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The link between math anxiety and performance does not depend on working memory: A network analysis study

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ABSTRACT

Math anxiety (MA) and working memory (WM) influence math performance. Yet the interplay between them is not fully understood. Inconsistent results possibly stem from the multicomponent structure of math performance and WM. Using network analysis approach, we investigated the drivers of the MA, WM and math performance edges, and the contribution of each node to the network. First, 116 women completed a battery of tests and questionnaires. Second, we explored the generalizability of our model by applying it to a new data-set (Skagerlund et al., 2019; conceptual replication). The results revealed: (1) the links between MA and WM depend on specific task properties, specifically, WM tasks that require manipulation of numbers; (2) WM and MA are independently linked to math performance; and (3) each WM task is associated with different math abilities. The study provides a strong and reliable model showing the direct effects of math anxiety on math performance.

1. Introduction

Math abilities involve complex and dynamic interactions between working memory (WM) and mathematical knowledge (Peng, Namkung, Barnes, & Sun, 2016; Usai, Viterbori, & Traverso, 2018). Affect towards math is another important factor in performance (for a review, see Suárez-Pellicioni, Núñez-Peña, & Colomé, 2013). Specifically, math anxiety (MA), referring to feelings of fear, tension, and apprehension in math-related situations (Ashcraft, 2002), plays a key role in math performance (Caviola et al., 2021; Chang & Beilock, 2016; Cipora, Szczygieł, Willmes, & Nuerk, 2015; Devine, Fawcett, Szűcs, & Dowker, 2012). Yet the findings on the interplay between MA, WM, and math performance are inconsistent. While some have demonstrated WM's mediation of the link between MA and math performance (Ashcraft & Kirk, 2001; Luttenberger, Wimmer, & Paechter, 2018; Maloney & Beilock, 2012; Szczygieł, 2021; Suárez-Pellicioni, Núñez-Peña, & Colomé, 2016), others have pointed to the unique and independent contributions of WM and MA to performance (Justicia-Galiano, Martín-Puga, Linares, & Pelegrina, 2017; Miller & Bichesl, 2004; Passolunghi, Cargnelutti, & Pellizzoni, 2019; Skagerlund, Östergren, Västfjäll, & Träff, 2019). In fact, recent findings suggest WM and MA explain a unique but also a shared portion of the variance in math performance (Buelow & Frakey, 2013; Donolato, Giofrè, & Mammarella, 2019; Skagerlund et al., 2019). The complexity of the interaction between MA, WM, and math performance may stem from the multi-component structure of both WM (Barrouillet, Bernardin, & Camos, 2004; Camos, 2017) and math performance (Mix & Cheng, 2012).

By taking into account various tests of WM with and without manipulation of math information, as well as distinct forms of math (i.

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e., calculation accuracy and math fluency; Fuchs et al., 2016), our goal was to examine whether task-specific properties can account for the links between the latent variables and how each test of WM, MA, and math performance contributes to these links. Previous research using regression and structural equation modeling (SEM) has provided important insights on how WM ability and MA correlate with math performance (e.g., Miller & Bichsel, 2004; Owens, Stevenson, Hadwin, & Norgate, 2014) and how WM and MA behave together (e.g., Skagerlund et al., 2019), respectively. However, the question of which properties of WM tasks are related to MA, and how they affect the WM-MA-math performance interaction is unanswered. To do this, it is necessary to examine the dynamics between several measurable tests of these variables simultaneously.

One way of answering this question is to take a network approach. The network approach, a complementary analysis to SEM, is a new framework for analyzing complex and abstract constructs and, as such, has gained traction in the field of mental disorders, for example, general anxiety (GA; Beard et al., 2016). By combining partial correlation and graph theory, this approach strives to find mutual associations among directly observable variables that might be masked by traditional statistical approaches (such as multiple regression; Epskamp & Fried, 2018) or interpreted in terms of broad, unobserved latent variables (e.g., WM; for a review, see Fried et al., 2017). Unlike a multiple regression analysis of a single dependent variable, partial correlation networks show linear prediction and multicollinearity among all variables, allowing for insight into predictive mediation (Epskamp & Fried, 2018). Arguably, network analysis may lead to a comprehensive model of the underlying nature of the links between MA, various WM tasks, and math performance in different math ability tests by: (1) revealing the relative and unique contribution of each measurable score/test to the complex network of interacting components; and (2) visualizing the dynamics among constituent elements in the network (Costantini et al., 2015).

Motivated by the ongoing "replicability crisis" in psychology (Johnson, Payne, Wang, Asher, & Mandal, 2017; Open Science Collaboration, 2015) and answering calls to promote the reproducibility of experimental research (Johnson et al., 2017; Open Science Collaboration, 2015), we extended our analyses to an online available data set collected in a different country (i.e., conceptual replication; Zwaan, Etz, Lucas, & Donnellan, 2017) made available by Skagerlund and colleagues (2019). By replicating our analyses on two separate data set, we can test the generalizability of the analyses on a broader population and thus can provide a stronger and more reliable model of the interplay between MA, WM, and math performance.

1.1. Working memory subsystems and math performance

WM has been found to be a strong predictor of math performance in both children (e.g., Alloway & Passolunghi, 2011; Xenidou-Dervou, Luit, Kroesbergen, den Bos, Jonkman, van der Schoot, & van Lieshout, 2018) and adults (e.g., Beilock & DeCaro, 2007). Simply defined, WM is a limited cognitive system that can temporarily store and manipulate information necessary for complex cognitive tasks (Baddeley, 1992). The multicomponent domain-general model of WM originally proposed by Baddeley and Hitch (1974) distinguishes between the central executive WM system, responsible for the manipulation of information and for processes of monitoring and control, and two storage subsystems. These subsystems include verbal WM (VWM; phonological loop), involved in the processing of verbal/speech-based information, and visuospatial WM (VSWM), dealing with the processing of spatial and visual information. In line with this domain-general view of WM, a medium to high correlation has been found between the VSWM and VWM subsystems (Gray et al., 2017).

Other theories claim WM integrates domain-specific abilities (e.g., Ericsson & Kintsch, 1995), and studies have shown the VSWM and VWM subsystems have different relationships with math performance (Allen & Giofrè, 2020; Ashkenazi & Danan, 2017). For example, VWM better predicts fact recall and basic math abilities, whereas VSWM is more relevant to math tasks with visuospatial elements, such as geometry (Allen & Giofrè, 2020). Some studies have found a more pronounced effect of VSWM on math performance (Allen, Higgins, & Adams, 2019; Giofrè, Donolato, & Mammarella, 2018; McKenzie, Bull, & Gray, 2003; Miller & Bichsel, 2004; St Clair-Thompson & Gathercole, 2006; Toll, Kroesbergen, & Van Luit, 2016), while others have found support for the influence of VWM (Ashkenazi & Danan, 2017; Hitch & McAuley, 1991; Wilson & Swanson, 2001), particularly for tasks with a high math-load (for a review, see Raghubar, Barnes, & Hecht, 2010). Using network analysis, we aimed to visualize the unique contribution of each observable WM task to the different math performance tests (Costantini et al., 2015).

1.2. Math anxiety

MA is a common phenomenon (Dowker, Sarkar, & Looi, 2016) with an estimated prevalence of 11% among school children (Devine, Hill, Carey, & Szűcs, 2018), 33% among adolescents (OECD, 2013), and 25% among university students (Perry, 2004). Note that these prevalence rates vary according to the assessment tools and the classification and assessment criteria used by researchers (Dowker et al., 2016). As in most cases of anxiety (Brown & Barlow, 1992; McLean, Asnaani, Litz, & Hofmann, 2011), MA is correlated with other anxiety subtypes, including GA (Ashcraft & Moore, 2009; Hart & Ganley, 2019; Hembree, 1990) and test anxiety (Cipora et al., 2015; Devine et al., 2012), and is more prevalent among women (Ashcraft, 2002; Devine et al., 2012; Devine et al., 2018; Gunderson, Park, Maloney, Beilock, & Levine, 2018; Hill et al., 2016). Importantly, it has been recently suggested that GA mediates the relationship between gender and math anxiety in children (Szczygiel, 2020), a relationship that continues into adulthood (Hart & Ganley, 2019).

However, MA is a unique anxiety disorder with a specific profile (Caviola et al., 2021; Cipora et al., 2015; Dowker et al., 2016; Suárez-Pellicioni et al., 2016) and a distinct pattern of neural activity (e.g., Pletzer, Kronbichler, Nuerk, & Kerschbaum, 2015). Accordingly, researchers have found correlations between various MA measures are significantly higher than those between MA and test anxiety (Buelow & Barnhart, 2017; Devine et al., 2012) or GA (Dowker et al., 2016). Similarly, a significant negative correlation has been found between MA, but not GA, and math performance (Chang & Beilock, 2016; Cipora et al., 2015; Devine et al., 2012; Hembree, 1990; Ma, 1999; Wang et al., 2015; Wu, Amin, Barth, Malcarne, & Menon, 2012).

1.3. Links between math anxiety, working memory, and math performance

There are claims that MA does not necessarily accompany reduced math performance (Ashcraft & Kirk, 2001; Ashcraft & Krause, 2007). However, anxiety-induced ruminations were shown to deplete WM resources (Ashcraft & Kirk, 2001; Luttenberger et al., 2018; Maloney & Beilock, 2012; Suárez-Pellicioni et al., 2016) and disrupt thinking processes (Chang & Beilock, 2016), even in simple math tasks without time limits (Ashkenazi & Danan, 2017; Maloney, Ansari, & Fugelsang, 2011; Suárez-Pellicioni, Núñez-Peña, & Colomé, 2014). While the majority of studies point to difficulties in VWM among math-anxious individuals (Ashcraft & Kirk, 2001; Ashcraft & Moore, 2009; Mammarella, Hill, Devine, Caviola, & Szűcs, 2015), some have found particular difficulties in VSWM (Ashkenazi & Danan, 2017; Maloney, Waechter, Risko, & Fugelsang, 2012). In contrast, a recent meta-analysis showed that the type of WM subsystem had no impact on the significant negative correlations between MA and WM (Caviola et al., 2021).

Supporting the role of WM in the math anxiety-performance link, findings demonstrated that this relation tends to get stronger as the complexity of math tasks increases (Ching, 2017; Vukovic, Kieffer, Bailey, & Harari, 2013, Vukovic, Roberts, & Green Wright, 2013). This kind of tasks, such as word problem solving and algebraic reasoning (, Vukovic, Roberts, et al., 2013), requires a higher level of working memory resources (Ching, 2017).

Recent findings challenge the common assumption that MA impairs performance solely by reducing WM capacity by showing WM and MA each explain a unique but at the same time a shared portion of the variance in math performance (Buelow & Frakey, 2013; Donolato et al., 2019; Caviola et al., 2021; Skagerlund et al., 2019). For example, WM was found to mediate the math anxiety-performance link, but this indirect effect was weak (Caviola et al., 2021). MA can also impair math performance directly (Justicia-Galiano et al., 2017; Miller & Bichesl, 2004; Passolunghi et al., 2019; Skagerlund et al., 2019; but see Szczygieł, 2021). A small number of studies take into account differences in the math anxiety-performance link for different aspects of math (Caviola et al., 2021). Using a multiple regression model, Miller and Bichesl (2004) found MA was the best predictor of math performance, with weaker correlations between WM and math performance, especially between VSWM and math performance.

1.4. Current study and hypotheses

The accumulative evidence points to a complex interplay between WM, MA, and math performance, but the interrelations are not fully understood. While several studies have demonstrated that WM mediates the link between MA and math performance (Ashcraft & Kirk, 2001; Luttenberger et al., 2018; Maloney & Beilock, 2012; Szczygieł, 2021; Suárez-Pellicioni et al., 2016), others have found MA and WM make unique contributions to math performance (Justicia-Galiano et al., 2017; Miller & Bichesl, 2004; Passolunghi et al., 2019; Skagerlund et al., 2019). Another unresolved issue is the contribution of unique WM task properties and WM subsystems (Buelow & Frakey, 2013). Recent findings show both subsystems of WM are important to math performance in different spheres (Allen & Giofrè, 2020; Ashkenazi & Danan, 2017), and math-anxious individuals show impairments in both VWM (Ashcraft & Kirk, 2001; Ashcraft & Moore, 2009; Mammarella et al., 2015) and VSWM (Ashkenazi & Danan, 2017; Maloney et al., 2012). These overgeneralized results possibly stem from the abstract definitions and multicomponent structures of math performance (Mix & Cheng, 2012), WM, and the way WM is tested (Barrouillet et al., 2004; Camos, 2017).

Using a powerful statistical approach, we investigated the correlations between the WM tasks and analyzed the unique contribution of each task to the larger network. We also assessed and visualized the dynamics among constituent elements of this complex network (Costantini et al., 2015), while controlling other covariances and taking into account the characteristics of the tests of each latent variable (i.e., WM and math performance). The findings complement those of classic models that collapse these complex traits into abstract variables (for a review, see Schmittmann et al., 2013).

We hypothesized a strong edge between MA and math performance (i.e., the relations between MA and math performance would not depend on WM; Skagerlund et al., 2019), and each WM node would have a unique edge pattern for the different math tests (Allen & Giofrè, 2020; Ashkenazi & Danan, 2017). Based on the previous finding that accuracy and fluency independently contribute to success in math (Fuchs et al., 2016), we examined both dimensions of calculation competence. Note that we focused on women, as MA is more prevalent among women (Ashcraft, 2002; Devine et al., 2012; Devine et al., 2018; Gunderson et al., 2018; Hill et al., 2016), although this sex gap may be affected by the dimension of MA which is being tested (Szczygiel, 2020).

2. Study 1

2.1. Participants

Using the R-package pwr (Champely, Ekstrom, Dalgaard, Gill, Weibelzahl, Anandkumar, & De Rosario, 2018), we calculated sample size according to the smallest correlations between the variables most relevant to our hypothesis. Based on $r = 0.23$ (VWM–Applied math performance; Miller & Bichsel, 2004), power = 0.7, and a significance level of 0.05, we concluded 115 subjects would be sufficient for our analysis. This number was validated post hoc in the network analysis (see Results section).

The final sample consisted of 116 women undergraduate and postgraduate (MA) students from the University of Haifa (M = 24.293 years, SD = 4.842 years). Participants belonged to various academic disciplines and had different seniority in university studies. All had normal or corrected-to-normal vision and no history of neurologically based impairments, such as ADHD or learning disabilities (e.

g., dyslexia and dyscalculia). Prior to data collection, participants signed a consent form approved by the institutional ethics committee (429/17) and received monetary compensation or course credit if they studied in the Faculty of Education (BA or MA).

2.2. Measures

2.2.1. VWM no math load- opposites task

The Opposites task (McKeough, 1982) does not involve any numerical properties. Participants listen to a set of words and are asked to verbally state the opposites of these words. Each set contains two to eight words. Participants receive one point for each remembered word, with an extra point if they maintain the order in which the words were read to them. This task has been used strictly in linguistic-based studies (Geva, 1995; Geva & Siegel, 2000). The Hebrew version of this task has been incorporated into a linguistic-based diagnostic tool kit used to assess both children and adults; it has high criterion-related validity and internal reliability (alpha $<$ 0.80 ; Shany, Zieger, & Ravid, 2001).

2.2.2. VWM with math load- N-Span task

The N-Span task is an adaptation of the validated and reliable (Unsworth, Heitz, Schrock, & Engle, 2005) automated Operation Span (OSPAN) task (Turner & Engle, 1989). It correlates well with other measures of WM capacity and has both good internal consistency (alpha = 0.78) and test-retest reliability (0.83). The N-span is designed to increase math-load. A math operation is shown on a computer screen (e.g., $(18 / 3) - 4 = 2$) for 2,500 ms, followed by a cue enabling participants to indicate, using the keyboard, whether the solution is correct or incorrect (without feedback). Immediately following the response, a number ranging from a single-digit to a three-digit number is presented. Participants complete five blocks in which the array of numbers presented increases from two to six and are then asked to recall the numbers, using pen and pencil. We calculated the number of items recalled.

2.2.3. VSWM no math load- Color Span Backwards task

In the Color Span Backwards task, an increasing series of colored discs, ranging from two to eight, is presented on a computer screen at a rate of one second per disc. Participants are asked to input colors in reverse order using a colored keyboard (Hasselhorn, Schumann-Hengsteler, Gronauer, Grube, Mähler, Schmid, Seitz-Stein, & Zoelch, 2012). We counted the sum of correct responses as the outcome score.

2.2.4. General anxiety

We used the online version of the Penn State Worry Questionnaire (PSWQ; Meyer, Miller, Metzger, & Borkovec, 1990), a 16-item self-report measure of excessive worry (e.g., "When I am under pressure, I worry a lot"). The items are rated on a 5-point Likert scale, ranging from 1 ("not at all typical") to 5 ("very typical"). The PSWQ has excellent internal consistency, $\alpha = 0.86$ to 0.95 (Molina & Borkovec, 1994), and has shown convergent and divergent validity for worry, anxiety, and depression (Brown, Antony, & Barlow, 1992; Molina & Borkovec, 1994). We obtained the total score by summing each item rating, with increasing scores reflecting an increased level of general anxiety. Cronbach's alpha for the PSWQ in our sample was 0.892, 95% CI [0.857, 0.919].

2.2.5. Math anxiety

We used an online version of the Mathematical Anxiety Rating Scale (MARS) brief (Suinn & Winston, 2003), a 30-item self-report questionnaire designed to test math anxiety. Items represent math-related situations that may give rise to anxiety (e.g., being given a set of multiplication problems to solve). Participants report their level of anxiety associated with each item on a scale ranging from 0 ("not at all") to 4 ("very much"). We obtained the total score by summing each item rating, with increasing scores reflecting an increased level of math anxiety. The MARS brief has excellent internal consistency of $\alpha = 0.96$ (Suinn & Winston, 2003). The coefficient alpha for the MARS brief in our sample was 0.96, 95% CI (0.946, 0.970).

2.2.6. Math fluency

We used the Math Fluency subtest of the Woodcock–Johnson III Tests of Achievement (McGrew & Woodcock, 2001) to assess automaticity with basic arithmetic facts. In this subtest, using paper and pencil, participants are required to quickly and accurately complete simple arithmetic problems within a three-minute time limit. Arithmetic computations include simple addition, subtraction, and multiplication operations presented in traditional written format. The number of correctly completed computations was totaled and converted to a standard score with equal intervals.

2.2.7. Calculation

We used the Calculation subtest of the Woodcock–Johnson III Tests of Achievement (McGrew & Woodcock, 2001) to measure the ability to perform mathematical computations in traditional written format. In this subtest, using paper and pencil, participants solve increasingly difficult calculation problems, starting with simple addition and moving to advanced geometry, trigonometry, and calculus questions, with no time limit. The number of correctly completed computations was totaled and converted to a standard score with equal intervals.

2.3. Procedure

Participants were invited to a single 1-hour session in a quiet room at the University of Haifa to complete the self-rating questionnaires and tests, administered in a random order. Note that participants were unaware of the study aim before arrival, and none refused to participate or left before study completion.

2.3.1. Network analysis

The entire network analysis procedure was based on Epskamp and Fried (2018). We used the R-package qgraph to estimate and visualize the network (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). We estimated Gaussian graphical models (GGMs). In these models, each test is represented by a node in the network, and the edges represent partial correlation coefficients between the nodes, with edge thickness representing the strength of a direct interaction between two nodes (De Nooy, Mrvar, & Batagelj, 2018). Based on Epskamp and Fried (2018) guidelines, we computed the network using the least absolute shrinkage and selection operator (LASSO). LASSO is used to reduce false-positive edges (Tibshirani, 1996). It identifies the edges that differ significantly from zero and most accurately reveal the underlying network. The tuning parameter (gamma) for the GLASSO estimation in our study was 0.55. A tuning parameter is chosen to minimize the extended Bayesian Information Criterion parameter and has been shown to accurately recover underlying network structures (Foygel & Drton, 2011). We determined node placement using Fruchterman and Reingold (1991) algorithm, which places connected nodes closer to each other and more connected nodes closer to the center.

Centrality. We computed the centrality for each node in the network. The higher the centrality of a node, the more strongly that node is connected to other nodes in the network (Borsboom & Cramer, 2013; Epskamp, Borsboom, & Fried, 2018). We assessed three centrality indices: strength, closeness, and betweenness. Strength comprises the sum of absolute edge weights connected to each node. Closeness refers to the inverse of the sum of the distances from one node to all other nodes in the network. Betweenness quantifies how often one node is on the shortest path to other nodes (Epskamp & Fried, 2018).

Robustness Check. Using the R-package bootnet (Epskamp & Fried, 2015), we calculated the stability of strength centrality by applying the correlation stability coefficient (CS-coefficient), a method based on bootstrapping ($N = 1,000$). The CS-coefficient represents the maximum number of cases that can be dropped, such that with 95% probability, the correlation between the original strength centrality estimates and the bootstrapped estimates is 0.7 or higher. A higher CS-coefficient indicates a more reliable interpretation of the order of centrality estimates (Epskamp et al., 2012; Epskamp & Fried, 2018). We compared the similarity of networks using the Network Comparison Test (van Borkulo, Epskamp, Jones, Haslbeck, & Millner, 2016).

2.4. Results

Descriptive statistics are presented in Table 1.

The correlation matrix is presented in Table 2. The results replicate previous findings by showing: (1) positive correlations between WM tasks (Gray et al., 2017); (2) positive correlations between MA and GA (Hembree, 1990; Ma, 1999); (3) positive correlations between WM and math performance (Raghubar et al., 2010); (4) negative correlations between MA, but not GA, and math performance (Chang & Beilock, 2016; Cipora et al., 2015; Devine et al., 2012; Hembree, 1990; Ma, 1999; Wang et al., 2015; Wu et al., 2012); (5) negative correlations between MA and WM (Ashcraft & Kirk, 2001; Ashcraft & Krause, 2007; Justicia-Galiano et al., 2017; Miller & Bichsel, 2004). The correlation matrix shows all "in cluster" correlations are significant (i.e., within traditional latent constructs).

Note that results from the traditional SEM analyses are presented in Supplement 1. Although this was not the focus of the study, the findings are consistent with previous work (Justicia-Galiano et al., 2017; Miller & Bichesl, 2004; Passolunghi et al., 2019; Skagerlund et al., 2019) showing MA is a unique and strong predictor of math performance.

The GGM network is visualized in Fig. 1. The network is composed of the following three theoretically assumed clusters: WM, anxiety (i.e., MA and GA), and math performance (i.e., math fluency and calculation). Of the possible 21 edges (i.e., links), only 12 are retained (for 95% CI around the edge, see Supplementary Figure S2; for sensitivity analysis, see Supplementary Figure S7). Predictability (i.e., variance of a node explained by its neighbors) ranges from 23% in the Color Span Backwards task to 53.4% in the MA questionnaire (i.e., MARS), and average predictability is 37%.

Several results are noteworthy. First, the most prominent connections are between anxiety measures (i.e., MARS and PSWQ), math tests (i.e., math fluency and calculation), and MA and each math test. Second, the only remaining edge between MA and WM relies on the math-loaded N-Span task. Third, even though all WM nodes are inter-correlated, there is a different edge pattern for math fluency and calculation and the different WM tasks. For the Opposites task (VWM with no math-load), both edges to math performance nodes remain. For the N-Span task (VWM with high math-load) only the edge to math fluency remains. For the Color Span Backwards task

Table 1
Descriptive statistics of research variables.

Observed variables	Latent Variable	Mean (*SD*)	Min–Max
Age		24.29 (4.84)	19–55
Opposites	Working	31.43 (10.81)	15–66
N-Span	Memory	41.26 (8.19)	8–60
Colors		7.33 (2.46)	3–14
PSWQ	Anxiety	48.94 (11.96)	22–77
MARS		77.78 (25.94)	35–139
Math Fluency	Math Performance	117.77 (25.07)	40–160
Calculation		28.5 (7.29)	16–48

Note. Opposites – VWM; N-Span – VWM; colors – VSWM; PSWQ (Penn State Worry Questionaire) – general anxiety; MARS – math anxiety.

Table 2
Correlation matrix of research variables.

Variable	1	2	3	4	5	6
1. Opposites	–					
2. N-Span	0.29***					
3. Colors	0.4***	0.31***				
4. PSWQ	0.03	0.03	0.03			
5. MARS	−0.19*	−0.3****	−0.24*	0.5***		
6. Math Fluency	0.42***	0.38***	0.18	−0.08	−0.48***	
7. Calculation	0.4***	0.32***	0.29*	−0.05	−0.49***	0.62***

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

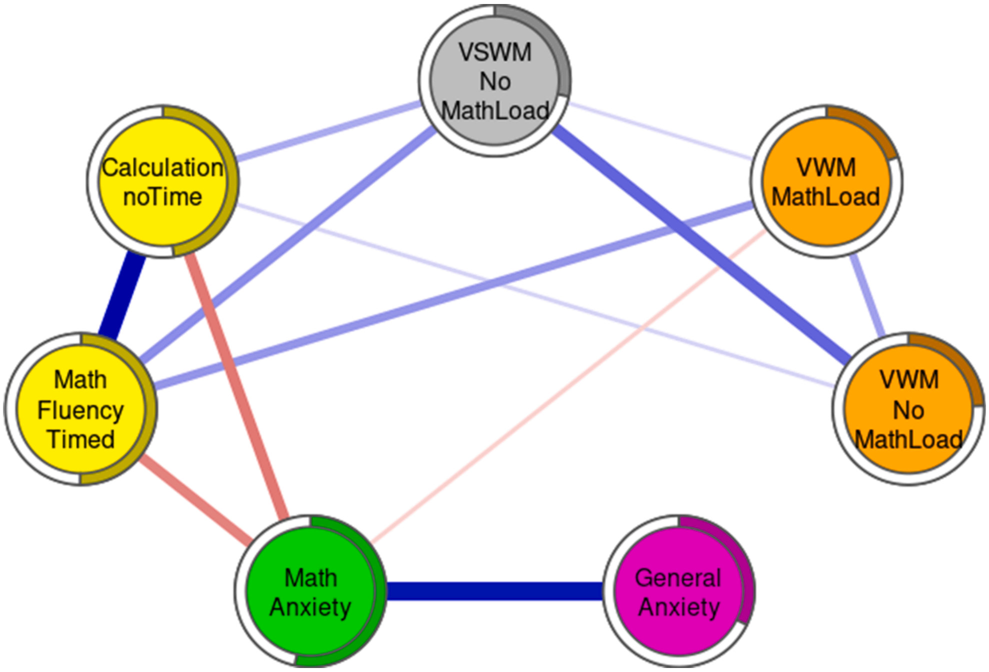

Fig. 1. Regularized Partial Correlation Network of Math Performance. *Note.* Edge thickness represents the strength of a direct interaction between two nodes. Blue and red edges indicate positive and negative relations, respectively. The pink node represents the GA measure. The green node represents the MA questionnaire. Yellow nodes represent math tests (i.e., calculation and math fluency). The gray node represents the VSWM task (the Color Span Backwards task). Brown nodes represent VWM tasks (i.e., the Opposites and N-span tasks). The colored area in the rings around the nodes depicts predictability.

(VSWM), only the edge to calculation remains. Fourth, GA only edge is to MA. Fifth, as there are two math performance nodes in the network, all remaining edges are after one math performance test was partialed out (i.e., MA is linked to fluency even when controlling for the three WM nodes, GA and calculation). Finally, while both N-Span and opposites test measure VWM, the edges between them and the colors task (VSWM) appear to be stronger, thou not significant (see supplementary fig 8. for edge comparisons).

In our network, math fluency is the most central node, followed by calculation. Thus, the model reaffirms that the focus of our analysis is on math performance. Centrality analysis shows that both math performance measures and MA are the most central in the network (see Supplementary Figures S3 and S4). Robustness analysis suggests the results are consistent when removing up to 28.4% of the participants (see Fig. 2), over the suggested threshold of 0.25 (Epskamp & Fried, 2018).

2.5. Discussion: Part 1

Traditional statistical methods examine the common variance and thus do not distinguish the unique contribution of each observable variable (Schmittmann et al., 2013). In an attempt to better understand the complex relations between WM, MA, and math performance, we looked at the “micro” level. Using the network approach, we examined the partial correlation matrix between MA, WM tasks with and without math load, and math performance in two different tests. In line with our hypotheses, the results demonstrate: (1) the relations between MA and WM are actually very weak, except for the WM task which involves manipulation of numerical information (i.e., N-Span); (2) MA is linked to math performance in a non-WM related manner; and (3) each WM task relates to different numerical tests.

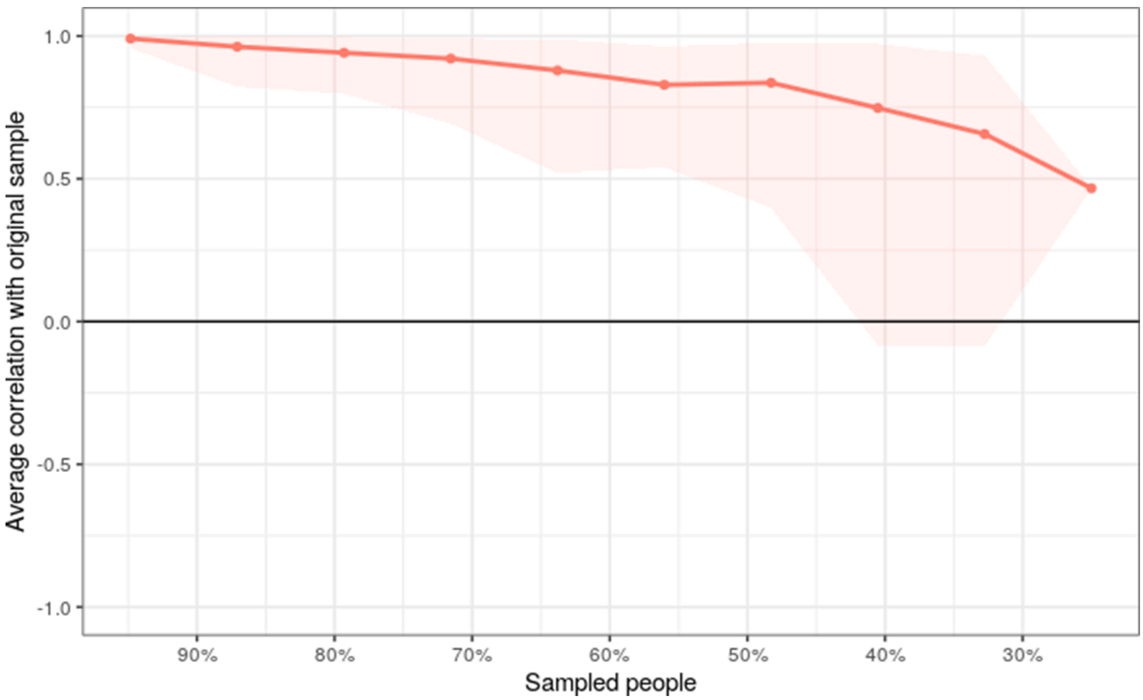

Fig. 2. Average Correlation of Results between Different Subsets and the Entire Sample. *Note.* Average correlations between centrality indices of the original network are constructed on the full data, with networks estimated on samples with fewer participants. Results are stable when up to 28.4% of participants are dropped.

However, our ambition was not only to show a valid model backed by our data but also to replicate the findings. To this end, in part 2, we used an available online dataset (Skagerlund et al., 2019) which includes university students of both sexes (i.e., conceptual replication; Zwaan et al., 2017). The modeling application thus represents an important first step towards the creation of a strong and reliable model of the cognitive and affective underpinnings of math performance (Costantini et al., 2015).

3. Study 2

3.1. Conceptual-Replication Sample: Confirmatory analysis

As mentioned above, we used data from Skagerlund and colleagues (2019) for the confirmatory analysis (https://doi.org/10.1371/journal.pone.0211283.s001). We describe the method very briefly here; for more details, see Skagerlund et al. (2019).

3.2. Participants

The sample consisted of 166 Swedish university students (83 men and 83 women, mean age = 24.03, *SD* = 3.39). Four subjects from the original sample who did not complete one or more of the tasks were removed from our analyses.

3.3. Measures

3.3.1. VWM with math load- digit Span tasks

Three versions of the digit span subtest from WAIS-IV were used to assess VWM: Digit Span Forward (DSF), Digit Span Backward (DSB), and Digit Span Sequencing (DSS). In all these tasks, participants hear a series of digits and are asked to repeat them out loud in the order they heard them, in a reverse order, and in an ordinal order, respectively. It is worth mentioning that the DSF might be considered a test of short-term memory (STM) not WM.

3.3.2. Math anxiety

Math anxiety was assessed using the Mathematics Anxiety Scale-UK (MAS-UK; Hunt, Clark-Carter, & Sheffield, 2011). Although the MAS-UK can be divided into three factors (everyday/social math anxiety, math observation anxiety, math evaluation anxiety), we used a total MAS-UK score in order to compare the two samples.

3.3.3. Calculation

Calculation was assessed using the Berlin Numeracy Test (BNT; Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012), in which participants are asked to solve four math word problems within a ten-minute time limit. Number of correctly solved problems was used as a measured of Calculation (possible max score: 4).

3.3.4. Fluency

Fluency was assessed using the test includes four subtests (addition, subtraction, multiplication, division; Gebuis & Van Der Smagt, 2011). In each subtest, participants complete increasingly difficult calculation problems within a two-minute time limit. Total correct problems across all condition was used as calculation score (max score can be 54 (problems) * 4 (subsets) = 208).

3.4. Results

The correlation matrix is presented in Table 3. Consistent with the correlation matrix of the research variables in our sample, the findings replicate findings of previous work: (1) positive correlations between WM tests (Gray et al., 2017); (2) positive correlations between WM and math performance (Raghubar et al., 2010); (3) negative correlations between MA and math performance (Chang & Beilock, 2016; Cipora et al., 2015; Devine et al., 2012; Hembree, 1990; Ma, 1999; Wang et al., 2015; Wu et al., 2012); (4) negative correlations between MA and WM (Ashcraft & Kirk, 2001; Ashcraft & Krause, 2007; Justicia-Galiano et al., 2017; Miller & Bichsel, 2004). The correlation matrix shows all "in cluster" correlations are significant.

The GGM network is visualized in Fig. 3. Of a possible 15 edges, 12 are retained. Predictability ranges from 20.8% in the MA questionnaire (i.e., the MAS-UK) to 43.9% in the math fluency test. Average predictability is 32.4%. The confirmatory network again outlines the three theoretically assumed clusters: WM, MA, and math performance. The math fluency test is the most central node, while the Calculation task plays a secondary role, reinforcing once again that the focus of our analysis is on math performance. As also shown in the regularized partial correlation network of our sample, the confirmatory network indicates the link between MA and math performance is not mediated by WM. Moreover, the only WM task linked to MA is the DSS, which requires manipulation of numbers. As in our sample, a unique pattern appears for each WM task and the math performance nodes. For the DSS task (VWM with high math-load), both edges to math performance nodes remain, with a stronger edge to math fluency. For the DSB task (VWM with low math-load), both edges to math performance nodes remain, with a stronger edge to calculation. For the DSF task (STM), only the edge to math fluency remains. Robustness analysis suggests the results are consistent when removing up to 36.1% of the participants (see Fig. 4).

In order to compare the network from study 1 with the network from study 2, we removed the GA node from the study 1 network, as the conceptual-replication sample did not include a measure of GA. Results show no significant differences between the networks, with network invariance test results, M = 0.22, p = 0.55, and global strength invariance test results, s = 0.08, p = 0.81.

3.5. Discussion: Part 2

By replicating the findings using an online available dataset (Skagerlund et al., 2019) which includes university students of both sexes (i.e., conceptual replication; Zwaan et al., 2017), we hoped to show we had created a strong and reliable model of the cognitive and affective underpinnings of math performance (Costantini et al., 2015). Similar to the first study, the link between MA and math performance was not mediated by WM; rather, WM and MA were independently linked to math performance. Importantly, MA was linked to WM only in a task involving manipulation of numerical information (i.e., the DSS). Moreover, in line with a small number of studies taking into account differences in the math anxiety-performance link with various aspects of math, this link was stronger as the complexity of math tasks increased (Ching, 2017; Vukovic, Kieffer, et al., 2013, Vukovic, Roberts, et al., 2013). Worth mentioning, the two studies used different methods to assess math performance. While the arithmetic tests, are more or less the same (i.e., the main difference is the separation to subsets in study 2), the calculation tests have a significant difference. The BNT is time constrained, it has less variance (range 0–4), low consistency in the sample ($\alpha = 0.41$) and it is less comprehensive than the Woodcock–Johnson III Tests of Achievement (Skagerlund et al., 2019). Nevertheless, when juxtaposed, the two studies complement each other and address each other's limitations.

Table 3
Correlation matrix in the conceptual-replication sample.

Variable	1	2	3	4	5
1. DSF	–				
2. DSB	0.46***	–			
3. DSS	0.49***	0.43***	–		
4. MA	−0.16*	−0.25**	−0.28***	–	
5. Math Fluency	0.39***	0.4***	0.46***	−0.44***	–
6. Calculation	0.25**	0.38***	0.32***	−0.29***	0.5***

Note. *$p < .05$, **$p < .01$, ***$p < .001$. DSF (digit span forward) – short-term memory; DSB (digit span backward) – VWM; DSS (digit span sequencing) – VWM.

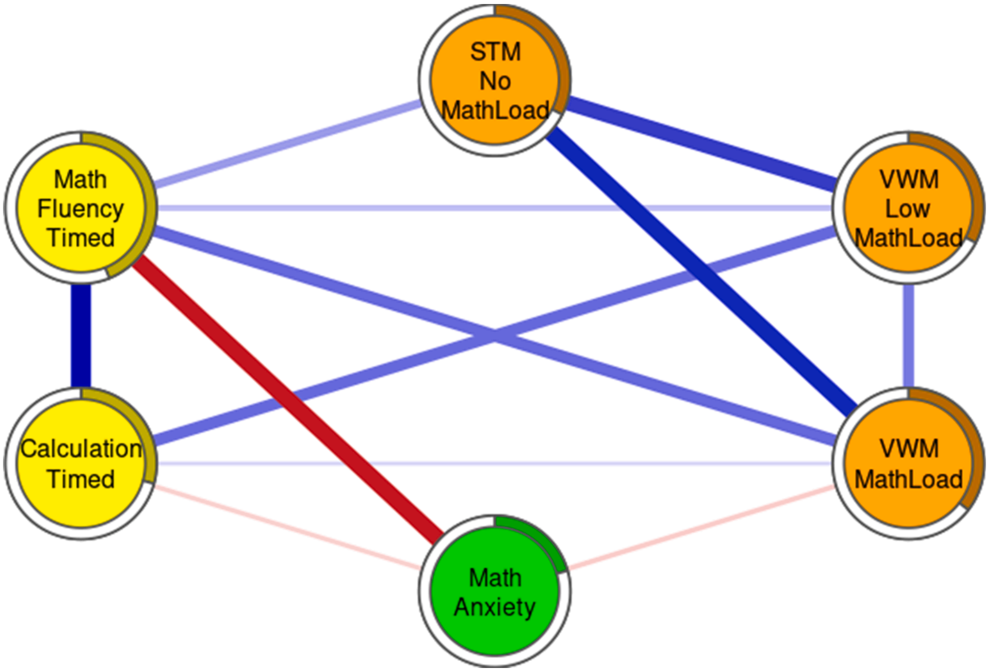

Fig. 3. Regularized Partial Correlation Network of Math Performance in the Confirmatory Sample. *Note.* Edge thickness represents the strength of a direct interaction between two nodes. Blue and red edges indicate positive and negative relations, respectively. The green node represents the MA questionnaire. Yellow nodes represent math tests (i.e., Calculation and math fluency tests). Orange nodes represent the VWM tasks (i.e., the three versions of the Digit Span subtest). STM no math load – digit span forward, VWM low math load – digit span backward, VWM math load – digit span sequencing. The colored area in the rings around the nodes depicts predictability.

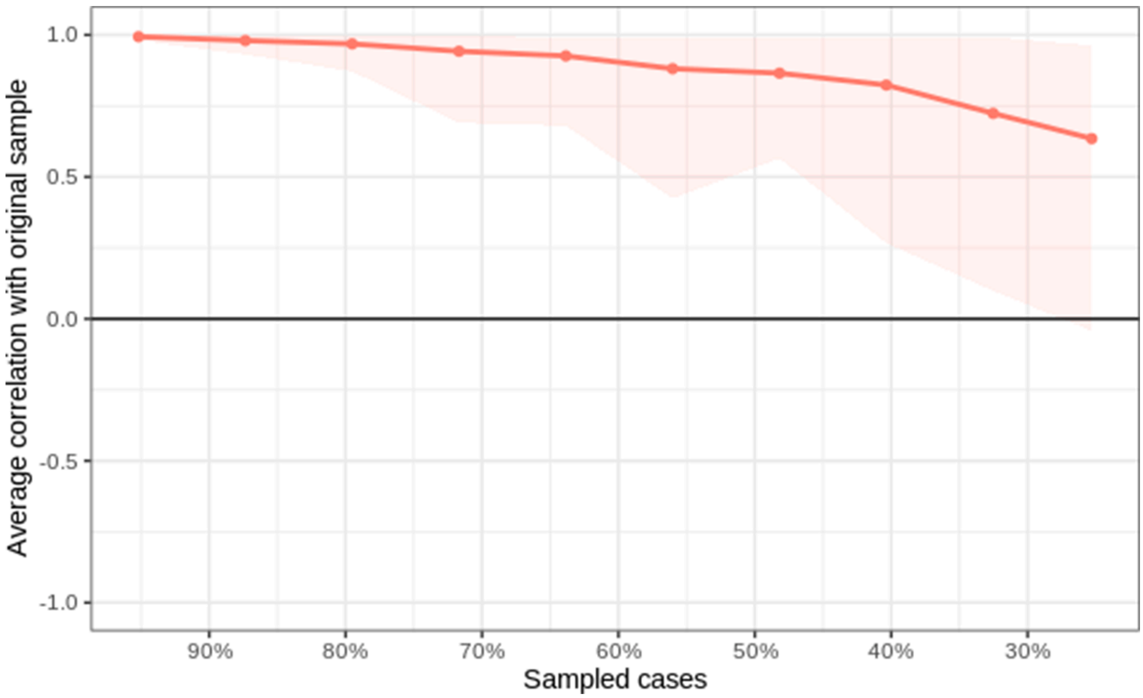

Fig. 4. Average Correlations of Results between Different Subsets and the Entire Confirmatory Sample. *Note.* Average correlations between centrality indices of the original network were constructed on the full data, with networks estimated on samples with fewer participants. Results are stable when up to 36.1% of participants are dropped.

4. General discussion

The primary purpose of the two studies was to provide a comprehensive model of the nature of the links between MA, WM, and math performance. Our powerful statistical approach enabled us to distinguish between the unique contribution of each observable variable (Schmittmann et al., 2013) and visualize the dynamics among constituent elements in the network (Costantini et al., 2015). Our results clearly show WM and MA independently relate to math performance.

The results have important implications for the current theoretical understanding of MA. Based on traditional statistical analyses, such as regression models (e.g., Miller & Bichsel, 2004) and SEM (e.g., Skagerlund et al., 2019), the dominant account has two main ideas at its core. First, MA individuals are understood to have general difficulty in math (the math anxiety-math performance link) (Barroso et al., 2021; Foley et al., 2017; Zhang, Zhao, & Kong, 2019), with the accumulated evidence emphasizing the significance of both WM (e.g., Beilock & DeCaro, 2007; Xenidou-Dervou et al., 2018) and MA (e.g., Suárez-Pellicioni et al., 2013) to math performance. Second, WM is understood to act as a mediator in the link between MA and math performance (Ashcraft & Kirk, 2001; Luttenberger et al., 2018; Maloney & Beilock, 2012; Szczygieł, 2021; Suárez-Pellicioni et al., 2016).

The first core idea of links between MA, WM, and math performance is supported by our data. Yet by using network analysis and complementary informative metrics, we have expanded the model to show the correlations between MA, WM, and math performance depend on specific task properties. Thus, the data presented here significantly challenge the second core claim. In line with our hypotheses, data from our sample and the conceptual replication suggest: (1) the correlations between MA and WM depend on the degree of math-load rather than WM subtypes properties; (2) the edges' strength suggest WM and MA are independently linked to math performance, or at least are linked through math-related stimuli in the WM task; (3) each WM node has a unique pattern of edges for the different numerical tests.

Importantly, we replicated our results using an online available dataset collected in a different country for a different population by Skagerlund and colleagues (2019). Hence, the study provides a reliable model of the cognitive and affective underpinnings of math performance.

4.1. *Uncovering the math anxiety–performance link*

Consistent with previous findings, we found higher levels of MA were associated with decreased math performance (Chang & Beilock, 2016; Cipora et al., 2015; Devine et al., 2012; Hembree, 1990; Ma, 1999), particularly in more complex math tasks (Ching, 2017; Vukovic, Kieffer, et al., 2013, Vukovic, Roberts, et al., 2013), and reduced WM (Ashcraft & Kirk, 2001; Ashcraft & Krause, 2007; Justicia-Galiano et al., 2017; Miller & Bichsel, 2004; see supplementary Figures S5 and S6 for visualization of the Pearson correlation matrix). Yet partial correlation analysis of our sample and the conceptual-replication sample revealed the most prominent connections were between MA and math tests. MA was only linked to WM tasks involving manipulation of numerical information, suggesting the MA-WM link is explained by the need to interact with the numbers.

The absence of an edge between the no math load WM tasks and MA or even GA nodes in the partial correlation network means those constructs are conditionally independent (Costantini et al., 2015). According to clinically focused theories (Mathews & MacLeod, 2005; Ouimet, Gawronski, & Dozois, 2009), impairments in WM are not the result of anxiety, but may act as a risk factor for the etiology of anxiety. In line with these theories and findings on the independent contribution of WM and MA to math performance (Justicia-Galiano et al., 2017; Miller & Bichesl, 2004; Passolunghi et al., 2019; Skagerlund et al., 2019), our results challenge the common assumption that anxiety-related processes use up WM resources (Ashcraft & Kirk, 2001; Luttenberger et al., 2018; Maloney & Beilock, 2012; Szczygieł, 2021; Suárez-Pellicioni et al., 2016).

Based on the Attentional Control Theory (Eysenck, Derakshan, Santos, & Calvo, 2007), another possible pathway through which MA can affect math performance is attentional control. Although we did not specifically address attentional control in this study, the theory suggests MA impairs the functioning of goal-directed cognitive systems (Orbach, Herzog, & Fritz, 2020; Pletzer et al., 2015; Suárez-Pellicioni et al., 2013; Suárez-Pellicioni et al., 2014; Van den Bussche, Vanmeert, Aben, & Sasanguie, 2020) and increases attention to threat-related stimuli (i.e., attentional bias; Rubinsten, Eidlin, Wohl, & Akibli, 2015; Suárez-Pellicioni, Núñez-Peña, & Colomé, 2015). Consequently, attention is directed almost exclusively to the anxiogenic stimuli, thus impairing the ability to concentrate on the task at hand (Cisler & Koster, 2010). Given the benefits of network analysis, future research should examine the underlying relationships between MA, WM, the attentional control or active control required to perform a task, and math performance.

4.2. *Dimensionality of working memory*

WM has been found to be a strong predictor of math performance (e.g., Alloway & Passolunghi, 2011; Beilock & DeCaro, 2007; Xenidou-Dervou et al., 2018), and each WM subsystem has different relations with math performance (Allen & Giofrè, 2020; Ashkenazi & Danan, 2017). However, there are inconsistencies in findings for the subsystems. While some studies have indicated a more pronounced effect of VSWM on math performance (Allen et al., 2019; Giofrè et al., 2018; McKenzie et al., 2003; Miller & Bichsel, 2004; St Clair-Thompson & Gathercole, 2006; Toll et al., 2016), others have demonstrated the influence of VWM (Ashkenazi & Danan, 2017; Hitch & McAuley, 1991; Wilson & Swanson, 2001), particularly with a high math-load (for a review, see Raghubar et al., 2010).

Consistent with the latter line of research, we found WM was positively related to math performance (Raghubar et al., 2010), with math performance more strongly correlated with VWM than VSWM (Ashkenazi & Danan, 2017; Hitch & McAuley, 1991; Wilson & Swanson, 2001). At first glance, the network analysis showed the same trend; the edge between the VSWM task and math performance was weaker than the edge between VWM and performance, as VWM tasks were correlated to both calculation and math fluency.

However, the edge between WM and math performance was probably more task-dependent than domain-dependent (i.e., VWM or VSWM; Raghubar et al., 2010). The replication sample only included VWM and STM tasks, so the results cannot really address this question. However, as the replication sample data still show different patterns for the different WM tasks and math performance, it seems the way we measure WM is extremely important.

To sum up, when all other observable measures in the network were tested, all WM tasks clustered together, but each WM task had a unique pattern of edges with the different math tests. These results challenge recent work that has found both VWM and VSWM play a crucial role in math performance (Allen & Giofrè, 2020; Ashkenazi & Danan, 2017).

4.3. Future directions

The study makes an important first step towards the understanding of the cognitive and affective underpinnings of math performance by revealing the underlying nature of the links between them. Future studies will have to test the model in the general (non-student) population with more participants. A recent meta-analysis (Zhang et al., 2019) suggests the math anxiety-performance link is stronger among senior high school students, followed by junior high school, university, and elementary students. These differences might influence the edges between MA, WM, and math performance. Note that although only women university students participated in our study, the conceptual-replication sample included university students of both sexes. For the generalizability of inferences, conceptual replications are valuable (Zwaan et al., 2017). However, direct replications, wherein a hypothesis from the original study is repeated in a similar experimental paradigm, are needed to verify the robustness of the findings (Pashler & Harris, 2012) and reduce false-positive conclusions (Zwaan et al., 2017).

Further research should also address causal inferences. The network approach expands our understanding of the origins of the links between latent variables and the degree of contribution of each WM task to the network, but it lacks directionality.

Finally, MA was assessed through participants' self-reports of their anxiety level in math-related situations using the MARS brief (Suinn & Winston, 2003). Future studies should consider assessing state MA using implicit measures, such Skin Conductance Response and Heart Rate Variability (e.g., Qu et al., 2020), in order to assess inaccessible cognitive and emotional structures that are processed automatically (Rubinsten, 2015). In this vein, the differentiation between state and trait WM may be particularly relevant in the study of MA in math-related situations (Ashcraft, 2002). We took the degree of math-load into account when evaluating a trait-level WM, but WM resources are most likely influenced by situational factors as well (Ilkowska & Engle, 2010). Thus, to effectively test the common assumption that anxiety-related processes deplete WM resources, leading to a decrease in task performance (Ashcraft & Kirk, 2001; Luttenberger et al., 2018; Maloney & Beilock, 2012; Szczygieł, 2021; Suárez-Pellicioni et al., 2016), online assessment forms for both state math anxiety and WM resources should be implemented (Caviola et al., 2021).

In addition, understanding the contribution of each WM subsystem rather than each observable task of WM may shed light on the complex relationships between WM, MA, and math performance. In such research, it is important to consider that young adults may use a phonological recoding of visual stimuli, in tasks such as the Color Span Backwards task (Palmer, 2000) we used to measure VSWM; thus, they may rely on VWM to solve the task. Similarly, it can be argued that the Digit Span Forward (DSF) task used in the conceptual-replication sample is a short-term memory task, not a VWM task, because there is no manipulation or interference to inhibit (e.g., Swanson & Luxenberg, 2009).

4.4. Conclusions

The research provides a strong and reliable model of the interplay between MA, WM, and math performance. Because we opted to use partial correlations between observable tests in our own data as well as a secondary dataset with different populations instead of latent models, our findings demonstrate first, that the relationship between MA and WM is dependent on task properties and is pronounced only in WM tasks involving numerical information. Second, MA has a direct link to math performance. Third, each WM task has a unique tie to math performance. Ultimately, more emphasis should be put on WM task selection, and the unique properties (e.g., math load) of the task and how it relates to the theoretical framework (e.g., WM-MA link) being studied. Future research should carefully consider the relationships between directly measurable variables of WM and math performance that might be masked by traditional statistical approaches or interpreted in terms of unobserved latent variables.

Open practice statement

The materials and data can be found at https://osf.io/xuk3b/right635 and none of the studies were preregistered.

CRediT authorship contribution statement

Nachshon Korem: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Lital Dachas-Coehn:** Investigation, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing. **Orly Rubinsten:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.concog.2022.103298.

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