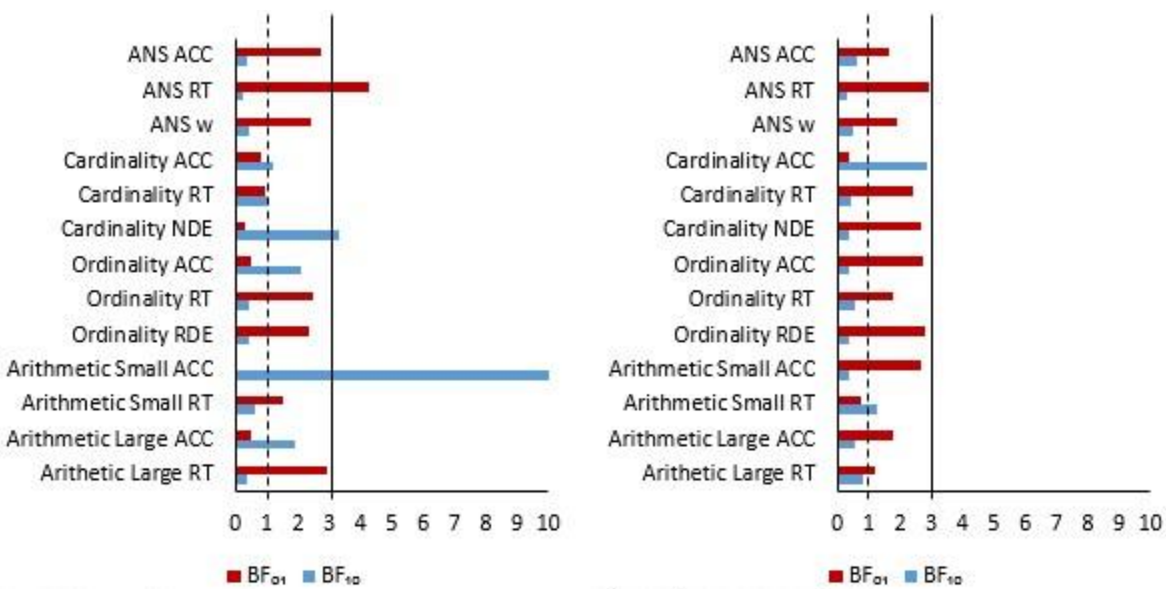
Domain-specific Abilities

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)

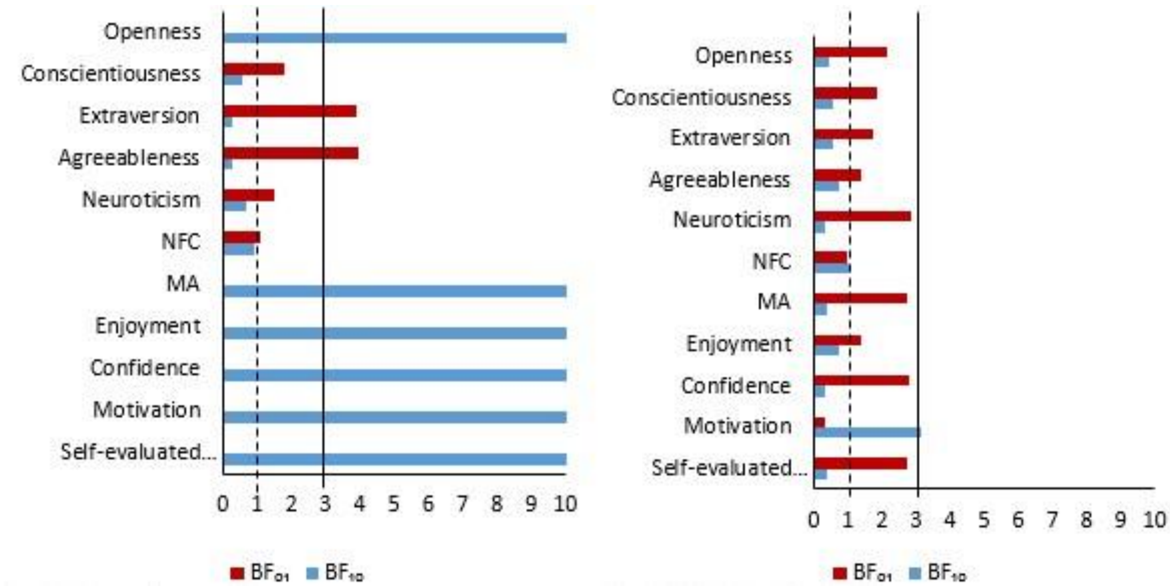
Variable		Math *M* (*SD*)	Non-Math *M* (*SD*)	Math. LE *M* (*SD*)	Math. HE *M* (*SD*)
Approximate Number System	ACC	0.87 (0.04)	0.86 (0.05)	0.87 (0.04)	0.87 (0.04)
	RT (in seconds)	0.91 (0.20)	0.93 (0.30)	0.91 (0.24)	0.91 (0.14)
	w	0.18 (0.05)	0.19 (0.07)	0.18 (0.05)	0.17 (0.05)
Symbolic numerical magnitude 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 ($\text{meanRT}_{2;3} > \text{meanRT}_{1}$). 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