Going Beyond Intelligence: A Systematic Investigation of Cognitive Abilities and Personality Traits of Experts in Mathematics

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Abstract

While the cognitive foundations for mathematical abilities have been investigated thoroughly in individuals with and without mathematical difficulties, our current knowledge about the cognitive abilities as well as the personality traits associated with mathematical expertise is still scarce. In this study we systematically investigated which domain-general (working memory [WM], patterning, visual statistical learning [VSL]) and domain-specific cognitive abilities (approximate number system [ANS], symbolic numerical magnitude comparison, ordinality, arithmetic), as well as personality traits (Big Five, need for cognition [NFC], attitudes towards mathematics), are related specifically to mathematical expertise. To this end, we compared 42 mathematicians with 42 non-mathematicians from fields with no to minimal mathematical content. In contrast to previous research, this study included not only mathematicians with lower expertise (Bachelor and Master students) but also mathematicians with higher expertise (faculty members of the institute of mathematics) to provide a more differentiated look at mathematical expertise. Mathematicians and non-mathematicians were matched for age, sex, educational level and, importantly, for general intelligence. All analyses were done with Bayesian statistics to investigate differences and similarities across these groups. After controlling for intelligence, the results showed that mathematicians and non-mathematicians had very similar profiles. They were comparable in WM capacity, VSL, and general patterning abilities; only in the patterning domain time did mathematicians solve more items. Both groups performed equally in ANS and the ordinality task. However, mathematicians had a more accurate mental representation of symbolic numbers and a better arithmetic fact knowledge. Similarities also emerged in NFC and the Big Five, except for openness where mathematicians were less open to experiences. Unsurprisingly, mathematicians had a more positive attitude towards mathematics than non-mathematicians. Comparing mathematicians with lower and higher expertise did not reveal differences in domain-general and domain-specific abilities. This also applied to the personality traits; the groups did not differ except for the motivation to do mathematics, in which the faculty members were more motivated than the students. Overall, these findings contribute to a deeper and more differentiated understanding of mathematical expertise.

Keywords

Mathematical expertise, intelligence, cognitive abilities, personality traits, Bayesian statistics

Introduction

There is increasing awareness that mathematical competencies are key cognitive abilities in modern societies. They are equally important for life success as literacy (Parsons & Bynner, 2005). In light of the paramount importance of math competencies, they have been attracting an increasing amount of psychological research in the past decades. Most of this research, however, has focused on the development of numerical and mathematical thinking in children (e.g., Vogel et al., 2015) and on individuals showing an atypical development in terms of learning difficulties (e.g., developmental dyscalculia; e.g., Landerl et al., 2017; Vogel & Ansari, 2012). Much less is currently known about individual differences of math competencies in adults and even lesser about the psychological foundations of mathematical expertise. In particular, it is not clear if expert mathematicians show a specific cognitive ability and personality profile. Or if mathematicians rather have a similar ability profile as experts from other academic fields and only differ by having a higher interest in mathematics. This information can contribute to a better understanding of the individual preconditions and cognitive mechanisms for attaining high performance levels. The aim of the present study was to provide the first systematic investigation of cognitive abilities and personality traits related specifically to mathematical expertise. In both ability and personality, we distinguished between constructs that are considered more domain-general (i.e., aspects that are associated with different cognitive domains) and constructs that are considered more domain-specific (i.e., aspects specifically related to the domain of mathematics).

Cognitive Abilities

Domain-general Cognitive Abilities

Intelligence is the most prominent domain-general predictor of educational achievement (Roth et al., 2015) and has been found to be related to mathematical expertise (Cipora et al., 2016; Popescu et al., 2019). Cipora et al. (2016) compared 14 advanced Ph.D. students in mathematics with two different control groups of 15 individuals each, of equal academic standing. One group used advanced mathematics in their daily work, but individuals were not mathematicians per se (e.g., communication, chemistry, engineering) and the other group had none or little mathematical experience (e.g., humanities, social sciences). Mathematicians outperformed both groups in the Advanced Raven Matrices Test indicating a higher fluid intelligence of math experts compared to the control groups. In a more recent study, Popescu et al. (2019) used the Wechsler Intelligence Scale to compare the IQ of 19 mathematicians (academics at doctoral or postdoctoral level) to those of 19 non-mathematicians (equal academic standing from the field of humanities). While mathematicians showed better performance in the performance IQ section (e.g., matrix reasoning and block design subtest), there was no evidence for group differences in the verbal IQ section (e.g., vocabulary and similarities subtest). The observed differences in intelligence need to be considered when interpreting differences in other cognitive factors (e.g., numerical abilities). In fact, almost all previous studies comparing experts in mathematics with those in other fields, have not taken intelligence as a confounding variable into consideration. Either they did not assess intelligence (e.g., Castronovo & Göbel, 2012; Dowker et al. 1996) or did not control for differences in intelligence when interpreting group differences in other cognitive abilities (e.g., Popescu et al., 2019). This is an important limitation, because intelligence correlates consistently with other cognitive abilities (e.g., Colom et al., 2008; Zippert et al., 2019) and, therefore, could be responsible for some of the reported differences between mathematicians and non-mathematicians in domain-specific and/or domain-general abilities. This assumption is supported by the data from Cipora et al. (2016). When fluid intelligence was included as a covariate, the beforehand significant result that mathematicians possessed a spatially more flexible numerical representation, became nonsignificant. In the present study, we overcame this limitation by matching mathematicians with non-mathematicians in general intelligence.

Another classical domain-general ability, which is thought to be important for mathematical abilities, is working memory (WM; Geary, 2011). WM is a domain-general ability that is often listed as a predictor of mathematical achievement. A recent meta-analysis (Peng et al., 2016) including 27,860 participants of different ages found a significant medium correlation between mathematics and WM (r = .35). In addition, the results of this study showed that the relation between WM and mathematics is stronger among individuals with mathematical difficulties compared to typically developing individuals. However, no studies with mathematically gifted or high-performing individuals were included in this meta-analysis. To the best of our knowledge, only one study has so far investigated WM capacity in mathematicians. Popescu et al. (2019) found that mathematicians (compared to non-mathematicians) had a higher capacity in a backward digit span task, providing first evidence that the link between WM and mathematical achievement can also be observed in math experts.

More recently, patterning abilities have moved into the focus of empirical research (MacKay & De Smedt, 2019). They can be described as abilities to abstract rules that define a predictable sequence of items and to extend the sequence (Pasnak, 2017). Abstracting the rules of sequences is, however, also a feature of some intelligence tests (e.g., number series, Raven's Matrices) suggesting that patterning could be rather an aspect of a broad domain-general ability like fluid intelligence. Despite positive medium sized correlations between patterning and intelligence measures, patterning abilities uniquely predicted arithmetic skills above fluid intelligence (Burgoyne et al., 2019). Patterning abilities may be related to mathematical achievement because mathematics inherently involves identifying, extending, and describing predictable sequences in objects and numbers (Resnik, 1997; Steen, 1988). Typical patterning tasks are either pattern extension tasks, with items varying in different parameters such as shape, size or color (e.g., red – blue – blue – red – blue – blue – …; Fyfe et al., 2017), or missing item tasks, in which a series of items with an underlying pattern has one missing item (2 – 4 – ? – 6 – 8; Kidd et al., 2013). First longitudinal evidence suggest that patterning abilities are not only associated with math competencies in children but also are a developmental foundation of math competencies (Kidd et al., 2013; Rittle-Johnson et al., 2019; Schmerold et al., 2017). They even predicted mathematical abilities in children when intelligence and WM was taken into account (β = .24 - .61; MacKay & De Smedt, 2019; Zippert et al., 2019). However, there is no study yet on the relevance of patterning abilities in adults or in mathematicians.

Another concept that is conceptually close to patterning, and could therefore relate to math competencies, is statistical learning. Statistical learning is the ability to extract the underlying regularities of sensory input across time and space (Siegelman, Bogaerts, Christiansen, et al., 2017). In a typical visual statistical learning (VSL) task, a sequential stream of meaningless shapes is presented on a computer screen and participants are tested whether they can detect associative patterns that are hidden within the sequential presentation. While statistical learning has been demonstrated to be associated with language and reading abilities in children as well as in adults (Arciuli & Simpson, 2012; Gabay et al., 2015; Hsu et al., 2014; Schmalz et al., 2019; Siegelman, 2020), there is very little evidence on the relation between statistical learning and mathematics. Zhao and Yu (2016) showed that the numerosity estimation of an array of dots was more difficult when the arrays displayed statistical regularities (containing repeated pairs of colored dots across trials) compared to when the dots were randomly arranged. VSL and numerosity estimation was thus suggested to rely on similar mechanisms. Further, Levy and colleagues (2020) compared female adults with mathematical learning difficulties (MLD) to a matched control group. Individuals with MLD performed significantly worse in a VSL task than the control group. While the control group displayed above chance statistical learning, the MLD participants did not show such a pattern. The result that VSL is impaired in individuals with low math competencies raises the question if VSL is in return exceptionally good in individuals with high mathematical expertise.

Domain-specific Cognitive Abilities

In addition to the aforementioned domain-general abilities, previous research has identified a number of domain-specific abilities that are argued to be critical for the development of math competencies. Among them are basic numerical abilities and arithmetic competencies. Basic numerical abilities include the approximate number system (ANS), symbolic numerical magnitude processing and symbolic numerical order processing (ordinality).

The ANS is a cognitive faculty responsible for the perception of numerical quantities (i.e., sets of objects). To measure ANS abilities, typically two dot arrays are presented on a computer screen. Participants, without counting, have then to decide as quickly and as accurately as possible which of the dot arrays is the numerically larger one (Price et al., 2012). Increasing evidence suggests that this ability is positively related to math competencies in children as well as in adults, albeit the effect is only small to medium in magnitude (r = .24, Schneider et al., 2017; Halberda et al., 2012). Castronovo and Göbel (2012) examined the link between ANS and mathematical performance in 34 experts (undergraduate and postgraduate students of mathematics) and 37 non-experts in mathematics (undergraduate and postgraduate students of psychology). Contrary to the results in typically developing children and adults, all measures of ANS precision were not correlated with math competencies, neither in the mathematics experts nor in the non-experts. Furthermore, there was also no significant difference between the two groups in ANS acuity. Similarly, Popescu et al. (2019) found no group differences between mathematicians and non-mathematicians in ANS precision. However, both studies did not systematically control for differences in intelligence. Therefore, an explicit control for intelligence is needed to further validate the findings that ANS does not differ after having reached a certain level of mathematical expertise.

In the past two decades, symbolic numerical magnitude processing has gained importance as a precursor competence for higher numerical as well as math competencies (Merkley & Ansari, 2016). Performance in this ability is typically assessed through a number comparison task in which two single-digit Arabic numbers are presented simultaneously on a computer screen, and participants have to indicate as fast and accurately as possible, which of the two numbers is the larger one. An important indicator for symbolic numerical magnitude processing, next to overall performance measures of response times and accuracy, is the numerical distance effect (NDE). The NDE reflects an inverse relationship between the response time individuals need to compare two numerals and the numerical distance that separates them. This measure is thought to reflect the acuity of the individual's mental representation of symbolic numbers (Holloway & Ansari, 2009; Vogel, Goffin, et al., 2017). Individuals are faster and more accurate when the distance is large (e.g., 2 - 7) compared to when the distance is small (e.g., 2 - 3; Moyer & Landauer, 1967). In addition to response time and accuracy, the NDE in response times is associated with mathematical achievement in children as well as in adults (De Smedt et al., 2009; Goffin & Ansari, 2016; Hohol et al., 2020; Holloway & Ansari, 2009; Schneider et al., 2017; Vogel et al., 2015). In contrast to the non-significant results in the ANS, Castronovo and Göbel (2012) provided evidence that mathematicians are better at comparing symbolic magnitudes than non-mathematicians. Specifically, mathematicians were in general more accurate and had a smaller NDE of accuracy but a comparable NDE of response times. More recently, however, Hohol et al. (2020) did not find differences in mean response times and in the NDE of response times between advanced Ph.D. students in mathematics (the same participants as in Cipora et al., 2016) and corresponding reference groups (engineers, social scientists, and a reference group from the general population). These inconsistent findings highlight the need for further research regarding the association of symbolic numerical magnitude processing and mathematical expertise.

Especially in later development, symbolic numerical order processing, also called ordinality processing, is a better predictor of math achievement than symbolic numerical magnitude processing (Lyons et al., 2016). In typical ordinality tasks, three single-digit numbers are presented on a computer screen, and individuals have to judge if those numbers are in order (ascending or descending) or not (mixed). As in symbolic numerical magnitude comparison, better performance is related with higher mathematical achievement in children as well as in adults (e.g., Goffin & Ansari, 2016; Lyons & Ansari, 2015; Sommerauer et al., 2020; Vogel et al., 2017). In addition to overall performance measures (response times and accuracy), the reverse distance effect (RDE), which is characterized by faster and more accurate responses when the distance between numbers is one compared to larger numbers, has turned out to be a potential predictor of mathematical achievement in adults (Vogel et al., 2019). The RDE has been assumed to reflect the automatic retrieval and access to number sequences (Vogel et al., 2019). No studies have yet been done in expert mathematicians. Consequently, it is unknown if ordinality processing is specifically related to math competencies at this level of mathematical expertise.

Another essential step in the development of math competencies is the acquisition of procedural knowledge of how to solve arithmetic problems and the establishment of declarative knowledge of arithmetic facts (e.g., the multiplication table). There are two common stereotypes on the relation between arithmetic abilities and mathematical expertise. One is that mathematical experts are “human calculators” who solve arithmetic problems very fast and without errors. The other is that they are particularly bad at arithmetic and not willing to use their brain for such profane demands. The truth seems to lie in-between: While some mathematicians are also calculation prodigies, expert calculators do not necessarily possess exceptional complex mathematical competencies (Pesenti, 2005). Consequently, the performance of mathematicians is in general not comparable to calculation prodigies (Dowker, 2019). Still, most mathematicians are more accurate in arithmetic than individuals from other fields of expertise (Dowker, 1992; Dowker et al., 1996; Popescu et al., 2019). However, most studies on arithmetic competencies in math experts used a verbal arithmetic task (Popescu et al., 2019) or Levine's (1982) computational estimation task (Dowker, 1992; Dowker et al., 1996; Popescu et al., 2019). Albeit these studies showed that mathematicians had better arithmetic abilities than the respective control groups, both tasks focused on procedural knowledge. Therefore, it is unknown if experts in mathematics also have a better arithmetic fact knowledge.

Domain-General Personality Traits and Domain-Specific Personality Facets

Beyond the cognitive ability profile of mathematicians, we investigated domain-general and domain-specific aspects of personality. Personality traits and interests have been found to be important for career choices (Robertson et al., 2010), and their investigation can, thus, provide a more comprehensive picture of the psychological correlates of mathematical expertise. In contrast to cognitive abilities, there is very scarce evidence on personality traits in expert mathematicians.

The most prominent domain-general personality model is the Big Five model. The five traits are openness to experiences (individuals with high scores have many interests, are imaginative, creative, curious, and are willing to explore the world), conscientiousness (individuals with high scores are goal-oriented, mindful to details, well organized, disciplined, and careful), extraversion (individuals with high scores are emotionally expressive, enthusiastic, and like to be around people), agreeableness (individuals with high scores are empathic, trustable, cooperative, and often engage in pro-social behavior), and neuroticism (individuals with high scores are anxious, emotional instable, sad, and are irritated easily; Costa & McCrae, 2012). Clariana (2013) found that a science group, comprising students of mathematics, technology, and computer sciences, scored lower on neuroticism than students from humanities and students from educational sciences. The science group also scored higher on openness than students from educational sciences but comparable to students of humanities on agreeableness and conscientiousness. Hu and Gong (1990) compared 50 professional mathematicians to 50 professional writers and to a population-based control group using the Eysenck Personality Questionnaire, which includes the factors neuroticism and extraversion. Mathematicians scored lower on psychoticism and neuroticism, but also on extraversion compared to the two other groups. In addition to the Big Five traits, need for cognition (NFC) is a promising candidate to differentiate between mathematicians and non-mathematicians. NFC is the tendency to engage in and enjoy cognitive processes (Cacioppo & Petty, 1982), and is not only an important predictor for tertiary academic success (Richardson et al., 2012), but can also predict interest in sciences (Feist, 2012). However, it is unknown whether NFC is specifically elevated in mathematicians, given that mathematics is an academic field with numerous unsolved problems (Guy, 2004; Neumann, 2001), or whether NFC is equally strong in academics of different domains. With this study we aimed to move beyond the existing fragmentary evidence on personality traits and the stereotypes on "how mathematicians are" towards a clearer picture on personality traits of mathematicians.

To our knowledge, there are no studies yet on domain-specific personality facets in mathematicians. However, in the general population math anxiety, attitudes towards mathematics, and self-efficacy in mathematics have been linked to math achievement. Math anxiety is the presence of a fear that emerges in situations in which mathematics has to be applied (Beilock & Maloney, 2015). Higher math anxiety is not only negatively related to mathematical achievement in adults (Schillinger et al., 2018), but individuals with higher math anxiety also avoid math and consequently math-related careers (Beilock & Maloney, 2015; Chipman et al., 1992). Attitudes towards mathematics are affective responses to mathematics often including the liking or disliking of mathematics (enjoyment), the tendency to engage in or avoid mathematical activities (motivation) and the belief that one is good or bad at mathematics (confidence; Neale, 1969). A meta-analysis indicated that attitudes towards mathematics and achievement in mathematics are positively, albeit weakly, related (Ma & Kishor, 1997). Finally, a positive self-belief is related to higher academic achievement in general (Valentine et al., 2004) and this is also true in the domain of mathematics. Math self-efficacy can positively predict mathematical achievement (Grigg et al., 2018; Shen & Pedulla, 2000) but is, as attitude towards mathematics, negatively affected by math anxiety (Bhowmick et al., 2017).

The Present Study

As outlined above, the picture of the psychological correlates of higher-level math competencies and mathematical expertise is quite fragmentary. In particular, it is unclear whether mathematicians possess a particular profile of cognitive abilities and personality traits. The main goal of the present study was to systematically compare (adult) mathematicians and non-mathematicians in a broad range of domain-general and domain-specific abilities as well as personality traits. The groups were not only matched in typical demographic variables but also in their general intelligence, thus, overcoming the potential confound of intelligence. While previous studies have used only traditional frequentist analyses, we conducted Bayesian analysis. In this vein, we could not only provide evidence for differences between the groups but also evidence for similarities of the groups.

In contrast to previous research that focused on either students of mathematics (Castronovo & Göbel, 2012) or faculty members (Dowker et al., 1996), we included both mathematicians with lower expertise (completing a bachelor or master's degree) and mathematicians with higher expertise (faculty members who work as doctoral candidates, post-doctoral researchers, and professors). We compared their profiles with individuals of lower as well as higher expertise in academic domains not related to mathematics (e.g., humanities, languages, law). In addition to the comparison between mathematicians and non-mathematicians, we, for the first time, explored which variables were associated with the level of mathematical expertise. To this end, we compared mathematicians of lower and higher expertise.

Based on the existing evidence reviewed above, we expected mathematicians to have a higher WM capacity than non-mathematicians, to be better at symbolic numerical magnitude processing indicated by a higher accuracy and a smaller NDE of response times and to solve arithmetic problems faster and more accurate. We expected mathematicians to be similar to non-mathematicians in their ANS. Some abilities have been repeatedly found to be related to mathematical achievement in the general population, but have never been investigated in mathematicians, like patterning and ordinality. Still, we regarded the evidence from those studies as convincing enough to assume that mathematicians will solve more items in the patterning task than non-mathematicians as well as display a faster response time, a higher accuracy and a smaller RDE in the ordinality task. Since statistical learning is conceptually close to patterning ability and impaired in individuals with MLD, we took an exploratory look at this ability in mathematicians. Furthermore, supported by evidence from research in the general population, we assumed that mathematicians (compared to non-mathematicians) show lower math anxiety, a more positive attitude towards mathematics and higher self-evaluated competencies in mathematics. However, considering the sparse literature on domain-general personality traits of mathematicians, no hypotheses could be derived about the Big Five personality traits and need for cognition.

Methods

Participants

One hundred and five adults were recruited from Austrian universities, mainly from the University of Graz. From this sample, individuals were allocated to four matched groups: mathematicians with lower expertise, mathematicians with higher expertise, non-mathematicians with lower expertise, and non-mathematicians with higher expertise. Mathematicians were defined as individuals who study or have studied mathematics. Non-mathematicians were defined as individuals who study or have studied a subject with no to minimal explicit mathematical content. Non-mathematicians were recruited from the following subjects: Teaching (different subjects; N = 8), Law (N = 5), Musicology (N = 4), Translation (N = 4), Philosophy (N = 3), History (N = 3), German Philology (N = 3), Classical Philology (N = 2), Medicine (N = 2), Archeology (N = 1), Dental Medicine (N = 1), Geography (N = 1), Art History (N = 1), Pedagogy (N = 1), Sport Studies (N = 1), Theology (N = 1), and Music Pedagogy (N = 1). Individuals with lower expertise were defined as currently completing a bachelor or master's degree at an Austrian university, while individuals with higher expertise already obtained at least a master (or comparable) degree and currently work at an Austrian university (either as a doctoral candidate, as a post-doctoral researcher fellow or as a professor). All participants had German as their native language. Individuals with lower expertise were reimbursed with 50 € for their time, participants with higher expertise, who were significantly harder to recruit, received 100 €. The Ethics Committee of the University of Graz approved this research, and all participants gave informed consent.

The following procedure was performed to match individuals of the four groups. First, non-mathematicians were matched to mathematicians regarding sex, age, and professional experience (years spent studying and working in their field of expertise). This matching was done by recruiting the mathematicians first and then finding non-mathematical study twins. In a second step, mathematicians and non-mathematicians were matched on general intelligence. In the original sample, mathematicians (M = 185.81, SD = 27.99) had a higher general intelligence score than non-mathematicians (M = 164.54, SD = 26.08; BF01 = 0.01, BF10 = 204.85) highlighting the importance of this step. Matching was done at group level by excluding non-mathematicians with low intelligence and mathematicians with high intelligence.

The final sample consisted of 84 individuals, 42 were mathematicians (25 men, 17 women) and 42 were non-mathematicians (25 men, 17 women). To ensure that intelligence-matched mathematicians and non-mathematicians differed only in their amount of mathematical expertise, we compared their performance in specific intelligence domains (numerical, verbal, and figural) and their performance in a mathematical achievement test, measuring higher-level math competencies. Additionally, we asked participants to estimate the overall time they spent with mathematics in their lives and to report their final math grade in school as well as their grade average in their field of study (for further information on the measurements, see the Instruments section). Evidence was strong that mathematicians had a higher mathematical achievement score (effect size delta (δ) = 1.99, 95% Credible Interval (CI) [1.46, 2.53]), better grades in mathematics during school (δ = -1.40, 95% CI [-1.89, -0.91]) and spent approximately four times as much time with mathematics than non-mathematicians did (δ = 0.78, 95% CI [0.34, 1.23]). As ensured by the matching procedure, mathematicians and non-mathematicians were similar in general intelligence (δ = 0.18, 95% CI [-0.22, 0.59]). However, there was anecdotal evidence that mathematicians had higher numerical intelligence (δ = 0.44, 95% CI [0.03, 0.87]), while non-mathematicians had higher verbal intelligence (δ = -0.42, 95% CI [-0.85, -0.01], see Table 1).

Table 1. Descriptive statistics and Bayesian statistics (Bayesian t-test) for mathematicians (Math.) and non-mathematicians (Non-math.)

Variable	Math. *M* (*SD*)	Non-math. *M* (*SD*)	*BF01* *No difference*	*BF10* *Difference*
Age (years)	29.31 (12.00)	29.07 (8.62)	4.37	0.23
Experience (years)	10.35 (11.92)	9.37 (8.68)	4.06	0.25
General intelligence (raw score)	176.57 (22.85)	171.79 (23.67)	2.98	0.34
Numerical intelligence (raw score)	58.29 (12.67)	51.74 (13.55)	0.55	1.81
Verbal intelligence (raw score)	42.81 (7.57)	46.36 (7.25)	0.46	2.16
Figural intelligence (raw score)	75.48 (10.53)	73.69 (12.42)	3.52	0.28
Mathematical achievement (raw score)	**28.41 (2.74)**	**18.79 (6.04)**	**0.00**	**408,800,000,000**
Hours spent with mathematics	**19,351 (21,325)**	**4,651 (12,139)**	**0.01**	**116.76**
Math grade (1 to 5)[b]	**1.19 (0.46)**	**2.33 (1.00)**	**0.00**	**3,928,000**
Grade average (1 to 5) [b]	2.13 (2.19)	1.75 (0.69)	2.64	0.38

Note. Bayesian t-tests analyses, BF01 represents evidence for the null hypothesis (no difference between groups); BF10 represents evidence for the alternative hypothesis (difference between groups). BFs bigger than 1 indicate anecdotal evidence, BFs bigger than 3 provide moderate evidence, BFs bigger than 10 provide strong evidence (Jeffreys et al., 1961). Abilities where the Bayes analyses show moderate or strong evidence for group differences are bolded.

[b] in Austria the grades are 1 (very good), 2 (good), 3 (average), 4 (enough) and 5 (not enough), students receiving a 5 fail

Because this study also intended to explore which variables are associated with the level of mathematical expertise, we compared 21 mathematicians of lower expertise (14 men, 7 women) and 21 mathematicians with higher expertise (11 men, 10 women). There was strong evidence that the two groups differed in age (δ = -1.27, 95% CI [-1.99, -0.58]), experience (δ = -1.30, 95% CI [-2.01, -0.61]) and time in their life they have spent with mathematics (δ = -1.21, 95% CI [-1.90, -0.53]). This was due to the definition of the different levels of expertise, with mathematicians with lower expertise (LE) being students and mathematicians with higher expertise (HE) being university employees who have already obtained a master's degree. Mathematicians with HE were significantly older, had more experience in their field, and had spent more hours in their life with mathematics. However, there was anecdotal evidence that mathematicians with different amount of expertise were similar in intelligence, mathematical achievement and in grades (see Table 2).

Table 2. Descriptive statistics and Bayesian statistics (Bayesian ANCOVA) for mathematicians with lower expertise (Math. LE) and mathematicians with higher expertise (Math. HE)

Variable	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)	*BF01 No difference*	*BF10 Difference*
Age (years)	**22.38 (2.85)**	**36.24 (13.65)**	**0.00**	**406.30**
Experience (years)	**3.36 (2.32)**	**17.33 (13.55)**	**0.00**	**543.59**
General intelligence (raw score)	177.00 (19.29)	176.14 (26.42)	2.54[a]	0.39[a]
Numerical intelligence (raw score)	58.52 (12.89)	58.05 (12.76)	2.91[a]	0.34[a]
Verbal intelligence (raw score)	42.29 (6.97)	43.33 (8.25)	2.56[a]	0.39[a]
Figural intelligence (raw score)	76.19 (7.54)	74.76 (13.01)	2.06[a]	0.49[a]
Mathematical achievement (raw score)	28.05 (3.38)	28.76 (1.92)	2.90[a]	0.35[a]
Hours spent with mathematics	**7,386 (4 358)**	**31,317 (24,751)**	**0.00**	**243.59**
Math grade (1 to 5)[b]	1.24 (0.54)	1.14 (0.36)	2.36[a]	0.42[a]
Grade average (1 to 5)[b]	2.29 (0.89)	1.97 (3.00)	1.85[a]	0.54[a]

Note. Bayesian t-tests analyses, BF01 represents evidence for the null hypothesis (no difference between groups); BF10 represents evidence for the alternative hypothesis (difference between groups). BFs bigger than 1 indicate anecdotal evidence, BFs bigger than 3 provide moderate evidence, BFs bigger than 10 provide strong evidence (Jeffreys et al., 1961). Abilities where the Bayes analyses show moderate or strong evidence for group differences are bolded.

[a] age was included as a covariate in the null model

[b] in Austria the grades are 1 (very good), 2 (good), 3 (average), 4 (enough) and 5 (not enough), students receiving a 5 fail

Instruments

Demographical and Control Variables

Demographical variables

Participants reported their sex, age, mother language, handedness, highest level of education, and their field of study. We used several questions to assess mathematical expertise. First, participants were asked to state the grade in mathematics that they received in their last year of school. Further, as an indicator for their amount of experience we asked participants to indicate in which semester they are currently enrolled. If they already graduated, we asked the participants to indicate how many years of working experience they have in their current field and to report their grand average of their course evaluations at the University. Finally, participants were instructed to estimate the number of hours they spent with mathematical activities to the present day (including school lessons, doing homework, studying, extracurricular mathematical activities, etc.).

Berlin Intelligence Structure Test, short version (BIS-T)

The Berlin Intelligence Structure Test (Jäger et al., 1997) is a structured paper-pencil assessment of intelligence. We used the short version of this intelligence test, consisting of 15 subtasks. Each subtask is a different combinations of one of the three domains of intelligence (numerical, verbal, and figural) as well as of one of the four operational abilities (processing speed, memory, reasoning, and creativity) described in the Berlin intelligence structure model (Jäger, 1984). The internal consistencies of the separate scales are considered appropriate (Cronbach's $\alpha = .75 - .89$; our sample: Cronbach's $\alpha = .72 - .77$). The processing time was approximately 45 minutes. For further analyses, raw scores of the tasks were summed up for each of the three subscales and all raw scores were summed up for a general intelligence score. General intelligence scores ranged from 0 to 312, numerical intelligence scores from 0 to 72, verbal intelligence scores from 0 to 60 and figural intelligence scores from 0 to 180.

Mathematics test for selection of personnel (M-PA)

The mathematics test for selection of personnel (Jasper & Wagener, 2013) is a paper-pencil test originally constructed to assess mathematical abilities for job applications and was used to assess performance in higher-order mathematics. The official short version consists of 31 mathematical problems, has a good internal consistency (Cronbach's $\alpha = .89$; our sample: Cronbach's $\alpha = .92$) and correlates very high ($r = .93$) with the long version (Japer & Wagener, 2013). Mathematical topics covered are fractions, conversion of units, exponentiation, division with decimals, algebra, geometry, roots, and logarithm. The processing time is limited to 15 minutes. For further analyses, all correct answers were counted, resulting in a raw score ranging from 0 to 31.

Domain-general Abilities

Working Memory (WM)

Working Memory was assessed with a complex span paradigm based on Berkowitz Biran (2017) and included a numerical, a verbal and a figural complex span task. In the complex span task, two tasks had to be carried out simultaneously, one storage and one processing task. In the storage part, simple items had to be remembered in the correct order and recalled at the end of each trial. In the processing part simple judgments had to be made. Storage and processing parts were presented alternating throughout each trial. In the numerical WM task, simple additions and subtractions with operands from 1 to 10 had to be judged according to their correctness. The storage part had numbers as items to be remembered. In the verbal WM task, simple German sentences had to be judged according to their truth content; letters from A to Z had to be remembered. In the figural WM task, patterns consisting of black blocks had to be judged according to their symmetry; the storage part consisted of locations of black squares in a pattern of black and white squares. To prevent a response bias exactly 50% of the processing stimuli were correct. The order of the three domains was randomized for each participant. After two practice trials with a span of three and four, participants had to work on six trials with each a different set size. Set sizes ranged from four to nine. Each trial started with a fixation point for 1000 ms followed by the first processing task, which was presented until an answer was made or 3000 ms elapsed. Answers were made by clicking on the left arrow key and right arrow key on the keyboard. After the processing stimulus an interval of 100 ms with a blank screen appeared, followed by the storage item, which was presented for 1000 ms. After all items were presented, a question mark appears on the screen and the participants had to type in the presented numbers and letters with the keyboard. In the figural WM task, the same pattern of nine squares appeared, all white this time. The participants had to click with the mouse on the squares, which were presented in black before. Participants were instructed to reproduce the stimuli in the before presented order and guess rather than leave one out when they did not remember an item. Within a trial, the items to be stored as well as the processing stimuli were randomly ordered and included no repetition. In each domain, the trials varying in set size were randomly ordered, so that the participants could not predict the length of the next trial. The processing time was approximately 15 minutes. Berkowitz Biran (2017) reported a good internal consistency for the complex span tasks (Cronbach's αs: numerical = .79, verbal = .89, figural = .81). For reliability estimation from our sample, we used the split-half (odd-even) method with the Spearman-Brown adjustment. Reliability from our sample was acceptable (numerical = .74, verbal = .68, figural = .77). For further analyses, a working memory capacity score for each domain was calculated. The capacity was calculated by adding up the number of correctly recalled items per domain resulting in scores ranging from 0 (if no item was recalled correctly) to 39 (if all items in each trial were recalled correctly). Additionally, a mean WM capacity score was calculated by averaging the scores of the three domains.

Patterning

To measure patterning ability in adults, two patterning tasks for children (MacKay & De Smedt, 2019; Fyfe et al., 2017) were adapted. Five patterning tasks in different domains were presented randomly to each participant. The domains were numbers, times on an analog clock (time), letters, three-dimensional fishes that are rotated (rotation), and geometrical objects varying in shape, size, and color (shape). Each task included six items in ascending difficulty. Except for the geometrical objects, each item consisted of five stimuli with one missing. In the geometrical objects task, 11 forms were presented. One of the stimuli was missing and indicated through a question mark. Participants had to complete the pattern by selecting one of four solution options presented below. Every part began with an instruction and two easy practice trials in which feedback was given. Each item started with a fixation cross for 1000 ms, the item itself was presented until an answer was given. Answers were given by typing in the number of one of the four presented solutions. For every part, a time limit of 3 minutes was given, resulting in 15 minutes for the whole paradigm. For further analyses, raw scores for each domain (0 to 6 items correct) and for the whole patterning task (0 to 30 items correct) were used. We estimated reliability from our sample using the internal consistency score Cronbach's α. Reliability for the specific domains were questionable (letter = .20, number = -.31, rotation = -.19, shape = -.06, time = .04). There are two reasons for this inappropriate internal consistency. First, the six items per domain were ascending in difficulty, therefore there was a large variance in item difficulty which decreases the reliability (Gulliksen, 1945). Second, each item was worked on by a different number of participants leading to further problems in calculating reliability. While the reliability for the sum score of the whole task clearly was better, it is still questionable (.63). This low reliability must be kept in mind when interpreting the results obtained from this task.

Statistical learning

To measure statistical learning, a visual statistical learning paradigm was constructed based on Siegelman, Bogaerts, and Frost (2017). Participants viewed, without any instruction, a sequential stream of meaningless shapes, which were, unknown to the participants, organized into triplets. The shapes in one triplet co-occurred with a transitional probability of 1, while the transitional probability of the shapes between triplets was much lower. After the presentation of 192 shapes/64 triplets, participants had to state, which triplet they felt is the most familiar. In sum, participants had to make 42 forced choices. Overall, this task had a processing time of approximately 15 minutes. For further analyses, the proportion of correctly answered items was used. According to Siegelman, Boegarts, and Frost (2017) this task had a very good reliability (Spearman-Brown corrected split-half = .83). However, the split-half reliability (Spearman-Brown adjusted) from our sample was questionable (.65). Additionally, only 7% of all individuals showed above chance performance. These limitations are addressed in more detail in the discussion.

Domain-specific Abilities

Approximate Number System (ANS)
To measure ANS we used the software Panamath (Halberda et al., 2008; http://panamath.org). In this ANS task, two dot arrays, one blue and one yellow one, were presented simultaneously beside each other and the participants had to identify the dot array containing more dots without counting. The ratio between the dot arrays varied from 1.1 to 2.0, with all items distributed evenly across ratios. To prevent participants from answering based on overall surface of the dots (more dots = larger surface), the ratio between surface and number of dots was varied. The dot arrays were composed of 5 to 30 dots. Overall, 120 items were presented, which approximately took 5 minutes. After the instruction, the task started with a fixation cross. Dot arrays were presented for a maximum of 700 ms or until an answer was given, to eliminate the possibility of afterimages, a 200 ms mask was presented after each trial. Between each trial a blank space appeared for 1200 ms. If the yellow dot array was larger, participants had to press F on the keyboard, if the blue dot array was larger J had to be pressed. In half of the trials the yellow dot array was the larger one, the other half, the blue one was larger. We estimated reliability from our sample using the split-half (odd-even) method with the Spearman-Brown adjustment. Reliability for response time was good (.88) For further analyses we used the accuracy, the response time, and the weber fraction (w) which was calculated by Panamath and is an index for how good individuals are in discriminating two dot arrays. A smaller w indicates a more precise ANS.

Symbolic numerical magnitude comparison
In the symbolic numerical magnitude comparison task, two numbers (Arabic digits) were presented side by side and the participants had to judge which number is the larger one (after Moyer & Landauer, 1967). To prevent a response bias, in half of the trials the larger number was on the left side, in the other half on the right side. Answers were given by clicking either the left arrow key on the keyboard if the left number was larger, or the right arrow key if the right number was the larger one. The task started with an instruction and practice trials that provided feedback, afterward all 72 possible combinations of the numbers 1 to 9 were presented twice, resulting in 144 trials which took approximately 5 minutes. The usage of all possible combinations also led to numerical distances between number pairs from 1 to 8. Each trial started with a fixation point for 500 ms, afterwards the two numbers were presented for a maximum of 1500 ms. If the participant answered before the end of 1500 ms, a blank screen was presented until 1500 ms were reached. For further analyses, proportion of correctly answered items (ACC) and response time (RT) were used. The numerical distance effect (NDE) was calculated according to Goffin and Ansari (2016) by subtracting the mean response time of the distances 6, 7, and 8 from the mean response time of the distances 1, 2, and 3 and dividing it by the mean response time of the distances 1, 2, 3, 6, 7, and 8 (NDE = ($\text{meanRT}_{1;2;3}$ – $\text{meanRT}_{6;7;8}$) / $\text{meanRT}_{1;2;3;6;7;8}$)). Bigger scores therefore indicate a larger distance effect and a less accurate mental representation of symbolic numbers. We estimated reliability from our sample using the

split-half (odd-even) method with the Spearman-Brown adjustment. Reliability for response time was very good (.99), reliability for the NDE was questionable (.38). More information on how the relatively low reliability of the NDE may affect the interpretability of the results is provided in the discussion.

Ordinality
In the ordinality task participants had to judge if three numbers (Arabic digits) presented on the screen were ordered according to size or not (after Vogel et al., 2017). Only numbers from 1 to 9 were used with the distance between number one and two being the same as the distance between number two and three. Possible distances were 1, 2 and 3 with each distance presented equally often. 25% of the numbers were ordered ascendingly, 25% were ordered descendingly and 50% were not ordered. Participants had to press the left arrow key if the numbers were not ordered and the right arrow key if they were ordered. The task started with an instruction and practice trials that provided feedback. Afterwards, 176 number triplets were presented, which took about 8 minutes. Each trial started with a fixation point for 500 ms, the number triplets were presented for a maximum of 2000 ms. If participants answered before, a blank screen was presented until 2000 ms were reached. For further analyses, proportion of correctly answered items (ACC) and response time (RT) were used. We calculated a reverse distance effect (RDE) following the approach from Goffin and Ansari (2016) for the ascending trials, because the relationship of the RDE and arithmetic seems to be stronger for numerically ascending in-order trials compared to descending in-order trials (Vogel et al., 2019). The RDE was calculated by subtracting the mean response time of the distance 1 from the mean response time of the distances 2, and 3 and dividing it by the mean response time of the distances 1, 2, and 3 (RDE = ($meanRT_{2;3}$ – $meanRT_1$) / $meanRT_{1;2;3}$)). Bigger scores therefore indicate a larger reverse distance effect. We estimated reliability from our sample using the split-half (odd-even) method with the Spearman-Brown adjustment. Reliability for response time was very good (.99), reliability for the RDE was questionable (-.09). More information on how the insufficient reliability of the RDE may affect the interpretability of the results is provided in the discussion.

Arithmetic
To assess arithmetic abilities a multiplication task was presented. The multiplication task focused on arithmetic fact as well as procedural knowledge. Therefore, single-digit multiplications and two-digit multiplications were presented. Participants started with 62 single-digit multiplications (e.g., 6 x 2), which are considered as small problems typically retrieved from memory (arithmetic fact knowledge). After a short break, 32 two-digit multiplications, later called large problems, had to be solved, which typically require calculation procedures. The task started with practice trials with implemented feedback and took approximately 15 min. Multiplications were presented in a random order. Each trial started with a fixation point for 1000 ms followed by a multiplication. Participants had to press the enter key as soon as they knew the answer, afterwards they typed in the answer using the keyboard. To approve the given answer and go to the next multiplication the space bar had to be pressed. For further analyses, the proportion of correctly solved small multiplications (small ACC) and the mean response time (small RT) as well as the proportion of correctly solved large multiplications (large ACC) and the mean response time (large RT) were used. We estimated reliability from our sample using the split-half (odd-even) method with the Spearman-Brown adjustment. Reliability for response time of the small multiplications was very good (.97), reliability for the response time of the large multiplications was also very good (.96).

Domain-General Personality Traits

Big Five
The Neo-FFI-30 is a 30-item questionnaire (Körner et al., 2008) to assess the big five personality traits (openness, conscientiousness,

extraversion, agreeableness, neuroticism). Participants had to state on a 5-point Likert scale how strongly they agree or disagree to statements about their personality. All five traits show an appropriate internal consistency (Cronbach's α = .67 - .81; our sample: Cronbach's α = .72 - .77). For further analyses, items were recoded according to the manual and an aggregated score for each trait was computed. Scores ranged from 1 to 5 with higher scores indicating stronger trait characteristics.

Need for cognition

Need for cognition is the tendency to engage in and enjoy effortful analytic activity and was measured through a 33-item need for cognition scale for adults (Bless et al., 1994). Participants had to read a statement and must choose on a 7-point Likert scale how strongly they agree or disagree. The need for cognition scale has a high internal consistency (Cronbach's α = .86; our sample: Cronbach's α = .91). For further analyses, items were recoded according to the manual and an aggregated score was computed with score ranging from 1 to 7 with higher scores indicating a higher need for cognition.

Domain-Specific Personality Facets

Math anxiety

We used the German adaptation of the Abbreviated Math Anxiety Scale (AMAS-G; Schillinger et al., 2018) to measure math anxiety. Participants had to rate on a 5-point Likert Scale how anxious they feel in a certain situation. Five items described situations in which mathematical content must be learned (learning math anxiety) and four items referred to situations in which mathematical performance is evaluated (math evaluation anxiety). The internal consistency of the AMAS-G is high (Cronbach's α = .89; our sample: Cronbach's α = .90), and in our sample the two subscales correlated high ($r(80) = .70$, $p < .001$), therefore a mean math anxiety score, ranging from 1 to 5, with higher scores indicating higher math anxiety, was used for further analyses.

Attitude towards mathematics

We measured attitude towards mathematics with three questions asking how much participants enjoy mathematics, how confident they feel doing mathematics, and how motivated they are in mathematics. Participants answered on a 5-point Likert scale, in further analyses, each of the three questions is analyzed separately.

Self-evaluated competencies in mathematics

Participants had to self-evaluate their competencies by stating how confident they feel while dealing with different everyday mathematical situations (e.g., how good are you at calculating 15% tip?). Eight questions were given, and participants answered using a 6-point Likert scale. The eight questions had a sufficient internal consistency in our sample (Cronbach's α = .78), therefore, for further analyses, a mean score ranging from 1 to 6 was calculated with higher scores indicating higher self-evaluated math competencies.

Procedure

The study consisted of two test sessions: an online test session and a group test session. One to 56 days (M = 15.76, SD = 12.25) were between the online and the group test session. The online test session was created with Limesurvey and comprised the following parts: First, general information about the study was given, participants had to give informed consent and create a code to guarantee anonymity. Afterwards, the online test session started with the assessment of demographic data, followed by questions on the attitude towards mathematics, math anxiety and self-evaluations of their math competencies. Finally, participants completed the NEO-FFI-30 and the NFC questionnaires, and gave their contact information to be invited to the second test session. The participants needed approximately 15 minutes to complete the online test session.

In the second test session, domain-general as well as domain-specific abilities were assessed in a group setting (max. four participants) with paper-pencil as well as computerized tasks. All computerized tasks were presented on a 15" Lenovo Laptop, and, except for the ANS task, had been programmed with PsychoPy. Depending on the individual speed of the participants, this part took between two and a half and three hours including two short breaks after one and two third of the time. The sequence of the tasks was the following: BIS (45 min) – *Break* – WM (15 min) – Symbolic numerical magnitude processing (5 min) – Arithmetic (10-20 min) –,ANS (5 min) – Patterning (15 min) – *Break* – MPA (15 min) – Ordinality (7 min) – VSL (15 min). After completion of the last task, participants were thanked for their participation and reimbursement was provided.

Statistical Analyses

We used Bayesian Analyses in the free access software JASP (Jasp Team, 2020; Goss-Sampson, 2020) for all group comparisons. In traditional frequentist analyses a non-significant effect is often interpreted as evidence for the null hypothesis, however only a small number of the non-significant effects are caused by the null hypothesis being true. In contrast, Bayesian analysis can not only provide information about the likelihood the alternative hypothesis (differences between groups) but also information about the likelihood of the null hypothesis (similarities between groups; Brysbaert, 2019). Bayesian analyses provided a Bayes factor (BF), which is a ratio that weights the likelihood of the data under the null-hypothesis against the likelihood of the data under the alternative–hypothesis. BF01 provided evidence for the null hypothesis, i.e., no difference between groups. BF10, in contrast, provided evidence for the alternative-hypothesis, i.e., difference between groups. However, BF10 and BF01 cannot be viewed as independent because they are mathematically related (BF10 = 1 / BF01). The larger the BF is, the stronger is the evidence in support of one of the two hypotheses. We classified the strength of the evidence according to Jeffreys (1961). If the BF was larger than 1 but less than 3, the evidence was anecdotal and not considered as sufficient. BFs between 3 and 10 indicated moderate evidence for the corresponding hypothesis and BFs above 10 were assumed as strong evidence.

Two types of Bayesian analyses were conducted. First, we ran Bayesian t-tests to find evidence for similarities and differences between mathematicians and non-mathematicians. Second, we ran Bayesian ANCOVAs with age as a covariate to find evidence for similarities and differences between mathematicians with lower expertise and mathematicians with higher expertise. The latter procedure was chosen because mathematicians with higher expertise were on average 14 years older than mathematicians with lower expertise. In all analyses, the default setting for Bayesian t-test as implemented in JASP (Cauchy prior with a width of 0.707) were used.

Both the data from the intelligence matched sample ($N = 84$), and the data from the full sample ($N = 105$), as well as the analysis scripts are available at the Open Science Framework (https://osf.io/cf6bd/).

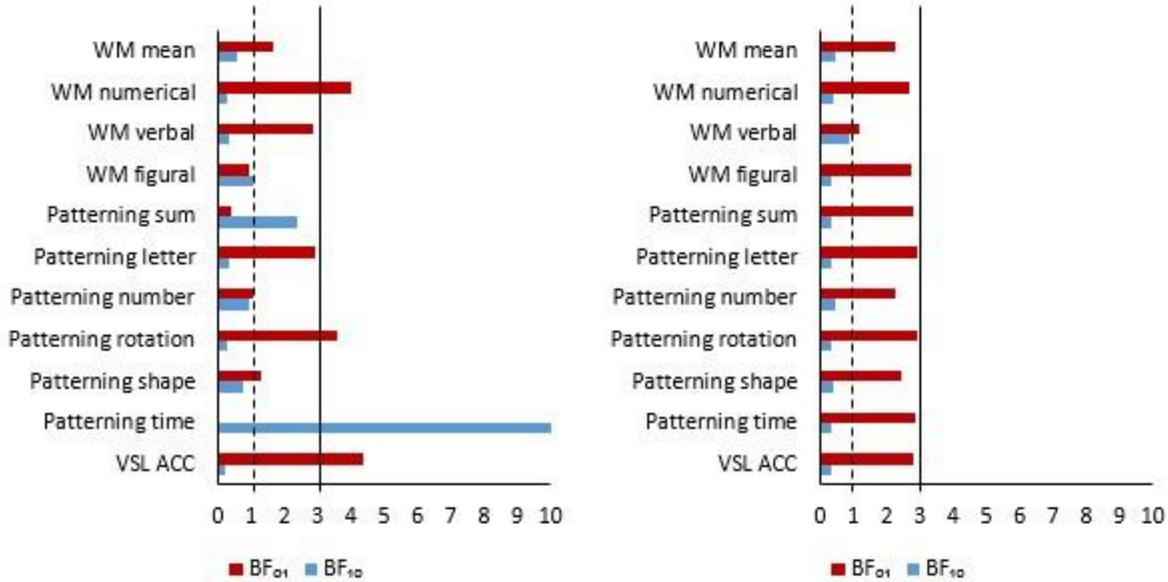
Results

Domain-general and Domain-specific Cognitive Abilities

Domain-general Abilities

Bayesian statistics depicted in Figure 1a show evidence for or against group differences between mathematicians and non-mathematicians in domain-general abilities. We expected mathematicians to solve more items in all patterning tasks, however they only performed better in one patterning domain. Strong evidence (BF10 = 172; $\delta = 0.81$, 95% CI [0.36, 1.26]) showed that mathematicians solved more patterning items in the domain time. However, we found moderate evidence for similarities in the patterning domain rotation as well as anecdotal evidence for similarities in the domains shape, number, and letter, which was unexpected. The large BF in the domain time led to anecdotal evidence for the result, that mathematicians solved more patterning items in total ($\delta = 0.45$, 95% CI [0.04, 0.88]). Contrary to our expectations, there was moderate evidence for similarities in numerical WM capacity, and anecdotal evidence for similarities in general WM capacity as well as for verbal WM capacity. Evidence regarding the figural WM task, remained inconclusive. Moderate evidence showed mathematicians and non-mathematicians being equally good in the VSL task.

Figure 1b displays BFs for the comparison of mathematicians with lower expertise to mathematicians with higher expertise in domain-general abilities. There was anecdotal evidence that mathematicians with lower expertise were as good ss mathematicians with higher expertise when it comes to working memory, patterning abilities as well as to visual statistical learning. All descriptive statistics of the domain-general abilities are presented in Table 3.



1a. Math. vs. Non-math. *1b. Math. LE vs. Math. HE*

Figure 1a. & 1b. Bayesian t-tests analyses (1a) and Bayesian ANCOVAS with age as covariate which is added to the null model (1b), BF01 represents evidence for the null hypothesis (no difference between groups); BF10 represents evidence for the alternative hypothesis (difference between groups). BFs above the dashed line (BF > 1) indicate anecdotal evidence, BFs above the solid line (BF > 3) provide moderate evidence. BF not depicted entirely (BF > 10) provide strong evidence (Jeffreys et al., 1961).

Table 3. Descriptive statistics for domain-general abilities in mathematicians (Math.) and in non-mathematicians (Non-math.) as well as in mathematicians with lower expertise (Math. LE) and in mathematicians with higher expertise (Math. HE)

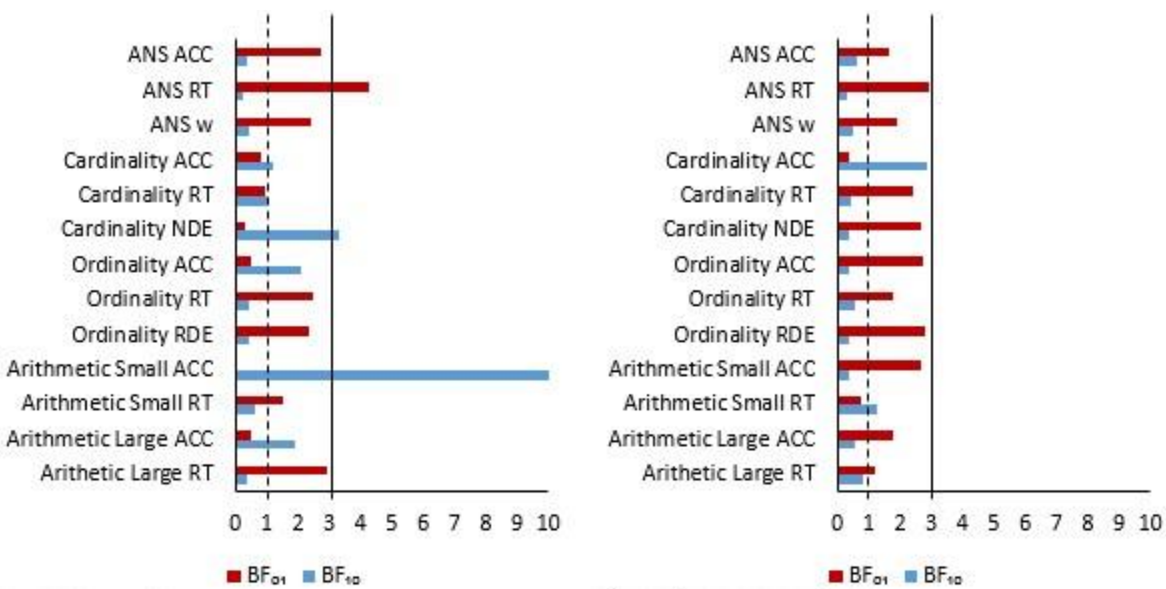
Variable		Math. *M* (*SD*)	Non-math. *M* (*SD*)	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)
Working Memory (number of items remembered correctly)	Mean (0-39)	28.88 (5.30)	27.18 (5.06)	28.85 (5.07)	28.91 (5.65)
	Numerical (0-39)	31.31 (6.87)	30.66 (6.18)	31.27 (7.57)	31.34 (6.28)
	Verbal (0-39)	30.18 (5.89)	28.79 (6.88)	29.37 (6.12)	30.99 (5.68)
	Figural (0-39)	25.15 (8.22)	22.08 (6.70)	25.91 (6.91)	24.39 (9.46)
Patterning (number of items solved correctly)	Sum (0-30)	14.55 (3.60)	12.71 (3.60)	14.57 (3.06)	14.52 (4.16)
	Letter (0-6)	3.05 (1.21)	2.79 (1.28)	3.05 (1.12)	3.05 (1.32)
	Number (0-6)	2.88 (1.19)	2.38 (1.34)	2.95 (0.81)	2.81 (1.50)
	Rotation (0-6)	3.19 (1.07)	3.36 (1.19)	3.10 (1.04)	3.29 (1.10)
	Shape (0-6)	3.02 (1.24)	2.62 (0.96)	3.19 (1.33)	2.86 (1.15)
	Time (0-6)	**2.41 (0.94)**	**1.57 (0.97)**	2.29 (0.96)	2.52 (0.93)
Visual Statistical Learning	ACC	0.52 (0.11)	0.51 (0.12)	0.51 (0.11)	0.52 (0.12)

Note. Abilities where the Bayes analyses show moderate or strong evidence for group differences are bolded.

Domain-specific Abilities

Bayesian statistics depicted in Figure 2a show evidence for or against group differences between mathematicians and non-mathematicians in domain-specific abilities. We observed strong evidence (BF10 = 185; δ = 0.81, 95% CI [0.37, 1.26]) that mathematicians solved small multiplications more accurately than non-mathematicians. The same finding was visible for the accuracy of large multiplications even tough evidence for this difference was only anecdotal (δ = 0.43, 95% CI [0.02, 0.86]). Both findings were as expected. In contrast, anecdotal evidence indicated that both mathematicians and non-mathematicians solved small as well as large multiplications equally fast. There was moderate evidence for similar speed in the ANS, and anecdotal evidence for similarity in ACC and the Weber fraction (w), which was in line with our hypotheses. As expected, moderate evidence showed that mathematicians had a smaller NDE than non-mathematicians (δ = -0.49, 95% CI [-0.92, -0.07]) in the symbolic numerical magnitude comparison task (cardinality). The results regarding response time and accuracy of the symbolic numerical magnitude comparison task were inconclusive. In the ordinality task, there was anecdotal evidence for group differences in ACC with mathematicians being more accurate (δ = 0.44, 95% CI [0.03, 0.87]) which was in line with our expectations. However, there was also anecdotal evidence for similarities in RT and in the RDE, which is in contradiction with our expectations.

Figure 2b displays BFs for the comparison of mathematicians with lower expertise to mathematicians with higher expertise in domain-specific abilities. Anecdotal evidence showed that mathematicians did not differ in ANS due to the amount of expertise they have. Regarding symbolic numerical magnitude comparison, anecdotal evidence indicated that mathematicians with higher expertise solved the task more accurately than mathematicians with lower expertise but not faster. In addition, the groups did not differ in their NDE. Similar to the ANS, mathematicians did not differ in ordinality as indicated by the anecdotal evidence. Regarding arithmetic abilities, anecdotal evidence suggested that mathematicians with lower and higher expertise solved small and large multiplications equally accurate, results regarding response time were inconclusive. Descriptive statistics of the domain-specific abilities are presented in Table 4.



2a. Math. vs. Non-math. *2b. Math. LE vs. Math. HE*

Figure 2a. & 2b. Bayesian t-tests analyses (2a) and Bayesian ANCOVAS with age as covariate, which is added to the null model (2b), BF01 represents evidence for the null hypothesis (no difference between groups); BF10 represents evidence for the alternative hypothesis (difference between groups). BFs above the dashed line (BF > 1) indicate anecdotal evidence, BFs above the solid line (BF > 3) provide moderate evidence. BF not depicted entirely (BF > 10) provide strong evidence (Jeffreys et al., 1961).

Table 4. Descriptive statistics for domain-general abilities in mathematicians (Math.) and in non-mathematicians (Non-math.) as well as in mathematicians with lower expertise (Math. LE) and in mathematicians with higher expertise (Math. HE)

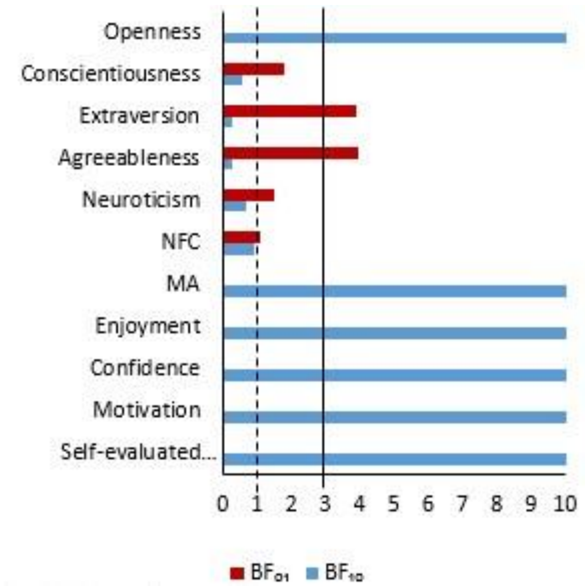
Variable		Math *M* (*SD*)	Non-Math *M* (*SD*)	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)
Approximate Number System	ACC	0.87 (0.04)	0.86 (0.05)	0.87 (0.04)	0.87 (0.04)
	RT (in seconds)	0.91 (0.20)	0.93 (0.30)	0.91 (0.24)	0.91 (0.14)
	w	0.18 (0.05)	0.19 (0.07)	0.18 (0.05)	0.17 (0.05)
Symbolic numerical magnitude comparison task (Cardinality)	ACC	0.98 (0.02)	0.97 (0.02)	0.98 (0.01)	0.99 (0.01)
	RT (in seconds)	0.49 (0.08)	0.45 (0.12)	0.46 (0.05)	0.52 (0.09)
	NDE	**0.11 (0.05)**	**0.14 (0.06)**	0.11 (0.04)	0.10 (0.06)
Ordinality	ACC	0.90 (0.07)	0.85 (0.10)	0.89 (0.05)	0.90 (0.08)
	RT (in seconds)	0.88 (0.14)	0.84 (0.18)	0.84 (0.11)	0.92 (0.15)
	RDE	0.01 (0.07)	-0.01 (0.10)	0.00 (0.07)	0.02 (0.07)
Arithmetic (Multiplication)	Small ACC	**0.99 (0.02)**	**0.96 (0.04)**	0.98 (0.02)	0.99 (0.02)
	Small RT (in seconds)	1.62 (1.12)	1.96 (0.89)	1.32 (0.73)	1.92 (1.36)
	Large ACC	0.93 (0.07)	0.90 (0.07)	0.92 (0.08)	0.94 (0.05)
	Large RT (in seconds)	5.88 (3.35)	6.53 (2.82)	5.32 (1.97)	6.44 (4.30)

Note. Abilities where the Bayes analyses show moderate or strong evidence for group differences are bolded.

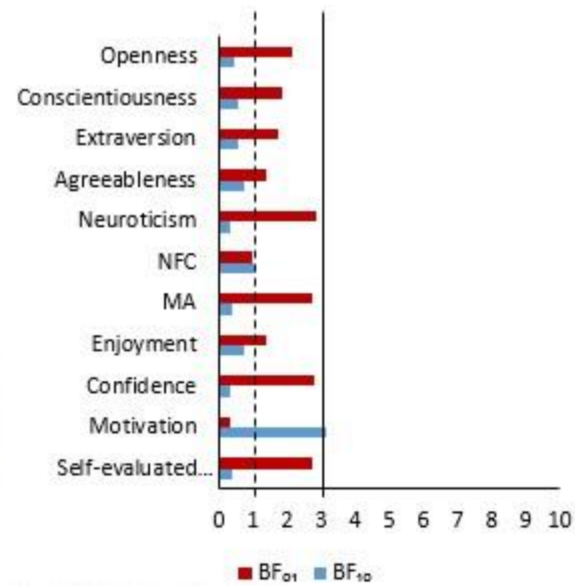
Domain-general Personality Traits and Domain-Specific Attitudes

In the domain-general personality Bayesian analyses, depicted in Figure 3a, we observed strong evidence for differences in openness (BF10 = 171; δ = -0.81, 95% CI [-1.26, -0.36]) with non-mathematicians showing higher openness than mathematicians did. Regarding the other Big Five personality traits conscientiousness, extraversion, agreeableness as well as neuroticism, and need for cognition, the BFs provided moderate to anecdotal evidence for similarities. Thus, except for openness, evidence suggested that mathematicians and non-mathematicians were rather similar in domain-general personality traits. Regarding NFC, results were indecisive.

We found strong evidence for group differences in all domain-specific attitudes. As expected, mathematicians (compared to non-mathematicians) showed lower math anxiety (BF10 = 309 915; δ = -1.26, 95% CI [-1.74 -0.79]), enjoyed mathematics more (BF10 = 4.31E+8; δ = 1.65, 95% CI [1.14, 2.16]), were more confident in mathematics (BF10 = 716 894; δ = 1.31, 95% CI [0.83, 1.79]), had a higher motivation in mathematics (BF10 = 2.37E+9; δ = 1.73, 95% CI [1.22, 2.25]), and self-evaluated their competencies in mathematics better (BF10 = 611; δ = 0.89, 95% CI [0.44, 1.35]).



3a. Math. LE vs. Math. HE



3b. Math. LE vs. Math. HE

Figure 3a. & 3b. Bayesian t-tests analyses (3a) and Bayesian ANCOVAS with age as covariate, which is added to the null model (3b), BF01 represents evidence for the null hypothesis (no difference between groups); BF10 represents evidence for the alternative hypothesis (difference between groups). BFs above the dashed line (BF > 1) indicate anecdotal evidence, BFs above the solid line (BF > 3) provide moderate evidence. BF not depicted entirely (BF > 10) provide strong evidence (Jeffreys et al., 1961).

Figure 3b displays BFs for the comparison of mathematicians with lower expertise to mathematicians with higher expertise in domain-general as well as domain-specific personality aspects. Mathematicians with higher expertise were more motivated in mathematics compared to mathematicians with low expertise, which was shown with moderate evidence (BF10 = 3.17). In contrast, mathematicians with lower expertise did not differ from mathematicians with higher expertise in the other domain-specific attitudes, even though evidence was only anecdotal. They displayed a similar amount of math anxiety, enjoyed math similarly, were comparably confident in mathematics and evaluated their competence in mathematics similarly. Regarding domain-general personality traits anecdotal evidence showed that the Big Five personality traits did not differ depending on amount of mathematical expertise. Results regarding need for cognition were again indecisive. Descriptive statistics of the domain-general personality traits and domain-specific personality facets are presented in Table 5.

Table 5. Descriptive statistics for domain-general personality traits and domain-specific personality facets in mathematicians (Math.) and in non-mathematicians (Non-math.) as well as in mathematicians with lower expertise (Math. LE) and in mathematicians with higher expertise (Math. HE)

Variable		Math. *M* (*SD*)	Non-math. *M* (*SD*)	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)
Domain-general personality traits					
Big Five (Likert 1-5)	Openness	**3.53 (0.71)**	**4.11 (0.61)**	3.38 (0.65)	3.68 (0.74)
	Conscientiousness	3.85 (0.59)	4.03 (0.56)	3.68 (0.62)	4.02 (0.51)
	Extraversion	3.29 (0.62)	3.36 (0.63)	3.36 (0.66)	3.21 (0.58)
	Agreeableness	3.80 (0.72)	3.87 (0.66)	3.64 (0.74)	3.95 (0.69)
	Neuroticism	2.27 (0.63)	2.50 (0.76)	2.27 (0.64)	2.26 (0.62)
Need for Cognition (Likert 1-7)		5.33 (0.56)	5.06 (0.78)	5.15 (0.53)	5.51 (0.54)

Variable	Math. *M* (*SD*)	Non-math. *M* (*SD*)	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)
Domain-specific personality facets				
Math Anxiety (Likert 1-5)	**1.51 (0.41)**	**2.33 (0.77)**	1.53 (0.44)	1.49 (0.39)
Enjoyment of mathematics (Likert 1-5)	**4.55 (0.55)**	**2.98 (1.18)**	4.43 (0.60)	4.67 (0.48)
Confidence in mathematics (Likert 1-5)	**3.88 (0.74)**	**2.71 (0.94)**	3.86 (0.57)	3.91 (0.89)
Motivation in mathematics (Likert 1-5)	**4.43 (0.59)**	**2.81 (1.13)**	**4.24 (0.63)**	**4.62 (0.50)**
Self-evaluated math competencies (Likert 1-6)	**4.69 (0.54)**	**4.12 (0.64)**	4.64 (0.33)	4.74 (0.69)

Note. Personality traits where the Bayes analyses show moderate or strong evidence for group differences are bolded.

Discussion

The aim of the current study was to systematically investigate the cognitive abilities and personality traits related to mathematical expertise while controlling for intelligence. Mathematical expertise was defined in terms of formal education. We compared mathematics students as well as faculty members at mathematical institutes to individuals of equal academic standing from domains not related to mathematics. Both groups were matched for general intelligence to avoid the confounding influence of intelligence on domain-general as well as domain-specific abilities. In addition, we separately looked at the specific influence of mathematical expertise by comparing mathematicians of lower (students) and higher (faculty members) expertise. All analyses were done with Bayes statistics to provide not only evidence for differences between groups, as is done with traditional frequentist analyses, but also evidence for similarities.

Domain-general Cognitive Abilities

Intelligence is an important predictor for educational achievement, especially in the domain of mathematics (Roth et al., 2015). This relationship between intelligence and mathematical achievement is a well-established finding and also present in individuals with high mathematical expertise. In previous studies, it was found that mathematicians had a higher IQ than individuals of equal academic standing from other fields of expertise (Cipora et al., 2016; Popescu et al., 2019). We replicated this finding in our original sample of 105 participants (see 2.1. Participants). Since intelligence was correlated with several other domain-general as well as domain-specific cognitive abilities in the original full sample, but also in our intelligence matched sample (see Table A1), it was important to control for this confounding variable when examining differences between expertise groups. Still, it must be mentioned, that by matching for general intelligence we probably also have screened out useful variance. Nonetheless, as our question was whether factors above intelligence explain differences between mathematicians and non-mathematicians, this question can only be addressed by matching mathematicians and non-mathematicians in general intelligence.

After controlling for intelligence, we observed strong evidence for a difference between mathematicians and non-mathematicians in only one task, namely in the patterning task in the domain of time. While there are no studies on patterning abilities in adults, let alone in mathematical experts, evidence from studies in children (e.g., MacKay & De Smedt, 2019; Zippert et al., 2019) suggested that mathematicians and non-mathematicians may also differ in their patterning abilities. Therefore, the above-mentioned finding was in line with our hypothesis. However, contrary to our hypothesis that mathematicians have better pattering abilities, mathematicians performed equally well as non-mathematicians in the other four patterning domains (letter, number, rotation, and shapes). However, the evidence in favor of similar performance in these domains was only anecdotal for letter, number, and shape and moderate in the domain of rotation. This domain-specificity could be due to the task demand. Patterning in the domain time was the most difficult task with on average two out of six items solved, compared to an average of three items in the other domains. This difficulty may have arisen from the requirement (a) to transform the analogue clock into a digital format, (b) to do calculations in a duodecimal (12) numeral system for hours and a sexagesimal (60) numeral system for minutes (De Vlieger, 2013) and (c) to transform the results back from digital to analogue. Mathematicians can be expected to have more experience using different numeral systems and also have better calculation competencies (as also observed in our data), resulting in an advantage in solving this complex patterning task. This explanation was corroborated by our correlational results (see Table A1). The number of items solved in the domain time showed a positive correlation with mathematical achievement (r = .42) and numerical intelligence (r = .42). Those correlations were the highest out of all patterning domains, even higher than the correlations between the number of items solved in the domain number and mathematical achievement (r = .32) as well as numerical intelligence (r = .36). Thus, these results suggest that mathematicians do not have better patterning abilities per se, but rather have an advantage in solving patterns with high mathematical demands.

For working memory, there was stronger evidence for similarities between mathematicians and non-mathematicians than for differences. These findings stand in contrast to previous results and our hypothesis that mathematicians have a higher WM capacity than non-mathematicians. Moderate evidence for similarities was observed in the numerical WM task, and anecdotal evidence for the verbal and general WM score. Only in the figural WM task, there was anecdotal evidence for mathematicians having a higher capacity (BF10 = 1.05). However, since evidence for similarities was almost equally strong (BF01 = 0.96), we concluded that the evidence was inconclusive. WM was found to be not only related to mathematics in the general population (Friso-van den Bos et al., 2013; Peng et al., 2016; Raghubar et al., 2010) but also impaired in children with difficulties in mathematics (Passolunghi & Siegel, 2004; Menon, 2016). Further, mathematically gifted children and adolescents expressed better WM abilities compared to a control group (Leikin et al., 2013; Swanson, 2006), and mathematicians had a higher WM capacity than non-mathematicians (Popescu et al., 2019). A plausible explanation for our diverging results lies in the matching for general intelligence. Working memory capacity and general intelligence have been found to be highly correlated constructs (Ackerman et al., 2005; Oberauer et al., 2005), which was also evident in our data (r = .48, see Table A1). One assumption why this relationship exists is the view that both general intelligence as well as WM partly rely on the same cognitive processes. Reasoning is needed to successfully perform in intelligence as well as in WM tasks (Diamond, 2013; Jäger, 1984). Next to additional processing requirements, WM tasks require short-term memory, and short-term memory is frequently included in the measurement of general intelligence (Colom et al., 2008). This was also the case in our study where the BIS-T included three tasks measuring the operational ability "memory". Those shared processes seem to be responsible for the high correlation between general intelligence and WM. If intelligence is controlled for, much of the variance in WM is removed and WM does not remain a unique predictor. Evidence for this assumption comes from Popescu et al. (2019) as well as to some extent from our own data. Popescu et al. (2019) found mathematicians to have a higher WM capacity (measured with a backward digit-span task) compared to non-mathematicians. But mathematicians also had a higher performance IQ, which was not considered when discussing the difference in WM. When analyzing unmatched groups in our sample, we found moderate evidence towards mathematicians having a higher figural WM capacity than non-mathematicians. This supported our notion, that the divergent findings regarding WM capacities in previous studies can be explained by the control for general intelligence.

Since mathematics inherently involves the identification of predictable sequences in objects and numbers (Resnik, 1997), we also investigated potential group differences in visual statistical learning (Bogaerts et al., 2020). Recent evidence suggested that VSL may not only be related to language and reading abilities (Schmalz et al., 2019; Siegelman, 2020) but also to mathematics (Levy et al., 2020; Zhao & Yu, 2016). However, this was not the case in our study. On the one hand, moderate evidence showed that mathematicians performed similarly to non-mathematicians in the VSL task. On the other hand, performance in the VSL task was neither correlated with measurements of numerical intelligence and mathematical achievement nor with arithmetic as well as with basic numerical abilities. When the correlations were calculated for mathematicians and non-mathematicians separately, visual statistical learning correlated positively with general intelligence (r = .45) and mean working memory capacity (r = .38) in the non-mathematicians. However, these results must be interpreted very carefully due to methodological issues. Additional to the questionable reliability, only 7% of all individuals showed above chance performance in this task, showing a floor effect. In the study by Siegelman, Bogaerts and Frost (2017), 60% performed above this threshold and even though we used the exact same task, our reliability measure was significantly worse. Therefore, our VSL task may not have provided reliable information about the statistical learning abilities of the majority of our sample. A plausible explanation for this low performance could be that the VSL task was the last task in the test session. In contrast to previous studies, participants already had spent over two hours completing demanding cognitive tasks before engaging in the VSL task. Even though the VSL is designed to work without overt attention, there is still the possibility that participants were cognitively too exhausted to detect the transitional probabilities embedded in the sequential stream of meaningless shapes.

Domain-specific Cognitive Abilities

The strongest evidence for a group difference in domain-specific cognitive abilities emerged in arithmetic (multiplication tasks). In line with our hypothesis, we observed strong evidence (BF10 = 185) that mathematicians were more accurate in solving small multiplications. However, anecdotal evidence suggested that both groups solved the small problems at the same speed. There is broad consensus that the dominant process for solving single-digit multiplications is the direct retrieval of the solution from an arithmetic fact network in long term memory (Ashcraft, 1992; Campbell & Epp, 2005). This suggests that mathematicians (compared to non-mathematicians) have a better arithmetic fact network in terms of stronger associative strengths between problems and the respective answers. Since the ability to retrieve arithmetic facts constitutes a prerequisite for the learning of more complex mathematical knowledge (De Smedt, 2016), this finding seems plausible. In addition, as expected, mathematicians showed better performance in the procedural arithmetic task as reflected in anecdotal evidence for group differences in accuracy of the large (two-digit) multiplications. Those results are consistent with other studies on mathematicians that found mathematicians having a better procedural knowledge (Dowker, 1992; Dowker et al., 1996; Popescu et al., 2019).

Our data supported the hypothesis that mathematicians did not have a better ANS. While ANS was found to be positively related to mathematical competence in the general population (Schneider et al., 2017) and in highly mathematical gifted adolescents (Wang et al., 2017), the studies on ANS in mathematicians implicated that ANS is not related to mathematics at this level of mathematical expertise (Castronovo & Göbel, 2012; Popescu et al., 2019). Moderate evidence proved that mathematicians performed similarly to non-mathematicians in response time and accuracy in an ANS task. Even though the evidence for group similarities in ANS acuity (w) was only anecdotal, it was three times larger than evidence for group differences. Our findings were similar to previous findings in mathematical experts, even though we used a conceptual slightly different ANS task and task demands therefore differed to some extent. While we presented two dot arrays simultaneously, Castronovo and Göbel (2012) and Popescu et al. (2019) sequentially compared a target dot array to a reference dot array leading to a higher WM demand compared to the simultaneous presentation (Price et al., 2012). Still, our study corroborated that there are no differences in ANS after a certain level of mathematical expertise is achieved.

We expected mathematicians to be better at symbolic numerical magnitude processing as indicated by a higher accuracy and a smaller NDE. Supporting our hypothesis, moderate evidence showed that mathematicians had a considerably smaller NDE in the symbolic magnitude comparison task compared to non-mathematicians This indicates that mathematicians have a more accurate mental representation of symbolic numbers and is consistent with results found in the general population (e.g., De Smedt et al., 2009; Schneider et al., 2017). However, this contradicts the results from studies focusing on mathematical experts using a symbolic numerical magnitude comparison task. Even though both Castronovo and Göbel (2012) as well as Hohol et al. (2020) found a robust NDE, mathematicians had an equal sized NDE as non-mathematicians. One possible explanation for this diverging finding could be the fact that both aforementioned studies compared target numbers to a fixed standard while our participants had to compare two simultaneously presented numbers. A recent study raised doubt if the comparison with a fixed standard really taps into the same cognitive processes as comparing two different numbers. Maloney et al. (2019) concluded that especially the NDE is not equivalent in simultaneous presentation compared to comparison to a standard. However, one constraint when interpreting the NDE is the inadequate reliability. The NDE is a difference score, and these generally produce low reliabilities as the correlation between the component scores subsume the majority of their systematic variance (Draheim et al., 2019). In contrast, when using a different task to measure the mental representation of symbolic numbers, mathematician do indeed seem to have a more accurate but also a more flexible mental spatial representation of symbolic numbers. In a study by Sella et al. (2016) mathematicians and academically matched individuals from humanities had to position diverse numbers spatially on a number line. Mathematicians were more accurate at spatial mapping positive, but not negative numbers and the performance in this basic numerical skill could predict group membership. The higher flexibility of mental spatial representation of symbolic numbers is shown by Cipora et al. (2016) who provided evidence that mathematicians did not reveal a Spatial-Numerical Association of Response Codes. While participants typically respond faster to smaller magnitudes with the left hand, and to larger magnitudes with the right hand, this was not the case in mathematicians. For accuracy and response time no reliable evidence was found, neither for group differences nor for similarities. These findings contradict, at least to some extent, the results by Castronovo and Göbel (2012) who, on the one hand, did not find differences in response time between mathematicians and a control group but, on the other hand, found a higher accuracy of mathematicians. However, while Castronovo and Göbel (2012) used a two-digit numerical magnitude comparison task we, as well as Hohol et al. (2020), used single-digits number comparison which were significantly easier than two-digit number comparison (Mdn = 0.95, SD = 0.03). Both Hohol and colleagues (overall accuracy 96.9%) as well as our study showed a very high accuracy (M = 0.98, SD = 0.02) implicating a ceiling effect, which could be the reason for the indecisive results in regard to the accuracy. While the reliability for response time alone was excellent, another concern emerges with response times in general, namely that they are sensitive to speed-accuracy tradeoffs that may differ across groups of individuals (Draheim et al., 2019). While mathematicians seemed to reduce speed in favor of a higher accuracy in the symbolic numerical magnitude processing test (as indicated by a positive correlation of .55 between RT and ACC), non-mathematicians showed no correlation between response time and accuracy. Despite the limitations, deduced from the results that mathematicians exhibited a smaller NDE but similar response times as non-mathematicians, we presume the following. The differences in the NDE did not stem from the use of different response strategies but rather indicate that mathematicians haven a more accurate mental representation of symbolic numbers, probably caused by their greater experience with the symbolic number system.

Our study was the first to investigate ordinality processing within mathematical experts. Results in the general population revealed that a better overall performance (response time and accuracy combined) as well as a smaller RDE was associated with higher mathematical competence (e.g., Goffin & Ansari, 2016; Vogel et al., 2017). Additionally, a study comparing high math-ability children to a control group found a group difference in a number order task in favor of the high-achieving (Bakker et al., 2019). Therefore, we hypothesized mathematicians to be faster, more accurate and to have a smaller RDE than non-mathematicians in an ordinality processing task. However, this was only the case in accuracy and only with anecdotal evidence. Regarding the response times and the RDE anecdotal evidence showed that mathematicians and non-mathematicians performed similar. Mathematicians were more accurate compared to non-mathematicians in judging if three single-digit numbers were ordered or not although they did not need more time for those judgements. This heightened effectiveness in making ordinal judgments seemed to be related to better mathematical competences. A higher accuracy in the ordinality processing task was positively associated with a higher numerical intelligence (r = .49) as well as with a higher mathematical achievement score (r = .31). The response time in this task, which was similar for mathematicians and non-mathematicians, however, did not correlate with numerical intelligence and mathematical achievement (see Table A1). While the results regarding the overall performance measures were not surprising, we did not expect mathematicians to have a comparable RDE to non-mathematicians. This was the case because this measure has been assumed to reflect the automatic retrieval and access to number sequences, which we hypothesized to be better in mathematicians. Further, the RDE did not reveal a significant association with any of the other tasks (regardless of within the whole sample or within mathematicians and non-mathematicians separately), which was unexpected too. An explanation for the missing correlations could be the insufficient reliability, which is caused by the RDE being a difference scores (Draheim et al., 2019), as well as the low numbers of trials (n = 44) used to calculate the RDE. Another explanation for these results could be provided by a closer look at the descriptive statistics and the distribution plots. These revealed the RDE to be a rather indominant psychological phenomenon, which is in contrast to a dominant phenomenon, whose characteristic is that it is present in virtually all individuals and no individual shows a divergent effect (Rouder & Haaf, 2018). Vogel et al. (2021) showed that while the NDE is consistent and shows mostly quantitative differences between individuals, the RDE shows qualitative differences. This indicates that individuals may use different qualitative processing strategies while solving the ordinality task. We looked at the proportion of individuals who behaved in a manner consistent with the theoretical explanation, i.e., participants who showed the expected pattern of the RDE ($meanRT_{2;3} > meanRT_1$). The percentage of participants whose responses matched this pattern are labeled percent correct classifications (after Grice et al., 2020) and percent correct classification for the RDE was 45.24%. Less than half of the participants were consistent with the ordinal hypothesis and showed a typical RDE where number triplets with distance one were judged faster than triplets with the distance two and three. 24.86% were opposite of the ordinal hypothesis and showed a canonical distance effect, in which number triplets with distance two and three are judged the fastest. 11.90% were inconsistent with the ordinal hypothesis, meaning they who showed no distance effect at all or only differed by 10 milliseconds. Still, mathematicians and non-mathematicians were equally represented in all three groups.

Taken together, our results revealed that mathematicians had rather similar ability profiles as non-mathematicians after differences in intelligence have been taken into account. Moderate evidence for similarity was found in numerical WM, patterning abilities in the domain rotation, in the VSL task, and in ANS response time. In contrast, strong evidence for differences emerged in the domain time of the patterning task, in the accuracy of solving single-digit multiplications, and moderate evidence for differences emerged in the NDE in a symbolic numerical magnitude comparison task. Thus, mathematicians had the same domain-general abilities as non-mathematicians, apart from having better patterning abilities in the domain time, which required specific mathematical competencies. Further, mathematicians were not per se better at all domain-specific tasks; however, they did have a more accurate mental representation of symbolic numbers and better arithmetic fact knowledge.

Domain-general Personality Traits and Domain-specific Personality Facets

There are many stereotypes on "how mathematicians are," a few of them being that mathematicians are rather introverted (Bruss, 2011) as well as lonely, socially awkward, and boring (Piatek-Jimenez et al., 2020). However, there is not much psychological research on the domain-general personality traits of mathematicians. Existing studies either biographically described eminent mathematicians (e.g., James & Ioan, 2002) or mathematicians from a different socio-cultural background (e.g., Chinese participants, Hu & Gong, 1990) than is studied here. Therefore, we perceived the literature as too sparse to derive specific hypotheses. One thing that must be kept in mind when integrating the results into the existing literature is that a generalization of the results can only be done carefully to similar socio-cultural settings.

In the present study, we found moderate evidence that mathematicians were less open to experiences than non-mathematicians, but rather similar in extraversion and agreeableness. In conscientiousness and neuroticism, groups were also rather similar, albeit evidence was only anecdotal. In previous studies, Clariana (2013) found a science group, which included students of mathematics, to score higher on openness than students from educational sciences. We assume that our findings are not a result of mathematicians being less open to experiences but of non-mathematicians being more open. According to the manual of the Big Five personality test we administered (Körner et al., 2008) the mean score for openness of a large population-based sample (N = 2,508, 18-92 years) is 2.04 with the scale ranging from 1 to 5. Our non-mathematicians displayed a mean score of 4.11 while the mathematicians had a mean openness score of 3.53. However, educational level significantly influences openness to experiences and individuals with a higher level of education tend to be more open to experiences (Körner et al., 2008). Compared to the population-based sample, our participants had a higher education, explaining why scores of both groups were significantly higher than the mean score derived from the manual. In addition, we assume that the specific wording of the items in relation with the fields of expertise of the non-mathematicians may have contributed to the observed group difference. Out of the six items of the scale four items covered domains that were directly related to domains our participants were from (including philosophy, history of art, archeology linguistic sciences, musicology as well as theology). The respective items were "I'm bored by philosophical discussions," "I'm excited by motives, which I find in arts and in nature," "I'm not impressed by poetry," and "While reading literature or looking at a painting, I sometimes feel a shiver of excitement." In any case, the results that mathematicians were similar to non-mathematicians in extraversion, agreeableness, and neuroticism speak against the prejudices that mathematicians are socially awkward introverts. We hypothesized that mathematicians were also comparable to non-mathematicians in NFC, which is the tendency to engage in end enjoy effortful cognitive processes in general. However, evidence for this assumption was indecisive leading to no clear conclusion. Still, NFC does not seem to be a specific trait of mathematicians but rather a characteristic of individuals attending tertiary education, regardless of the domain.

While mathematicians and non-mathematicians are rather similar in domain-general personality traits, a different picture emerged in domain-specific personality facets. With strong evidence, mathematicians displayed lower math anxiety, showed a more positive attitude towards mathematics, and evaluated their math competencies better than non-mathematicians did. This supported our hypotheses, which we postulated based on studies in the general population finding the same pattern for individuals with higher mathematical achievement. Mathematicians are unlikely to suffer from significant math anxiety, and because of their experience in the field of mathematics they display a high confidence in doing mathematics and a higher confidence is associated with lower anxiety (Dowker, 2019) which is also visible in our data (r = -.65). Further, individuals with a highly negative attitude towards mathematics are unlikely to study mathematics and become professional mathematicians in the first place. Finally, mathematicians are known to show positive emotional reactions to mathematics (Dowker, 2019), which is in line with our finding that mathematics enjoying mathematics more, are more confident and more motivated to do mathematics than non-mathematicians. We suppose that these differences in domain-specific personality facets may already have been visible before mathematicians chose mathematics as their career, otherwise they would have engaged in a different domain. Nonetheless, not all individuals displaying this positive attitude towards mathematics will become mathematicians leaving the question open what the reasons are to pursue a career in mathematics. However, to answer this question, a longitudinal study would be needed.

In sum, mathematicians had a rather similar general personality profile as non-mathematicians, except from being less open to experiences. However, they did have a more positive attitude towards mathematics which is not surprising considering that they chose to become mathematicians.

Mathematicians with Lower Expertise vs. Mathematicians with Higher Expertise

Our study contributes to the understanding of the specific influence of mathematical expertise by not only including students of mathematics but also faculty members of mathematics and by investigating similarities and differences between those two expertise groups. We observed that mathematicians with lower expertise were equally intelligent as mathematicians with higher expertise and scored comparably on the mathematical achievement test. However, as the M-PA was constructed to measure mathematical achievement at the level of secondary education, we did not expect this test to differentiate between groups. Mathematicians with higher expertise had spent approximately four times as many hours with mathematics in their life and had been in the field of mathematics for 14 years more than mathematicians with lower expertise had. This advance in expertise caused mathematicians with higher expertise being significantly older which is why we decided to include age as a covariate to separate between age-related and expertise-related group differences.

Beforehand it must be emphasized that evidence for similarities was in almost all variables only anecdotal. Thus, we do not have substantial evidence and our interpretations should be regarded cautiously. Mathematicians had similar domain-general abilities regardless of the amount of expertise. WM capacity was comparable in mathematicians with lower and higher expertise indicating that additional experience in mathematics is not related to differences in WM capacity. WM capacity is typically found to decrease with age (Bopp & Verhaeghen, 2018; Fiore et al., 2012; Jaroslawska & Rhodes, 2019), which was not visible in our data. However, in contrast to the studies on age-related decrease in WM, our group of "older individuals" was relatively young (24-63 years, $M = 36.24$, $SD = 13.65$) compared to the "older individuals" in the above-mentioned studies. Further, all our participants were currently employed in jobs with high cognitive demands. Taken into account that the level of education has a positive impact on WM capacity and mitigates age-related declines in WM (Archer et al., 2018; Pliatsikas et al., 2019) this might explain why age also did not correlate with WM capacity in our data (see Table A1). While mathematicians outperformed non-mathematicians in the patterning domain time, presumably due to its high mathematical demand, no differences within mathematicians were found, neither in the domain time, nor in the other patterning domains or in general patterning. Further, data showed evidence that mathematicians with lower expertise had similar performance as mathematicians with higher expertise in a VSL task. However, due to the methodological issues already discussed in the section on domain-general cognitive abilities, we could not make a valid conclusion regarding VSL and the impact of varying amount of mathematical expertise.

Mathematicians with lower expertise displayed for the most part the same domain-specific abilities as mathematicians with lower expertise. ANS acuity was neither influenced by the amount of mathematical expertise nor by age. Age did not correlate with ANS in our sample, which is in contrast to the general population, where individuals attain the best ANS acuity at approximately 30 years and ANS precision shows a sustained age-relate decline from 30 to 85 years of age (Halberda et al., 2012). However, only a small number of mathematicians were older than 30 and those were highly educated, which may counteract against any age-related declines in ANS. The only domain-specific-ability where mathematicians with lower expertise differed from individuals with higher expertise was symbolic numerical magnitude comparison. Mathematicians with lower expertise were less accurate in comparing two single-digit numbers according to their numerical magnitude than mathematicians with higher expertise were. This was visible even when age was included as a covariate into the model, although the evidence for between group differences significantly decreased. However, the solution rate was almost perfect, 98% for mathematicians with lower expertise and 99% for mathematicians with higher expertise, indicating a ceiling effect (e.g., Austin & Brunner, 2003; Hessling et al., 2004; Schweizer et al., 2019). Therefore, it is important to not attach too much importance to this finding. Mathematicians with higher expertise were equally fast in solving the symbolic numerical magnitude comparison task as mathematicians with lower expertise when age was included into the model. In contrast, mathematicians with higher expertise were slower than mathematicians with lower expertise when age was not considered. This implicates that there was an age-related decline in the processing speed of comparing two single-digit numbers according to their numerical magnitude, which also was corroborated by a positive correlation between age and response time ($r = .57$). While mathematicians had a more accurate mental representation of symbolic numbers than non-mathematicians, implicated by a smaller NDE, there were no differences in NDE between mathematicians of lower and higher expertise. Likewise, while mathematicians and non-mathematicians could be differentiated by accuracy in an ordinality processing task, mathematicians displayed comparable numerical order processing abilities regardless of whether they had comparably low or high mathematical expertise. A similar picture emerged for arithmetic abilities, which did not differ between mathematicians of lower and higher expertise.

The result pattern that mathematicians with lower expertise were very similar to mathematicians with higher expertise continued when looking at the personality traits. Neither in the Big Five nor in NFC the evidence for group differences was strong enough to assume that mathematicians with different degrees of mathematical expertise differed from one another. This was similar in the domain-specific personality facets, although there was one exception, namely motivation in mathematics, in which the evidence for group differences was moderate. Mathematicians with higher expertise stated that they were more motivated in the field of mathematics than mathematicians with lower expertise. All mathematicians with higher expertise were faculty members doing mathematical research. To pursue a scientific career in academia a lot of effort and therefore motivation is needed; therefore, individuals who work as a scientific mathematician in academia should be highly motivated to do mathematics, which was shown in our data. In contrast, mathematicians with lower expertise, were bachelor or master students. Of course, not all of them will finish their studies, let alone obtain a Ph.D. and pursue a career in academia; a few of them will probably drop out, which could be due to a lack of motivation. Those diverse motivational characteristics of the mathematicians with lower expertise could account for the on-average lower motivation to do mathematics compared to the mathematicians with higher expertise.

Taken together, the variables we investigated did not differ depending on the amount of mathematical experience. This suggests that after reaching a certain level of mathematical expertise, additional mathematical experience seems to become irrelevant. Mathematicians with lower expertise were similar to mathematicians with higher expertise in domain-general and domain-specific abilities but also in personality traits. The only exception was that faculty members of the institute of mathematics were more motivated to do mathematics than students of mathematics were.

Limitations and Future Directions

The present findings should be interpreted in light of the limitations of this study. First, a special focus must be put on our control group. We decided to recruit our control group from subjects in which mathematical topics are not part of the curriculum (e.g., philosophy, history, law, medicine, music) similar to Popescu et al., (2019). This was also the reason why we decided to exclude individuals from the field of psychology because they receive at least some mathematical education (i.e., statistics) at the university (in contrast to Castronovo & Göbel, 2012, who compared students of mathematics to students of psychology). As it was beyond the scope of this study, we did not include a third group of individuals who are not mathematicians but who use advanced math in their everyday professional work (e.g., accounting, telecommunication, chemistry, as was done by Cipora et al., 2016; Dowker et al., 1996; Hohol et al., 2020). Therefore, we are not able to say whether the observed differences (higher patterning abilities in the domain of time, more accurate mental representation of symbolic numbers, better arithmetic fact knowledge, lower openness to experiences, more positive attitude towards mathematics of mathematicians) emerged because we compared two rather extreme groups. Consequently, we cannot conclude that these better domain-general as well as domain-specific abilities are unique to mathematicians. They may also hold true for individuals from other STEM fields (e.g., physics, chemistry, computer sciences). However, the results from Cipora et al. (2016) as well as from Dowker et al. (1996) suggested that mathematicians are unique in their abilities, even in comparison to individuals who use math in their everyday work. Still, future research should try to include a variety of control groups to provide an even more comprehensive picture of mathematical expertise. Second, our participants completed a large battery of tests to provide a systematic investigation of the psychological profiles related to mathematical expertise. We cannot exclude the possibility that the different tasks had confounding influences on each other. In addition, our participants overall completed nine cognitive tasks which could have induced fatigue. However, those circumstances applied to both groups; therefore, they should not be responsible for evidence of group differences or similarities. Third, a common problem in psychological research in general, and in expertise research in specific, is insufficient power. Insufficient power reduces to possibility to find a true effect as well as infatuates the possibility to find a false positive effect (Brysbaert, 2019). While no power calculations are available for Bayesian analyses yet, estimations are possible. According to Brysbaert (2019) two groups of 190 participants each are needed to identify between groups differences and two groups of 110 participants each to identify null effects. These numbers indicate that our study is underpowered, which can be the reason why we had a lot of inconclusive results. This may have been especially crucial when we compared mathematicians with higher and lower expertise. While a bigger sample size is definitely needed to increase power, we did our best to increase power by using a balanced design as well as using reliable measurements with multiple observations per participants. Fourth, the possibility to find a false positive effect is not only heightened by underpowered studies, but also when a large number of comparisons are done. While the large number of included variables and measurements is a strength of this study, it also is a limitation as it increases the chance to find a false positive effect. However, in contrast to traditional frequentist analyses, Bayesian analyses are better in finding more true positives and fewer false positives especially in small sample sizes (van Ravenzwaaij & Ioannidis, 2019). Kelter (2020) even proposes that the probability for false positives in Bayesian independent samples t-test is about half the sizes as in frequentist analyses.

Despite these limitations, the present study provides the broadest view on mathematical expertise yet, including not only domain-general and domain-specific abilities but also personality traits. In contrast to most previous studies, we systematically controlled for the confounding influence of general intelligence. Overall, mathematicians had a similar ability profile as non-mathematicians with only moderate evidence for better abilities of mathematicians in recognizing and continuing mathematical patterns, in the mental representation of symbolic numbers and in the arithmetic fact knowledge. Regarding personality, mathematicians had a more positive attitude towards mathematics but were less open to experience than non-mathematicians. Furthermore, it was the first study in which similarities and differences between individuals with lower and higher mathematical expertise were examined. However, additional experience in mathematics seems to be not related to differences in the variables we investigated. In this vein, the present study significantly contributes to a deeper and more differentiated understanding of mathematical expertise.

Authors' Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

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Appendix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	—																																							
2	.64***	—																																						
3	.74***	.20	—																																					
4	.74***	.40***	.20	—																																				
5	.32**	-.02	.39**	.21	—																																			
6	.48***	.32*	.24	.47***	.33*	—																																		
7	.32**	.26	.18	.27	.15	.73***	—																																	
8	.36**	.31*	.18	.31*	.30*	.75***	.35**	—																																
9	.41***	.18	.19	.49***	.30*	.80***	.35**	.41***	—																															
10	.46***	.24	.47***	.22	.45***	.37	.20	.27	.37**	—																														
11	.31*	.22	.23	.22	.32*	.30*	.22	.17	.29*	.71***	—																													
12	.32**	.24	.36**	.07	.32**	.26	.18	.22	.20	.69***	.32**	—																												
13	.25	.16	.26	.09	.16	.25	.01	.22	.32**	.58***	.31*	.23	—																											
14	.30*	.17	.24	.22	.21	.19	.07	.13	.22	.55***	.24	.20	.15	—																										
15	.26	-.08	.42***	.09	.41***	.17	.14	.11	.14	.63***	.35**	.36**	.17	.17	—																									
16	.26	.21	.14	.22	.18	.12	-.06	.19	.14	.13	.15	.04	.01	.18	-.01	—																								
17	.17	.02	.18	.13	.03	.13	.17	-.04	.15	.13	.06	.14	.07	.07	.05	-.09	—																							
18	-.11	.04	-.11	-.11	-.12	-.01	.14	-.14	-.01	.06	.07	.17	.07	.01	-.17	-.09	.32	—																						
19	-.20	-.04	-.19	-.16	-.05	-.13	-.15	.03	-.17	-.13	-.08	-.11	-.10	-.10	-.02	.08	-.98	-.34**	—																					
20	.08	-.07	.08	.11	.08	.02	-.09	.01	.11	-.10	.03	-.07	-.10	-.02	-.16	.02	.18	.09	-.22	—																				
21	-.24	-.06	-.23	-.17	-.07	-.30*	-.14	-.33**	-.22	-.19	-.05	-.20	-.29*	-.06	-.01	-.14	-.19	.02	.16	.31*	—																			
22	-.18	-.02	-.25	-.05	-.26	-.03	-.03	.03	-.05	-.27*	-.19	-.22	-.05	-.07	-.34**	.05	.05	.03	-.03	-.05	-.22	—																		
23	.40***	.03	.49***	.20	.31*	.33**	.20	.25	.30*	.34**	.22	.23	.21	.15	.26	.18	.34	.01	-.35**	.22	-.31*	-.24	—																	
24	-.42**	-.14	-.47**	-.20	-.1	-.25	-.13	-.22	-.22	-.31*	-.12	-.25	-.33**	-.19	-.08	-.22	-.14	-.02	.14	.12	.77	.03	-.43**	—																
25	-.18	-.03	-.18	-.14	.07	.06	.07	.11	-.02	-.20	-.19	-.07	-.16	-.07	-.14	-.14	-.05	-.14	.05	.08	.06	.18	-.21	.17	—															
26	.13	-.09	.22	.06	.25	.11	.07	-.03	.18	.30*	.14	.19	.19	.21	.24	.12	.42	.29*	-.45	.25	.09	.01	.41***	-.12	-.03	—														
27	-.25	-.17	-.33**	.01	-.32**	-.14	-.09	-.17	-.06	-.36**	-.20	-.42**	-.13	-.11	-.27	-.20	-.03	-.04	.01	.30*	.33**	.19	-.17	.46***	.05	-.17	—													
28	.08	-.12	.20	.02	.18	.11	.12	.10	.04	.20	.04	.16	.15	.11	.18	.20	.20	.04	-.19	.09	-.07	.12	.25	-.08	-.08	.44***	-.03	—												
29	-.24	-.19	-.33**	.02	-.25	-.21	-.18	-.20	-.10	-.33**	-.15	-.45**	-.13	-.05	-.24	-.05	-.01	.02	-.02	.18	.29*	.17	-.15	.39**	.03	-.15	.82	-.02	—											
30	-.18	.01	-.24	-.09	-.22	-.08	.09	-.13	-.14	-.26	-.11	-.13	-.11	-.27	-.22	.03	-.08	.03	.11	-.11	-.05	.02	-.09	.08	-.04	-.21	.09	-.20	.09	—										
31	.05	.11	-.01	.05	-.05	.01	-.02	.12	-.05	-.01	-.15	.12	-.01	-.02	.03	.03	-.16	-.18	.19	-.05	.10	-.20	-.11	.02	-.23	-.16	-.08	-.14	-.08	-.01	—									
32	.02	-.05	-.04	.13	-.03	.02	-.11	-.01	.13	-.01	-.02	-.11	.09	.03	.01	.06	-.02	-.15	-.01	.12	.14	-.10	.01	.01	.02	.03	.13	-.02	.30*	-.01	.23	—								
33	-.06	-.08	-.11	.06	-.03	.11	-.01	.16	.09	-.12	-.17	-.06	.04	-.03	-.15	.05	-.09	.21	.11	.05	-.04	.05	-.09	-.01	-.15	-.01	.03	.23	.09	.01	.26	.05	—							
34	-.22	-.02	-.28*	-.11	-.07	-.09	-.02	-.12	-.06	-.01	.10	-.01	-.04	.02	-.13	-.10	-.15	.11	.15	-.14	.01	.01	-.28*	.15	.07	-.30*	.11	-.13	.11	.17	-.31*	-.17	-.12	—						
35	.08	.03	.05	.08	.26	.05	.15	-.07	.05	.09	.02	.12	-.06	.01	.20	.01	.19	-.04	-.19	.03	.07	-.07	.10	-.02	-.05	.38**	-.12	.10	-.20	.26	.14	-.07	-.08	-.38**	—					
36	-.28*	.02	-.37**	-.16	-.62**	-.16	-.12	-.15	-.10	-.29*	-.10	-.15	-.14	-.19	-.37**	-.09	-.23	.08	.24	-.02	.01	.19	-.44**	.11	.07	-.42**	.27*	-.23	.24	.20	-.01	-.06	-.01	.45***	-.42**	—				
37	.09	-.12	.11	.13	.59***	.21	.12	.12	.22	.21	.11	.08	.01	.15	.33*	.09	.05	-.03	-.07	.05	.19	-.23	.18	.13	-.04	.38**	-.17	.16	-.06	-.04	-.06	.06	-.05	-.17	.46***	-.57**	—			
38	.20	-.14	.28*	.17	.63***	.19	.11	.16	.17	.33**	.21	.18	.14	.18	.37**	.12	.03	-.07	-.05	-.07	-.04	-.13	.31*	-.10	-.03	.29*	-.25	.14	-.12	-.18	.04	.06	-.03	-.27	.36**	-.70**	.59***	—		
39	.15	-.09	.18	.15	.69***	.29*	.14	.26	.26	.32*	.18	.14	.04	.26	.41***	.15	.01	-.12	-.03	.02	.11	-.25	.17	.09	-.04	.27	-.22	.17	-.14	-.14	.05	-.03	-.01	-.24	.43***	-.61**	.82***	.69***	—	
40	.22	-.02	.21	.21	.55***	.15	.07	.11	.15	.29*	.13	.25	.03	.19	.32**	.11	.06	-.11	-.09	.03	-.06	-.26	.38**	-.16	.05	.40***	-.32**	.25	-.24	-.16	.20	.11	.07	-.34**	.42***	-.64**	.56***	.60***	.61***	—

*BF10>3, **BF10>10, ***BF10>100

N = 84; 1. General intelligence; 2. Verbal intelligence; 3. Numerical intelligence; 4. Figural intelligence; 5. Mathematical achievement; 6. mean WM; 7. numerical WM; 8. Verbal WM; 9. Figural WM; 10. Patterning sum; 11. Letter sum; 12. Number sum; 13. Rotation sum; 14. Shape sum; 15. Time sum; 16. VSL accuracy; 17. ANS accuracy; 18. ANS response time; 19. ANS w; 20. Cardinality accuracy; 21. Cardinality response time; 22. NDE; 23. Ordinality accuracy; 24. Ordinality response time; 25. RDE; 26. small multiplications accuracy; 27. small multiplications response time; 28. Large multiplications accuracy; 29. Large multiplications response time; 30. openness; 31. conscientiousness; 32. extraversion; 33. agreeableness; 34. neuroticism; 35. NFC; 36. Math anxiety; 37. enjoyment; 38. confidence; 39. motivation; 40. Self-evaluated math competencies