nonsymbolic Fractions?

First, in line with prior work (Fazio et al., 2016; Rittle-Johnson et al., 2001), we coded item-level accuracy on the number line estimation task by dichotomizing PAE based on a cut-off value of 10% error[4] (i.e., PAE $\leq$ 10% was coded as correct, and PAE > 10% was coded as incorrect). The mean proportion correct for each item using this method can be found in Table A12. Then, we fit a logistic mixed-effects model predicting the likelihood of accuracy from MA, number format (symbolic, nonsymbolic), and their interaction. Task type was coded with symbolic fractions as reference. The final model included random slope of task by subject as well as subject- and item-level random intercepts.

The interaction between MA and number format was significant (see Table 7). As can be seen in Figure 5, MA significantly related to the likelihood of accuracy for both symbolic and nonsymbolic fraction tasks. However, as in Study 1, the relation between MA and accuracy was stronger for symbolic fractions than for nonsymbolic fractions.

Does the Relation Between MA and NLE Performance Vary Depending on Whether the MA Measure Aligns with the Behavioral Measure?

To test this question, we preregistered an approach of fitting several non-nested linear regression models, and comparing them to determine which model best fit the data. For number-line estimation performance with each number type (large whole numbers and fractions), we compared R^2, AIC, and BIC for a model with general MA as a predictor to models with whole-number MA, and fraction MA as predictors. We also compared the models using Cox tests. These analyses can be found in the Appendix (Tables A13 and A14). In general, our preregistered analyses support similar conclusions to those we describe below. In addition to these preregistered analyses, we also fit additional linear regression models including general MA and number-specific MA to address whether MA that was specific to the behavioral measure (i.e., fraction MA for fraction PAE and whole-number MA for whole-number PAE) explained additional unique variance when all types of MA were entered into the model. We ultimately decided to report those models here because they are easier to interpret. We entered all three types of MA: general, whole number, and fraction in separate models for whole-

[3] We also ran exploratory models (not preregistered) with three-way interactions with country to examine whether the effects of number type, symbolic versus nonsymbolic fraction format, and component size on the relationship between MA and performance varied by gender (see Tables A10 and A11 in the Appendix). As in Study 1, none of the models revealed significant three-way interactions with gender. In addition, we tested for gender interactions for RQ4 (which type of math anxiety is most predictive for different tasks). The interaction did not emerge as significant for any of the models (see Table A15 in the Appendix).

[4] The pattern of results did not change when we tested a cutoff value of 5% and 15%.

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Table 5

Descriptive Statistics and Correlations for Measures in Study 2

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. NLE-WN	0.24	0.21							
2. NLE-F	0.19	0.11	.38** [0.34, 0.42]						
3. Nonsym. comparison acc.	0.66	0.20	−.32** [−0.36, −0.28]	−.33** [−0.38, −0.29]					
4. MA	5.02	2.87	.20** [0.16, 0.25]	.25** [0.21, 0.29]	−.21** [−0.25, −0.16]				
5. MA-WN	3.94	2.76	.25** [0.21, 0.30]	.26** [0.22, 0.31]	−.23** [−0.28, −0.19]	.70** [0.67, 0.72]			
6. MA-F	5.27	3.04	.21** [0.17, 0.25]	.28** [0.24, 0.32]	−.21** [−0.26, −0.17]	.72** [0.70, 0.74]	.63** [0.61, 0.66]		
7. Trait anxiety	43.29	12.57	.02 [−0.03, 0.07]	−.00 [−0.05, 0.05]	−.06* [−0.11, −0.01]	.34** [0.29, 0.38]	.22** [0.18, 0.27]	.29** [0.25, 0.33]	
8. Age	46.01	16.94	−.10** [−0.14, −0.05]	−.04 [−0.08, 0.01]	.16** [0.11, 0.20]	−.14** [−0.19, −0.10]	−.15** [−0.19, −0.10]	−.16** [−0.20, −0.11]	−.28** [−0.32, −0.23]

Note. NLE-WN = mean PAE in number line estimationusing large whole numbers (with 1,000 and 1,000,000,000 as endpoints); NLE-WN = mean PAE in number line estimationusing fractions (with 0 and 5 as endpoints); Nonsym. Comparison Acc. = mean accuracy on the nonsymbolic comparison task; MA = general math anxiety (1–10 scale); MA-WN = MA relating to whole numbers (1–10 scale); MA-F = MA relating to fractions (1–10 scale); Trait Anxiety = sum score of trait anxiety. PAE is a measure of error and higher values reflect less accurate estimates. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014).
$^*p < .05$. $^{**}p < .01$.

number and fraction PAE. Multicollinearity was acceptable (all VIF values < 3) in all models.

As can be seen in Table 8, only whole-number MA significantly predicted whole-number PAE. This suggests that for whole numbers, the relation between MA and PAE does depend on whether the MA measure aligns with the behavioral measure.

The pattern of results for fraction PAE was different, as can be seen in Table 8. In this model, all three types of MA predicted fraction PAE, as did trait anxiety. This suggests that for fractions, both whole-number MA and fraction MA matter for performance, perhaps because people rely on whole-number strategies when reasoning about fractions (Alibali & Sidney, 2015) and whole-number knowledge is a predictor of fraction understanding (Hansen et al., 2015; Siegler et al., 2011). In other words, if one is anxious about whole numbers, this could relate to fraction performance. Our analyses above suggest the reverse is not true: fraction anxiety does not relate to whole-number PAE after accounting for whole-number anxiety. However, in both cases, MA was a stronger predictor of performance when it aligned with performance than when it did not.

We conducted similar analyses to address the exploratory question of which type of MA would be most predictive of nonsymbolic ratio comparison performance (again, our preregistered analyses can be found in the Appendix in Tables A13 and A14). The results of the linear regression analysis can be found in Table 8. The pattern of results for accuracy on the nonsymbolic comparison measure differed from that of NLE for both whole numbers and fractions. Only fraction-specific and whole-number-specific MA predicted performance, whereas general MA did not. This suggests that for nonsymbolic ratio comparison, the relation between MA and performance is stronger for specific types of MA than for general MA. However, both fraction-specific and whole-number-specific MA predicted unique variance.

General Discussion

This research adds to the understanding of how specific task features may impact the relation between MA and performance on NLE tasks that tap understanding of numerical magnitude. Measuring different aspects of core numerical abilities using the same task allows for powerful differentiation of effects. Across two large panels of adult participants, we investigated whether the relation between MA and math performance differed depending on task features, such as rational number type, number format, and component size. As shown in Table 9, we saw general support for our hypotheses across both studies, but in some instances, the strength of the relations was surprising. We did not anticipate that the MA-performance relation would be stronger for large whole numbers than for fractions (Study 2). This may have occurred because the large whole-number estimation task was more difficult than the fraction task (see PAE by number type in Table 5), and it is possible that this large, unfamiliar numerical range elicited more anxiety than fractions (Fitzsimmons et al., 2021; Landy et al., 2013). Also, it is possible that multiple specific types of MA predicted fraction performance, but not large whole-number performance because whole-number reasoning contributes toward fraction reasoning. In fraction tasks, adults rely both on strategies that directly tap fraction magnitudes and ones focused on whole-number numerator and denominator components (Fazio et al., 2016; Fitzsimmons et al., 2020a; Sidney, Thallur, et al., 2019; see also Alibali & Sidney, 2015).

Table 6

Linear Mixed-Effects Models for Number Line Estimation With Different Number Types in Study 2

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	21.92 (1.05)	20.95***	16.95	Subject (intercept)	88.72
MA	0.97 (0.10)	9.90***	2,097.04	Item (intercept)	7.75
Type	5.40 (1.69)	3.19**	11.00	Residual	323.31
Gender	−1.99 (0.51)	−7.95***	1,783.00		
Education	−4.06 (0.51)	−7.95***	1,783.00		
Age	−0.64 (0.26)	−2.41*	1,783.00		
Trait anxiety	−1.40 (0.28)	−5.08***	1,783.00		
Condition	−0.56 (0.50)	−1.11	1,783.00		
MA × Type	0.54 (0.09)	6.04***	21,467.00		

Note. Fractions, nonmales, no college education, and control condition were the reference groups; MA = mean-centered math anxiety.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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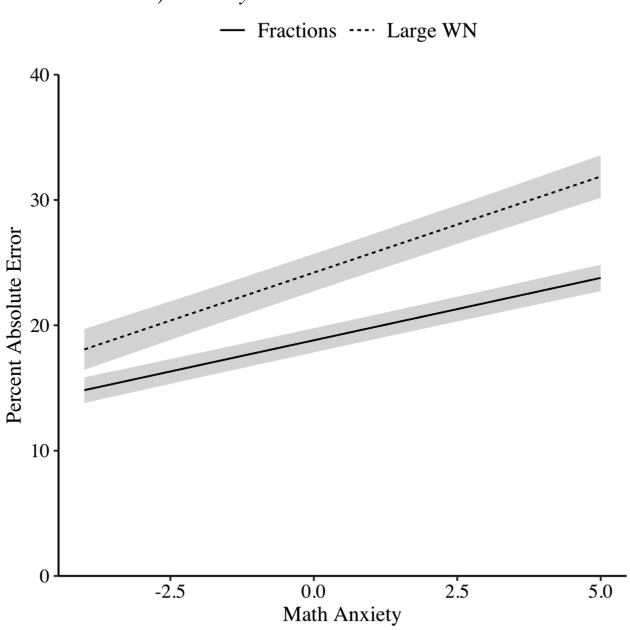
Relying on fraction strategies to reason about whole numbers may be less likely given the progression of typical instruction in U.S. schools (Common Core Standards Writing Team, 2018). That is, if one is anxious about whole numbers, that anxiety may have implications for reasoning about both large whole numbers *and* fractions. Whereas, if one has higher fraction MA and lower whole number MA, higher fraction MA may play less of a role in whole number reasoning.

In the current studies, we did not set out to find evidence for or against any particular account of the mechanisms underlying the relation between MA and math performance (e.g., Disruption Account, Reduced Competency Account, Interpretation Account). However, these accounts can help explain how task features may impact the relationship between MA and performance on numerical tasks. For example, in line with the Disruption Account, it could be that the task features elicit similar levels of MA, but the MA is more or less disruptive depending on the cognitive demands of the different task features. If different task features change the way working memory resources are recruited, for example, then anxious ruminations related to MA could be more disruptive for tasks that require more resources. We did not administer any working memory measures in these studies, so our data cannot address the effects of task features on working memory demands. Another possibility, more in accordance with the Reduced Competency Account and the Interpretation account, could be that task features elicit different levels of MA, which then interferes with performance. For example, certain task features may be more strongly related to past failures in math, and therefore elicit more MA which may interfere with performance (perhaps also by taxing working memory). Recent research suggests that perceptions of ease and difficulty are differentially related to attitudes about whole numbers and fractions, respectively (Mielicki et al., 2022). In addition, MA may relate to students' willingness to engage in study strategies that prioritize more difficult math content, and that choosing to engage in effortful strategies mediates the relationship between MA and math performance (Jenifer et al., 2022). Although we did not collect data on perceptions of the relative difficulty of different number types or formats, participants may have appraised them differently based on challenging past experiences with different number types (e.g., failing at fractions), which may have changed the relation between MA and performance.

Figure 4

Interaction Between MA and Type of Number (Fractions vs. Large Whole Numbers) in Study 2



Note. WN = whole numbers. Age, gender, and level of education were included in the model as covariates. Math anxiety (MA) was grand-mean-centered. Error ribbons represent standard error of the effect.

The difference in the strength of the relation between MA and performance on symbolic relative to nonsymbolic fractions observed in both studies could be interpreted as consistent with the Interpretation Account. In Study 1, participants performed similarly on the symbolic and nonsymbolic fraction tasks, whereas in Study 2, participants performed better on the nonsymbolic task relative to the symbolic task. Across both studies, however, the relation between MA and performance was stronger for symbolic relative to nonsymbolic fractions. Fractions are notoriously difficult mathematical content (Alibali & Sidney, 2015; Braithwaite & Siegler, 2018a; DeWolf & Vosniadou, 2015; Fazio et al., 2016; Fitzsimmons et al., 2020a; Opfer & DeVries, 2008; Siegler et al., 2011; Siegler & Thompson, 2014; Stafylidou & Vosniadou, 2004). As such, learners likely have some negative experiences unique to learning fractions, which may contribute to fraction-specific math anxiety and to the negative attitudes people hold toward fractions specifically (Mielicki et al., 2022; Sidney et al., 2021). Nonsymbolic fractions

Table 7

Logistic Mixed-Effects Models for Accuracy on Tasks With Symbolic and Nonsymbolic Fractions in Study 2

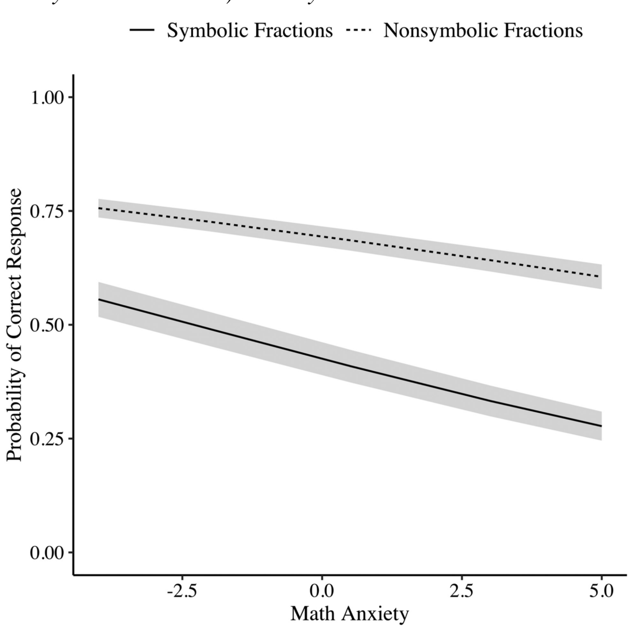
Fixed effects	Estimate (*SE*)	*z*-value	Random effects	Variance
Constant	−0.50 (0.15)	−3.30***	Subject (intercept)	1.21
MA	−0.13 (0.01)	−11.38***	Task type	1.08
Format	1.12 (0.18)	6.22***	Item (intercept)	0.19
Gender	0.07 (0.04)	1.74		
Education	0.35 (0.04)	7.90***		
Age	0.12 (0.02)	5.43***		
Trait anxiety	0.09 (0.02)	3.83***		
Condition	0.01 (0.04)	0.05		
MA × Format	0.05 (0.01)	4.53***		

Note. SE and $df = 48{,}317$ are used to represent standard error of the mean and degrees of freedom, respectively. Symbolic fractions, nonmales, no college education, and control condition were the reference groups; MA = mean-centered math anxiety.
$^{***}p < .001$.

(as they were instantiated in our current study) are likely not as common in math education as symbolic fractions, and thus people may not have the same number or strength of negative experiences related to nonsymbolic fractions as they do for symbolic fractions. In contrast, the difficulty people experience when learning symbolic fractions may contribute to the stronger negative relation between MA and performance on symbolic fraction tasks relative to nonsymbolic ones. Future research elucidating mechanisms underlying MA will need to account for the relations between MA associated with the specific features of a given math task and performance on the task.

Figure 5

Interaction Between MA and Number Format (Symbolic vs. Nonsymbolic Fractions) in Study 2



Note. Age, gender, and level of education were included in the model as covariates. MA (mean-centered math anxiety) was grand-mean-centered. Error ribbons represent standard error of the effect.

One strength of using these two large-scale datasets to answer similar questions was our ability to test for replication of findings. However, our data sets contained somewhat different tasks (i.e., the nonsymbolic tasks); therefore, in some instances, we have conceptually replicated rather than directly replicated our findings. Although our samples were collected around the same time from the same Qualtrics panels, we determined that only 30 participants overlapped across our two datasets (total $n = 3{,}822$) by comparing Qualtrics IDs and IP addresses. However, it is possible that there may have been additional unidentified overlapping participants.

It is also an open question for future research to assess why U.S. participants self-reported lower MA than participants in the United Kingdom and Canada and how and whether this lower MA relates to lower standardized math performance in the United States than these other countries (National Center for Education Statistics, 2021; Schleicher, 2019). Although not the focus of the current study, it is possible that instructional practices unique to each of the three countries included in these analyses could inform math achievement, content-specific math anxiety and attitudes, or both achievement and emotions related to math content. To our knowledge, systematic research relating to differences in fraction instruction across the United States, United Kingdom, and Canada is lacking. Moreover, even within the United States, there is no nationally mandated set of instructional practices, so these can differ widely across the states and urban and rural environments. However, there is research suggesting important differences in mathematics instruction across different countries and continents. For instance, several Asian countries rely more on analogies in instruction compared to the United States, and this difference has been linked to better math achievement (Richland et al., 2007). In terms of fraction-specific instruction, the United States emphasizes the part-whole interpretation of fractions more than the measurement interpretation, which is more common in Asian countries (Alajmi, 2012; Torbeyns et al., 2015). However, the part-whole interpretation is also more prevalent in European countries relative to Asian countries (Charalambous et al., 2010), thus it is unclear whether the United Kingdom, and Canada differ from the United States in this approach. Other work has shown that fraction division is underrepresented in U.S. textbooks relative to other fraction content (Braithwaite et al., 2017) and relative to some Asian countries (Son & Senk, 2010). However, other work has also shown that textbooks in the United States and China may both feature biased input related to fraction arithmetic (Braithwaite & Siegler, 2018b). Understanding the connection between content-specific MA and instructional practices is an important direction for future research.

Future work should also explore the extent to which the relation between MA and task performance varies by task feature and by gender. Negative math experiences may also be related to gender. Although gender differences were not focal in the current research, we did observe gender differences in MA. Specifically, nonmales reported higher MA than males across both studies, which is consistent with prior findings that females tend to report higher MA than males despite similar levels of math achievement (Else-Quest et al., 2010). In addition, prior work with U.S. samples examining negative attitudes toward fractions does suggest that women may be more likely to report fraction-specific negative attitudes relative to men (Mielicki et al., 2022; Sidney et al., 2021). Generally, even in the absence of gender differences in math achievement or

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Table 8
Linear Regression Summary for Specific Math Tasks With Different Types of MA as Predictors in Study 2

	Whole number PAE		Fraction PAE		Nonsymbolic comparison accuracy	
Variable	β (*SE*)	ΔR^2	β (*SE*)	ΔR^2	β (*SE*)	ΔR^2
Constant	0.20*** (0.04)	—	0.24*** (0.04)	—	−0.09* (0.04)	—
General MA	0.01 (0.04)	<.001	0.07* (0.04)	.002	−0.05 (0.04)	.001
Whole-number MA	0.20*** (0.03)	.020	0.17*** (0.03)	.012	−0.08* (0.03)	.003
Fraction MA	0.06 (0.03)	.002	0.12*** (0.03)	.007	−0.13*** (0.03)	.009
Gender	−0.29*** (0.05)	.020	−0.02 (0.04)	<.001	0.05 (0.05)	<.001
Education	−0.06 (0.05)	.001	−0.47*** (0.04)	.054	0.16*** (0.05)	.007
Age	−0.08*** (0.02)	.001	0.01 (0.02)	<.001	0.13*** (0.02)	.015
Trait Anxiety	−0.08*** (0.02)	.001	−0.12*** (0.02)	.012	0.05* (0.02)	.003
Condition	−0.06 (0.05)	<.001	−0.03 (0.04)	<.001	−0.03 (0.05)	<.001
R^2	0.10		0.16		0.09	
Adjusted R^2	0.09		0.15		0.08	
Residual *SE*	0.95		0.92		0.96	
F(8, 1,781)	24.40***		41.40***		20.90***	

Note. Standardized coefficients are reported here. Percent absolute error is a measure of error so higher values reflect less accurate performance. All models were based on 1,790 observations. ΔR^2 columns indicate the change in R^2 when that predictor is removed from the model. Nonmales, no college education, and control condition were the reference groups. MA = mean-centered math anxiety.
* $p < .05$. *** $p < .001$.

performance, women may experience lower math self-concept (John et al., 2022) and even lower item-level confidence on number line estimation (Rivers et al., 2021) and health-related math problems (Scheibe et al., 2022) relative to men. Given the persistent underrepresentation of women in STEM (National Center for Science and Engineering Statistics, 2021), understanding how math experiences, MA, and math attitudes vary by gender is an important direction for future work.

Despite the many strengths of this study, including the use of multiple datasets that allow for validation of findings, the geographically diverse samples, large-scale nature of recruitment, and the preregistered approach to data collection and analysis, several limitations must be noted. All data were collected cross-sectionally, and data were drawn from correlational survey measures. As such, we are unable to establish directionality or causality between measures of MA and math performance. However, our approach allows for some amount of within-person control, which allows us greater purchase on our questions of interest regarding number type.

Another potential limitation of this work is that we relied on single-item measures of MA, though this approach is common for measuring MA and has been shown to be strongly correlated with longer MA scales (Ashcraft, 2002; Hart & Ganley, 2019; Núñez-Peña et al., 2014). A recent meta-analysis showed that the correlation between MA measured with a single-item and math performance tends to be lower than the correlation between math performance and other measures of MA (Barroso et al., 2021). Although we did observe significant relations between MA and performance on the math tasks in this study, it is possible that some of these relations would be even stronger with a different measure of MA. Nevertheless, a single-item MA measure does not capture all of the nuance of this complex construct. Prior work has described the multifaceted nature of MA in a variety of ways. For instance, some work has distinguished between affective and cognitive components of MA (Ho et al., 2000; Liebert & Morris, 1967), whereas other work has distinguished between anxiety related to learning math and anxiety about having one's math performance evaluated (Cipora et al., 2015; Hopko et al., 2003). The

Table 9
Summary of Findings Across Study 1 and Study 2

Research question	Prediction	Findings from Study 1	Findings from Study 2
Does the relation between MA and performance vary by number type? (RQ1)	The relation will be strongest for fractions relative to other number types. We did not have specific predictions about other comparisons.	The relation was significant for all number types but was stronger for fractions and large whole numbers than for whole number frequencies and percentages.	The relation was significant for both number types but was stronger for large whole numbers than fractions.
Does the relation between MA and performance vary by number format (i.e., symbolic vs. nonsymbolic) fractions? (RQ2)	The relation will be stronger for symbolic than nonsymbolic tasks.	The relation varied by format and was stronger for symbolic than nonsymbolic tasks.	Replicated Study 1 with a different nonsymbolic task.
Does the relation between MA and performance on fraction estimation problems vary by component size? (RQ3)	The relation will be stronger for large- compared to small-component fractions.	The relation varied by component size but was stronger for small-component fractions.	Only assessed in Study 1.
Does the relation between MA and NLE performance vary depending on whether the MA measure aligns with the math measure? (RQ4)	Alignment between MA and behavioral measures should lead to stronger relations between MA and NLE for number-specific as opposed to nonspecific measures of MA.	Only assessed in Study 2.	The relation was stronger when the MA measure aligned with the math measure, but this varied by number type.

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association between MA and math performance is found to be different for different components of MA (e.g., Dowker, 2019b). For example, some work including both cognitive (i.e. concerns about how one is performing and the fear of failure) and affective (i.e., emotions of fear, nervousness, and tension with their associated physiological reactions, which occur in the presence of numerical stimuli, whether or not there is a threat of failure or evaluation; Wigfield & Meece, 1988) dimensions of MA, suggests that math performance is related to the affective but not the cognitive dimension (e.g. Dowker, 2019b; Sorvo et al., 2017). Future work should address how these different components of math anxiety may interact with different numerical task features to change the relationship between MA and performance on math tasks.

Constraints on Generality

Although we recruited large samples across two studies, and in Study 1 the samples were geographically diverse, the current studies do not test whether these findings generalize to participants not from Western, Educated, Industrialized, Rich, Democratic nations. Some prior work suggests that the negative relationship between MA and math achievement is present across countries (Foley et al., 2017) and geographic regions (Barroso et al., 2021), although there are also important between-country distinctions that may impact this relationship (Lau, Hawes, et al., 2022). For instance, the level of gender equality in a given country may contribute to gender differences in MA (Stoet et al., 2016). Similarly, the current studies do not test whether these findings generalize to different racial groups. A recent meta-analysis examining the relation between MA and math achievement suggests that the negative relationship between the two may also be similar across different racial groups (Barroso et al., 2021). However, this meta-analysis dichotomized race as more or less than 75% White, and thus does not capture the nuances of different racial identities. The effects of educational practices in math classrooms may vary for minority groups depending on whether these practices align with the specific values and norms of the minority communities (Dasgupta et al., 2022), which could have implications for the relationship between MA and performance on math tasks. In addition, in the current studies, we dichotomized gender into male and nonmale, which obviously excludes the experiences of people with gender identities that do not align well with these categories. Given that the samples of participants who did not identify as either male or female was quite small in both studies, future work is needed to better understand how our findings may apply to people with different gender identities. Finally, researchers have begun to explore how the intersection of racial and gender identities may also relate to math anxiety (Owusua et al., under review). This type of work is critical for understanding the complex dynamics that inform how individuals learn and do math, and to better support individuals in historically underrepresented groups. Thus, although the findings from the current studies reveal interesting potential moderators of the relation between MA and performance, future work is needed to test the generalizability of these findings.

Conclusions

By demonstrating the multifaceted connection between MA and math performance, our findings have implications for future MA interventions. Our research builds off prior work demonstrating varying associations of MA with various math skills (Dowker, 2019b). We showed that differences in numerical task features, within the same math task (i.e., number line estimation), also impact the association between MA and math performance. Thus, researchers and educators may be able to differentiate MA interventions by task features such as number type, format, and component size. Future research can also assess whether alerting both students and teachers that MA differs not only by math task, but also by task features such as number type reduces MA and improves learning for more difficult math topics. Our findings are an important step toward better understanding the link between MA and performance on math tasks.

Context

This work is the result of a collaboration of researchers across different laboratories and institutions, united by an interest in factors that relate to numerical competencies, and how these competencies, in turn, play out in real-world contexts. In the two studies described here, the authors address a set of preregistered research questions through a secondary data analysis of two large data sets exploring how numerical competencies relate to attitudes and perceptions of COVID-19.

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(*Appendix follows*)

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Appendix

Table A1

Demographic Characteristic for Study 1 and Study 2 Samples

Sample characteristic	Study 1			Study 2
Country	CA	UK	US	US
N	677	675	680	1,790
Age	54.80 (13.94)	54.20 (14.44)	70.10 (7.81)	46.00 (16.90)
Some college (%)	74	59	76	46 (46 nonmale)
Nonmale (%)	53	53	44	49
White (%)	78	91	94	73

Table A2

Number of Participants by Gender and Education Level for Each Country in Study 1 Sample

Country		Male	Nonmale
CA	Less than college	84	92
	College	237	266
US	Less than college	72	90
	College	309	209
UK	Less than college	134	143
	College	177	218

Table A3

Linear Mixed-Effects Models for Number Line Estimation With Different Number Types and Country Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	25.28 (2.01)	12.57***	18.49	Subject (intercept)	48.40
MA	1.04 (0.16)	6.50***	4,559.19	Item (intercept)	22.40
Type-WNF	−6.93 (2.76)	−2.51*	16.47	Residual	300.80
Type-P	−9.20 (3.38)	−2.72*	16.47		
Type-WN	−1.03 (2.90)	0.36	16.47		
Gender	−3.84 (0.37)	−10.38***	2,009.01		
Country (CA)	−0.32 (0.59)	−0.53	4,153.47		
Country (UK)	1.98 (0.60)	3.28**	4,049.23		
Education	−3.69 (0.40)	−9.30***	2,009.37		
Age	−0.71 (0.22)	−3.28**	2,009.27		
Trait anxiety	0.45 (0.20)	2.22*	2,009.70		
MA × Type-WNF	−0.31 (0.16)	−2.00*	38,199.44		
MA × Type-P	−0.82 (0.19)	−4.26***	38,190.98		
MA × Type-WN	0.05 (0.16)	0.28	38,187.22		
MA × Country-CA	−0.09 (0.21)	−0.42	4,785.80		
MA × Country-UK	−0.02 (0.21)	−0.11	4,754.38		
Type-WNF × Country-CA	−2.32 (0.56)	−4.15***	38,197.17		
Type-P × Country-CA	−2.00 (0.68)	−2.94**	38,190.22		
Type-WN × Country-CA	−2.55 (0.58)	−4.36***	38,191.60		
Type-WNF × Country-UK	−3.94 (0.56)	−7.05***	38,201.34		
Type-P × Country-UK	−5.57 (0.68)	−8.14***	38,192.07		
Type-WN × Country-UK	−4.24 (0.59)	−7.24***	38,191.55		
MA × Type-WNF × Country-CA	−0.11 (0.22)	−0.49	38,199.46		
MA × Type-P × Country-CA	0.20 (0.26)	0.77	38,198.03		
MA × Type-WN × Country-CA	−0.20 (0.23)	−0.89	38,199.94		
MA × Type-WNF × Country-UK	−0.08 (0.21)	−0.40	38,200.16		
MA × Type-P × Country-UK	0.35 (0.26)	1.34	38,192.56		
MA × Type-WN × Country-UK	−0.06 (0.22)	−0.25	38,191.76		

Note. Fractions, nonmales, the United States, and 13 years (of education) or less were the reference groups. MA = mean-centered math anxiety; WNF = whole-number frequencies (with 0 in 100 and 100 in 100 as endpoints); P = percentages (with 0%–5% as endpoints); WN = large whole numbers (with 1,000 and 1,000,000,000 as endpoints).
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

(*Appendices continue*)

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Table A4

Linear Mixed-Effects Models for Number Line Estimation With Symbolic and Nonsymbolic Fractions and Country Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	25.82 (1.82)	14.16***	9.79	Subject (intercept)	121.60
MA	1.07 (0.21)	5.13***	2,050.47	Format|subject	145.30
Format	−0.62 (2.97)	−0.21	7.66	Item (intercept)	16.70
Gender	−2.75 (0.50)	−5.55***	2,001.67	Residual	284.50
Country (CA)	−1.23 (0.78)	$-1.57^{\dagger}$	2,162.92		
Country (UK)	0.95 (0.79)	1.19	2,189.05		
Education	−4.28 (0.53)	−8.07***	2,000.92		
Age	−1.66 (0.29)	−5.71***	1,993.61		
Trait anxiety	0.39 (0.27)	1.42	1,998.38		
MA × Format	−0.71 (0.27)	−2.68**	1,998.47		
MA × Country-CA	−0.11 (0.28)	−0.38	1,991.21		
MA × Country-UK	−0.08 (0.28)	−0.29	1,992.22		
Format × Country-CA	−0.51 (0.95)	−0.53	1,998.30		
Format × Country-UK	−3.31 (0.95)	−3.48**	1,996.03		
MA × Format × Country-CA	0.65 (0.37)	1.78	2,001.93		
MA × Format × Country-UK	0.46 (0.36)	1.26	1,994.61		

Note. Symbolic fractions, nonmales, the United States, and 13 years (of education) or less were the reference groups. MA mean-centered math anxiety.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table A5

Linear Mixed-Effects Models for Number Line Estimation With Small and Large Rational Number Components and Country Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	22.83 (2.46)	9.28***	11.16	Subject (intercept)	51.90
MA	1.08 (0.16)	6.59***	3,438.16	Item (intercept)	34.20
Component	−1.35 (3.40)	−0.40	10.20	Residual	311.70
Gender	−3.74 (0.41)	−9.12***	2,007.86		
Country (CA)	−1.62 (0.62)	−2.63**	3,213.22		
Country (UK)	−0.40 (0.63)	−0.64	3,160.66		
Education	−4.15 (0.44)	−9.44***	2,008.57		
Age	−0.86 (0.24)	−3.56***	2,007.58		
Trait anxiety	0.10 (0.23)	0.45	2,009.93		
MA × Component	−0.31 (0.16)	−1.94	22,103.82		
MA × Country-CA	−0.32 (0.22)	−1.48	3,548.93		
MA × Country-UK	0.02 (0.22)	0.08	3,537.00		
Component × Country-CA	0.18 (0.57)	0.32	22,095.32		
Component × Country-UK	0.55 (0.57)	0.97	22,096.21		
MA × Component × Country-CA	0.36 (0.22)	$1.65^{\dagger}$	22,097.56		
MA × Component × Country-UK	−0.15 (0.22)	−0.71	22,097.83		

Note. Small components, nonmales, the United States, and 13 years (of education) or less were the reference groups. MA = mean-centered math anxiety.
$^{\dagger}p < .10$. **$p < .01$. ***$p < .001$.

(*Appendices continue*)

Table A6

Linear Mixed-Effects Models for Number Line Estimation With Different Number Types and Gender Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	27.08 (2.01)	13.51***	18.27	Subject (intercept)	48.40
MA	0.94 (0.12)	7.93***	4,426.52	Item (intercept)	22.40
Type-WNF	−9.51 (2.75)	−3.46**	16.24	Residual	301.20
Type-P	−13.03 (3.37)	−3.86**	16.24		
Type-WN	−0.83 (2.89)	−0.29	16.24		
Gender	−4.21 (0.46)	−9.17***	4,704.81		
Country (CA)	−1.95 (0.49)	−4.00***	2,010.35		
Country (UK)	−1.06 (0.50)	−2.11*	2,009.56		
Education	−3.67 (0.40)	−9.23***	2,010.20		
Age	−0.71 (0.22)	−3.29**	2,010.39		
Trait anxiety	0.45 (0.20)	2.23*	2,010.84		
MA × Type-WNF	−0.37 (0.11)	−3.19**	38,212.27		
MA × Type-P	−0.56 (0.14)	−3.95***	38,210.50		
MA × Type-WN	−0.06 (0.12)	−0.50	38,213.40		
MA × Gender	0.27 (0.18)	1.56	4,768.28		
Type-WNF × Gender	0.85 (0.46)	1.86	38,207.13		
Type-P × Gender	2.64 (0.56)	4.68***	38,198.09		
Type-WN × Gender	−1.04 (0.48)	−2.16*	38,199.98		
MA × Type-WNF × Gender	−0.17 (0.18)	−0.97	38,205.66		
MA × Type-P × Gender	−0.17 (0.22)	−0.78	38,201.81		
MA × Type-WN × Gender	−0.32 (0.19)	−1.71	38,204.02		

Note. Fractions, nonmales, and the United States were the reference group. MA: mean-centered math anxiety, WNF: whole-number frequencies (with 0 in 100 and 100 in 100 as endpoints), P: percentages (with 0%–5% as endpoints), WN: large whole numbers (with 1,000 and 1,000,000,000 as endpoints).
**p* < .05. ***p* < .01. ****p* < .001.

Table A7

Linear Mixed-Effects Models for Number Line Estimation With Symbolic and Nonsymbolic Fractions and Gender Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	27.04 (1.81)	14.91***	9.57	Subject (intercept)	121.60
MA	0.88 (0.16)	5.66***	2,095.83	Format|subject	145.80
Format	−3.24 (2.94)	−1.10	7.39	Item (intercept)	16.70
Gender	−3.90 (0.60)	−6.49***	2,005.77	Residual	284.50
Country (CA)	−1.51 (0.65)	−2.31*	2,000.26		
Country (UK)	−0.58 (0.67)	−0.86	1,996.65		
Education	−4.27 (0.53)	−8.03***	2,002.60		
Age	−1.67 (0.29)	−5.77***	1,994.76		
Trait anxiety	0.39 (0.27)	1.42	1,999.99		
MA × Format	−0.08 (0.20)	−0.39	2,000.94		
MA × Gender	0.25 (0.23)	1.07	1,991.24		
Format × Gender	2.66 (0.78)	3.39**	2,000.68		
MA × Format × Gender	−0.47 (0.30)	−1.55	2,003.49		

Note. Symbolic fractions, nonmales, the United States and 13 years (of education) or less were the reference groups. MA = mean-centered math anxiety.
**p* < .05. ***p* < .01. ****p* < .001.

(*Appendices continue*)

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Table A8
Linear Mixed-Effects Models for Number Line Estimation With Small and Large Rational Number Components and Gender Interaction Terms for Study 1

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	22.90 (2.46)	9.32***	11.09	Subject (intercept)	51.80
MA	0.87 (0.12)	7.07***	3,353.42	Item (intercept)	34.20
Component	−1.50 (3.39)	−0.44	10.10	Residual	311.70
Gender	−4.12 (0.47)	−8.72***	3,506.60		
Country (CA)	−1.52 (0.54)	−2.81**	2,008.21		
Country (UK)	−0.09 (0.56)	−0.16	2,008.01		
Education	−4.12 (0.44)	−9.36***	2,009.25		
Age	−0.85 (0.24)	−3.56***	2,008.71		
Trait anxiety	0.10 (0.23)	0.44	2,011.03		
MA × Component	−0.15 (0.12)	−1.32	22,093.66		
MA × Gender	0.22 (0.18)	1.22	3,538.62		
Component × Gender	0.79 (0.47)	1.68	22,094.57		

Note. Small components, nonmales, the United States, and 13 years (of education) or less were the reference groups. MA = mean-centered math anxiety.
$^{**}p < .01$. $^{***}p < .001$.

Table A9
Descriptive Statistics of Main Measures by Condition for Study 2

Measure	Control		Experimental			
	M	*SD*	*M*	*SD*	$t(1,788)$	*p* value
NLE-WN	0.25	0.21	0.24	0.20	1.00	.200
NLE-F	0.19	0.11	0.19	0.10	0.80	.400
Nonsym. comparison accuracy	0.67	0.20	0.66	0.20	0.40	.700
MA	5.06	2.92	4.99	2.83	0.50	.600
MA-WN	3.94	2.78	3.94	2.75	0.02	1.00
MA-F	5.30	3.04	5.23	3.04	0.50	.600

Note. NLE-WN = mean PAE for large whole numbers; NLE-F = mean PAE for fractions; MA = general math anxiety; MA-WN = MA for whole numbers; MA-F = MA for fractions.

Table A10
Linear Mixed-Effects Models for Number Line Estimation With Different Number Types and Gender Interaction Terms for Study 2

Fixed effects	Estimate (*SE*)	*t*-value	*df*	Random effects	Variance
Constant	21.38 (1.03)	20.76***	15.93	Subject (intercept)	69.00
MA	1.02 (0.12)	8.47***	1,786.84	Type|subject	273.62
Type	7.95 (1.79)	4.43**	13.91	Item (intercept)	7.79
Gender	−0.35 (0.47)	−0.73	1,781.92	Residual	258.73
Education	−4.86 (0.47)	−10.38***	1,782.00		
Age	−0.21 (0.24)	−0.89	1,782.00		
Trait anxiety	−1.28 (0.25)	−5.03***	1,782.00		
Condition	−0.36 (0.46)	−0.79	1,782.00		
MA × Type	0.12 (0.22)	0.52	1,786.00		
MA × Gender	−0.02 (0.17)	−0.13	1,781.95		
Type × Gender	−4.96 (0.91)	−5.43***	1,786.00		
MA × Type × Gender	0.61 (0.32)	1.92	1,786.00		

Note. Fractions, nonmales, no college education, and control condition were the reference groups; MA = mean-centered math anxiety.
$^{**}p < .01$. $^{***}p < .001$.

(*Appendices continue*)

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Table A11

Logistic Mixed-Effects Models for Accuracy on Tasks With Symbolic and Nonsymbolic Fractions With Gender Interaction Terms for Study 2

Fixed effects	Estimate (*SE*)	*z*-value	Random effects	Variance
Constant	−0.55 (0.15)	−3.59***	Subject (intercept)	1.21
MA	−0.12 (0.02)	−7.42***	Format|subject	1.08
Format	1.19 (0.18)	6.50***	Item (Intercept)	0.19
Gender	0.17 (0.06)	2.61**		
Education	0.35 (0.04)	7.89***		
Age	0.12 (0.02)	5.38***		
Trait anxiety	0.09 (0.02)	3.82***		
Condition	0.00 (0.04)	0.07		
MA × Format	0.04 (0.02)	2.40*		
MA × Gender	−0.02 (0.02)	−0.85		
Format × Gender	−0.13 (0.07)	−1.96		
MA × Format × Gender	0.02 (0.02)	0.88		

Note. SE and *df* = 48,314 are used to represent standard error of the mean and degrees of freedom, respectively. Symbolic fractions, nonmales, no college education, and control condition were the reference groups; MA = mean-centered math anxiety.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table A12

Proportion Correct for Each Fraction Number Line Estimation Item Using a 10% Accuracy Cutoff

Item	Value	PAE *M* (*SD*)	Proportion correct
1	1/19	14% (24%)	0.71
2	4/7	23% (22%)	0.46
3	7/5	20% (18%)	0.39
4	13/9	19% (17%)	0.39
5	8/3	18% (13%)	0.33
6	11/4	17% (13%)	0.36
7	10/3	18% (16%)	0.42
8	7/2	21% (18%)	0.38
9	17/4	21% (23%)	0.50

Note. PAE = percent absolute error.

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Table A13
Preregistered Regression Models for RQ4 in Study 2

	NLE-WN			NLE-F			Nonsym. comp. acc.		
Variable	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)
Constant	0.20*** (0.04)	0.21*** (0.04)	0.19*** (0.04)	0.25*** (0.04)	0.27*** (0.04)	0.24*** (0.04)	−0.09* (0.04)	−0.10* (0.04)	−0.08 (0.04)
MA	0.20*** (0.02)			0.27*** (0.02)			−0.20*** (0.02)		
MA-WN		0.25*** (0.02)			0.27*** (0.02)			−0.21*** (0.02)	
MA-F			0.20*** (0.02)			0.29*** (0.02)			−0.20*** (0.02)
Gender	−0.28*** (0.05)	−0.30*** (0.05)	−0.27*** (0.05)	−0.03 (0.04)	−0.07 (0.04)	−0.02 (0.04)	0.04 (0.05)	0.07 (0.05)	0.04 (0.05)
Education	−0.08 (0.05)	−0.07 (0.05)	−0.07 (0.05)	−0.49*** (0.04)	−0.48*** (0.04)	−0.47*** (0.04)	0.18*** (0.05)	0.17*** (0.05)	0.16*** (0.05)
Age	−0.09*** (0.02)	−0.08*** (0.02)	−0.09*** (0.02)	−0.01 (0.02)	0.002 (0.02)	0.002 (0.02)	0.14*** (0.02)	0.13*** (0.02)	0.13*** (0.02)
Trait anxiety	−0.09*** (0.03)	−0.07** (0.02)	−0.08** (0.02)	−0.12*** (0.02)	−0.08*** (0.02)	−0.11*** (0.02)	0.06* (0.03)	0.03 (0.02)	0.04 (0.02)
Condition	−0.06 (0.05)	−0.06 (0.05)	−0.06 (0.05)	−0.03 (0.04)	−0.03 (0.04)	−0.03 (0.04)	−0.03 (0.05)	−0.02 (0.05)	−0.03 (0.05)
R^2	0.07	0.10	0.07	0.13	0.13	0.14	0.07	0.08	0.07
Adjusted R^2	0.07	0.09	0.07	0.13	0.13	0.14	0.07	0.08	0.07
AIC	4,959	4,913	4,959	4,844	4,840	4,822	4,963	4,947	4,964
BIC	5,003	4,957	5,003	4,888	4,883	4,866	5,007	4,991	5,008
Residual *SE*	0.96	0.95	0.96	0.93	0.93	0.93	0.97	0.96	0.97
F(6, 1,783)	23.34***	31.68***	23.39***	44.70***	45.55***	48.87***	22.70***	25.52***	22.47***

Note. Standardized coefficients are reported here. All models were based on 1,790 observations. Nonmales, no college education, and control condition were the reference groups. NLE-WN = number line estimation with whole numbers, NLE-F = number line estimation with fractions, Nonsym. comp. acc. = Nonsymbolic ratio comparison accuracy.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table A14
Summary of Cox Tests for RQ4 in Study 2

Model comparison	Estimate (*SE*)	*z*	*p*
WN PAE			
WN vs. general	−7.16 (5.13)	−1.40	.163
General vs. WN	−40.45 (3.94)	−10.26	<.001
WN vs. fraction	−12.21 (4.94)	−2.47	.013
Fraction vs. WN	−43.25 (3.82)	−11.33	<.001
Fraction PAE			
Fraction vs. general	−30.14 (5.98)	−5.04	<.001
General vs. fraction	−45.84 (5.55)	−8.25	<.001
Fraction vs. WN	−39.67 (5.74)	−6.91	<.001
WN vs. fraction	−51.33 (5.42)	−9.47	<.001
Nonsymbolic comparison accuracy			
General vs. WN	26.03 (4.02)	6.47	<.001
WN vs. general	−14.62 (4.46)	−3.28	.001
General vs. fraction	−17.26 (4.03)	−4.29	<.001
Fraction vs. general	−18.17 (3.99)	−4.55	<.001
WN vs. fraction	−17.67 (4.30)	4.11	<.001
Fraction vs. WN	−29.23 (3.85)	−7.60	<.001

Note. WN = large whole numbers; PAE = percent absolute error.

(*Appendices continue*)

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Table A15

Preregistered Regression Models for RQ4 With Gender Interaction Terms for Study 2

Variable	NLE-WN			NLE-F			Nonsym. comp. acc.		
	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)	β (*SE*)
Constant	0.21*** (0.04)	0.21*** (0.04)	0.20*** (0.04)	0.25*** (0.04)	0.27*** (0.04)	0.24*** (0.04)	−0.09* (0.04)	−0.10* (0.04)	−0.09 (0.04)
MA	0.16*** (0.03)			0.28*** (0.03)			−0.21*** (0.03)		
MA-WN		0.21*** (0.03)			0.27*** (0.03)			−0.20*** (0.03)	
MA-F			0.17*** (0.03)			0.29*** (0.03)			−0.17*** (0.03)
Gender	−0.28*** (0.05)	−0.30*** (0.05)	−0.27*** (0.05)	−0.03 (0.04)	−0.07 (0.04)	−0.02 (0.04)	0.04 (0.05)	0.07 (0.05)	0.04 (0.05)
Education	−0.08 (0.05)	−0.07 (0.05)	−0.07 (0.05)	−0.49*** (0.04)	−0.48*** (0.04)	−0.47*** (0.04)	0.17*** (0.05)	0.17*** (0.05)	0.16*** (0.05)
Age	−0.09*** (0.02)	−0.08*** (0.02)	−0.09*** (0.02)	−0.01 (0.02)	0.002 (0.02)	0.002 (0.02)	0.14*** (0.02)	0.13*** (0.02)	0.13*** (0.02)
Trait anxiety	−0.08*** (0.03)	−0.07** (0.02)	−0.07** (0.02)	−0.12*** (0.02)	−0.08*** (0.02)	−0.11*** (0.02)	0.06* (0.03)	0.03 (0.02)	0.04 (0.02)
Condition	−0.06 (0.05)	−0.07 (0.05)	−0.06 (0.05)	−0.03 (0.04)	−0.03 (0.04)	−0.03 (0.04)	−0.03 (0.05)	−0.02 (0.05)	−0.02 (0.05)
MA × Gender	0.07 (0.05)			−0.004 (0.04)			0.02 (0.05)		
MA-WN × Gender		0.07 (0.05)			−0.01 (0.04)			−0.03 (0.05)	
MA-F × Gender			0.05 (0.05)			0.01 (0.04)			−0.05 (0.05)
R^2	0.07	0.10	0.07	0.13	0.13	0.14	0.07	0.08	0.07
Adjusted R^2	0.07	0.09	0.07	0.13	0.13	0.14	0.07	0.08	0.07
AIC	4,959	4,913	4,960	4,846	4,841	4,824	4,965	4,949	4,965
BIC	5,009	4,962	5,010	4,895	4,891	4,874	5,014	4,998	5,015
Residual *SE*	0.96	0.95	0.96	0.93	0.93	0.93	0.97	0.96	0.97
$F(7, 1{,}782)$	20.40***	27.50***	20.20***	38.30***	39.00***	41.90***	19.50***	21.90***	19.40***

Note. Standardized coefficients are reported here. All models were based on 1,790 observations.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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