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**XXXVI CICLO DEL DOTTORATO DI RICERCA IN**

**NEUROSCIENZE E SCIENZE COGNITIVE**

**THE ROLE OF MATH ATTITUDES AND COGNITIVE  
FACTORS IN MATH LEARNING AND SCHOOL CHOICES**

Settore scientifico-disciplinare: M-PSI/04 PSICOLOGIA DELLO SVILUPPO E PSICOLOGIA  
DELL'EDUCAZIONE

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**ANNO ACCADEMICO 2022/2023**



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## **Abstract**

In an increasingly complex and data-driven society, math learning is of primary importance for individual and collective development. Studies have demonstrated how affective-motivational and cognitive factors influence math learning. However, to date, research has primarily assessed the contribution of each factor separately, despite evidence indicating their interplay. The present dissertation aims to examine the interplay between affective-motivational and cognitive factors in math performance and STEM school choices, considering primary and middle school students. The studies presented in this thesis aim to: 1) explore how general and math anxiety influence Working Memory and math performance during primary school; 2) investigate the interaction between math anxiety and Working Memory and their influence on different math tasks; 3) assess how math anxiety and math self-efficacy can influence individuals' attentional bias toward math stimuli; and 4) explore how affective-motivational factors, gender, and math performance influence students' STEM school choices. The studies will be framed within a theoretical framework, detailing the methods and analytical processes employed. Findings will be presented and critically discussed in light of existing literature, offering new insights into the interplay between affective-motivational factors, cognition, math performance, and STEM choices.

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## 1. General introduction

In modern societies, having good math performance refers not only to the citizens' ability to understand and apply mathematical procedures in formal learning but also to the ability to interpret numerical information in various contexts of daily life. In recent years, there has been a progressive “*mathematization*” of society, a phenomenon that sees mathematical knowledge infused in commonly used technological devices, industrial development, decision-making processes, or everyday medical practices (Keitel et al., 1993). In this context, the ability of citizens to correctly interpret mathematical information becomes a foundational skill for a deep understanding of the dynamics that characterize the complex society we belong to. It is not surprising, therefore, that math performance is predictive of academic and occupational success (Bynner & Parsons, 1997; Rivera-Batiz, 1992), socioeconomic status (Gerardi et al., 2013; Gross et al., 2009), and individual health (Furlong et al., 2016; Gross et al., 2009). Scientific evidence indicates that individuals with math difficulties often lag behind their peers in various disciplines over time (Nelson & Powell, 2018), face a higher likelihood of educational dropout (Hakkarainen et al., 2015), have increased unemployment rates, and have diminished mental health (see Aro et al., 2019). Moreover, at a societal level, a mathematically literate population contributes to national prosperity, more informed participation in public life, and more effective collective decision-making (Foley et al., 2017; Henriksen, 2015; Peterson et al., 2011). Given the central role of math in both individual and societal development, it's crucial to evaluate the current state of the art in math learning and identify the factors that support its growth.



## 1.1 Math learning: an overview

Several international reports indicate that math proficiency has significantly declined in recent years. According to the last PISA report (OECD, 2023), it has been observed worldwide a general decrease in math performance following the COVID-19 pandemic period, likely due to the prolonged closure of schools (for a meta-analysis, see Betthäuser et al., 2023). Particularly, the PISA report highlights that 31% of the students who participated in the survey fail to reach a level considered basic in math. Despite the decline in math performance in an increasingly “*mathematized*” society, there is a continuous international demand for professionals trained in STEM fields (Science, Technology, Engineering, and Math), leading nations to worry about reducing the existing gap between the demand and supply of STEM professionals (European Commission, 2015; for a review see Henriksen, 2015). Additionally, numerous studies indicate that a persistent gender gap exists, with females less frequently opting for careers in STEM (Breda et al., 2023; Halpern et al., 2007).

Considering the national landscape, there is a considerable proportion of Italian students who do not achieve the minimum level in math (INVALSI, 2022). In particular, the prevalence of Italian students underperforming in math appears to increase with each school year, reaching 30 percent in elementary school and exceeding 40 percent in secondary school. Furthermore, notable regional differences are evident, suggesting that students in southern Italy exhibit lower math performance compared to their peers in the north. Another significant aspect is the pronounced gender gap in math performance observed in Italy, as indicated by the latest data from the PISA assessment (OECD, 2023), where girls tend to score lower than boys. In this context, a study by Giofrè and colleagues (2020), drawing on data from national assessments (i.e., INVALSI assessments), observed a gender gap to the disadvantage of girls, increasing from 2<sup>nd</sup> to 8<sup>th</sup> grade

and particularly pronounced in the northern regions of the country. In light of these national and international data, studies should monitor the factors impacting math performance in order to develop strategies for mitigating mathematical difficulties among students.

Psychological research underlines that specific cognitive and affective-motivational factors concur to influence math performance. For example, among cognitive factors, Working Memory has been shown to be crucial in supporting learning and execution of math tasks (e.g., Allen & Giofrè, 2021; Liang et al., 2022; Ramirez et al., 2016; Wong & Szücs, 2013). Research on affective-motivational factors has shown how general and specific forms of anxiety and low self-efficacy would undermine individuals' math performance (Namkung et al., 2019; Wang et al., 2014; Zhang et al., 2019; Živković et al., 2023). However, most studies have investigated the single contribution of these factors, although evidence indicates that affective-motivational and cognitive factors interact in influencing math performance (Ramirez et al., 2013, 2016; Pizzie & Kraemer, 2017; Rubinsten et al., 2015). In addition, some studies conducted on adults show that affective and motivational factors would trigger attentional bias toward math stimuli (e.g., Rubinsten et al., 2015) and influence STEM choices (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021; Wang, 2013). In this context, it remains unclear how affective and motivational factors, in interplay with cognitive factors, affect students' math performance and STEM school choices.

The general objective of this dissertation was to investigate how attitudes towards math, specifically affective-motivational factors, influence cognitive factors, math performance, and STEM school choices in primary and middle school students. In line with the methodological approaches of developmental psychology, the first two studies delved into the research on the interplay between affective and cognitive factors in math performance, focusing on primary students. Specifically, the first study (Chapter 2) longitudinally examined how general anxiety and

math anxiety, together with Working Memory, contribute to influencing math performance during primary school. The second study (Chapter 3) more specifically assessed how math anxiety interacts with visuospatial Working Memory, influencing math performance at the end of primary school.

In line with the assessment of affective-motivational and cognitive factors, we conducted two other studies that focused mainly on middle school students. Particularly, the third study (Chapter 4) evaluated how math anxiety, along with self-efficacy, influence attentional bias processes and vigilance and avoidance patterns towards math stimuli. The fourth study (Chapter 5) examined, using a three-years longitudinal design, the role of math anxiety, self-efficacy, gender and math performance in predicting students' STEM school choices.

## **1.2 Factors involved in math learning**

Math learning is a complex activity that involves a progressive build-up of knowledge, making it difficult for individuals with low math performance to catch up with their peers (Bodovski & Farkas, 2007; Martin & Rimm-Kaufman, 2015; Nelson & Powell, 2018). Possessing strong cognitive abilities and positive attitudes towards math can be crucial, offering individuals protective factors that would aid their math development. Considering cognitive factors, various studies have shown that they support learning from an early age throughout development. Among these are abilities like processing speed (Moll et al., 2016), intelligence (Giofrè et al., 2017; Peng et al., 2019), and Working Memory (Friso-van den Bos et al., 2013; Peng et al., 2016). Working Memory, in particular, is considered one of the most robust predictors of general academic success (e.g., Alloway & Alloway, 2010) and specifically math performance (e.g., Peng et al., 2016), acting as a protective factor starting from preschool age. Considering attitudes towards math, numerous studies have shown the influence of anxiety and motivational factors on math performance and

students' school choices. Specifically, popular theories in learning psychology, such as the Control Value Theory (CVT, Pekrun, 2006) and the Expectancy-Value Theory (EVS, Eccles & Wigfield, 2020), agree that students' expectations and value judgments regarding math and their own abilities exert a profound impact on their learning process and engagement in the subject (Berweger et al., 2022). These appraisals, therefore, would modulate individuals' attitudes, particularly emotional and motivational aspects, which play a main role in influencing math performance, cognitive processes, and STEM school choices (Eccles & Wigfield, 2020).

In the following sections, the role of cognitive and affective-motivational factors in math performance and STEM choices will be described. First, the focus will be on the role of Working Memory in math learning and performance. Secondly, the discussion will cover how general and math anxiety act negatively on math performance, cognition, and STEM school choices. Finally, the dissertation will delve into the role of motivational factors, highlighting their influence on math performance and STEM choices.

### ***1.2.1 Working memory***

Working Memory (WM) refers to a limited-capacity cognitive system responsible for the temporary storage and processing of information during task execution (Baddeley, 1986; Miyake & Shah, 1999). According to the most influential model, Baddeley's multicomponent model (1986), WM would consist of a central executive that would process and monitor information coming from two subsystems responsible for elaborating modality-specific information: the phonological loop and the visuo-spatial sketch pad. The phonological loop would be responsible for the storage of linguistic information, while the visuo-spatial sketch pad would be responsible for retaining visual and spatial information. In this context, based on Baddeley's (1986) theorizing, the two subsystems would be responsible for passive retention tasks, while the central executive

would have the task of coordinating, integrating, and actively processing information coming from the two subsystems. In addition to the multicomponent model, a continua model of WM has been proposed in the literature (Cornoldi & Vecchi, 2000, 2003), according to which the differences between the type of information processed (i.e., verbal or visuospatial information) and the degree of activity (i.e., passive and active processing) are represented along continua. Indeed, tasks may involve the execution of high-control processes, necessitating the integration and processing of information through demanding mental activity. Conversely, low-control tasks might involve passively retaining information, followed by its retrieval from memory without any manipulation. In the literature, high-control processes are referred to as WM, distinguishing them theoretically from more passive forms of memory retention (Bull et al., 2008; Gathercole et al., 2006; Swanson & Luxenberg, 2009).

WM plays a fundamental role in influencing math performance (Allen & Giofrè, 2021; Liang et al., 2022), supporting the execution of different math tasks such as math operations, math reasoning, and math problem solving (De Smedt et al., 2009; Giofrè et al., 2017; Lee & Bull, 2016; Passolunghi et al., 2016). Having low levels of WM would also be a risk factor for the development of math difficulties (Peng et al., 2016; Swanson & Beebe-Frankenberger, 2004). In fact, WM would be a fundamental resource in supporting the acquisition and application of strategies for solving math tasks. In fact, several findings have shown that math strategies place cognitive demands on WM, which would allow the student to support all those procedures involved in the task, such as the retrieval of an appropriate procedure, the decomposition of numbers, the application of carrying and borrowing rules, and the processing of partial results (Allen et al., 2020; Ramirez et al., 2016; Wong & Szűcs, 2013).

### ***1.2.2 General anxiety***

Several findings show how experiences of anxiety can interfere with an individual's learning and cognitive functioning. Among these, general anxiety (GA) is defined as the tendency of an individual to worry about everyday life events, behaviors, and personal abilities (Eysenck & Calvo, 1992; Hill et al., 2016), distinguishing it from specific discipline-related forms of anxiety such as math anxiety or reading anxiety (Donolato et al., 2020; Hill et al., 2016). GA is often associated with overall low school performance (Ialongo et al., 1995; Mazzone et al., 2007; Owens et al., 2012), poor motivation (Brumariu et al., 2023), and school refusal (Tekin & Aydın, 2022). Looking specifically at math, few studies have been conducted to delineate the contribution of GA to math performance. For instance, some evidence showed that it had a limited role compared to discipline-specific anxieties in predicting math performance (Hill et al., 2016; Donolato et al., 2020). Other evidence has suggested that in the early primary school years, math learning would be significantly influenced by a tendency to experience GA and then show in later school years a greater involvement of discipline-specific anxieties (Cargnelutti et al., 2017; Rubinsten et al., 2018). Similarly, a study by Wang and collaborators (2014) indicates how a genetic predisposition to GA may be a risk factor for the development of math-specific anxiety. In other words, GA would represent an early emotional risk factor that can influence the onset of specific forms of anxiety. Therefore, further studies are needed to investigate the role of GA from a developmental perspective, grasping how it may influence math performance and constitute a risk factor for the development of specific forms of anxiety in the early years of formal schooling.

### ***1.2.3 Math anxiety***

Among the most widely investigated affective constructs in the literature is math anxiety (MA). According to a popular definition, MA is referred to as: “*a feeling of tension and anxiety*

*that interferes with the manipulation of numbers and the solving of math problems in ordinary life and academic situations”* (Richardson & Suinn, 1972). In the literature, MA is often conceptualized as a state or trait that varies among individuals (Cipora et al., 2022). From a developmental perspective, several studies show that it would begin to develop as early as primary school (e.g., Ramirez et al., 2016; Tomasetto et al., 2021). In this context, the risk factors that determine its onset have not been uniquely identified, but researchers have suggested that it may have a multifactorial origin (Rubinsten et al., 2018). These include, for example, teaching styles, students' attitudes toward math, negative experiences with the discipline, and an individual tendency toward GA (Rubinsten et al., 2018; Wang et al., 2014).

Findings have shown that MA has a negative effect on math performance and STEM choices. Particularly, some meta-analyses have indicated that MA has a moderately negative effect on math performance (e.g., Caviola et al., 2022; Namkung et al., 2019; Zhang et al., 2019). This relationship would become more pronounced during development, peaking during middle school (e.g., Caviola et al., 2022; Namkung et al., 2019). MA, in addition to negatively affecting math performance, would lead the students to develop math avoidant behaviors (Ashcraft & Krause, 2007; Pizzie & Kraemer, 2017), further reinforcing their negative attitudes. In this context, MA also influences future academic and occupational choices (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021). In fact, it has been shown in the literature that individuals with high levels of MA would show a tendency to make STEM choices with a lower frequency (Ahmed et al., 2018; Daker et al., 2021; Meece et al., 1990), in favor of courses and occupations with less math content. However, there are still some open questions related to the effects of MA on math performance and STEM school choices. Evidence has shown that high levels of math anxiety do not necessarily lead to learning difficulties (Cipora et al., 2021; Devine et al., 2018), suggesting that other factors

may play a role in influencing math performance. Among these, for example, it has been proposed that MA has a detrimental effect on cognitive factors such as WM (e.g., Ramirez et al., 2016; Soltanlou et al., 2019) and the individual's attentional processes (e.g., Pizzie & Kraemer, 2017; Rubinsten et al., 2015). Furthermore, regarding STEM choices, evidence to date has focused on assessing how MA influences individuals' choices in higher education and occupational careers (e.g., Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021). However, little has been done to investigate how MA might affect STEM school choices during middle school.

#### **1.2.3.1 The interplay between factors: Math anxiety effects on Working Memory.**

According to Processing Efficiency Theory (PET, Eysenck & Calvo, 1992), WM would be a central construct for understanding the effects of anxiety on cognitive and math tasks. In fact, according to PET, anxiety would act negatively on WM (Ashcraft & Kirk, 2001; Owens et al., 2012), leading to lower accuracy and speed in the execution of tasks that require the involvement of WM resources. According to several authors (e.g., Justicia-Galiano et al., 2017; Ramirez et al., 2016; Soltanlou et al., 2019; Vukovic et al., 2013) this would also be the case with MA, which would adversely affect math performance by interfering with WM resources and making task execution more burdensome and susceptible to errors. To date, however, there is still an ongoing debate about which individuals are more susceptible to the negative effects of MA. Some authors argue that MA would primarily interfere with the performance of students with low-WM who would lack the resources to simultaneously manage intrusive anxiety-provoking thoughts and task demands (Miller & Bichsel, 2004; Soltanlou et al., 2019). Other authors, however, argue that MA hinders performance for those who have more WM resources and usually use cognitively demanding strategies when performing a math task (Beilock & Carr, 2005; Beilock et al., 2004; Ramirez et al., 2013, 2016). In light of this debate, further studies are needed to assess the complex



interaction between MA and WM resources by exploring different age groups and different math tasks. In fact, previous studies have mainly evaluated students attending the early years of primary school and used batteries that assessed general math performance (Ramirez et al., 2013, 2016; Vukovic et al., 2013).

**1.2.3.2 The interplay between factors: Math anxiety effects on attentional biases.** MA, in addition to affecting WM resources, also appears to alter the way individuals pay attention to math stimuli perceived as “threatening”, such as math-related words or numerical expressions. This phenomenon, called “attentional bias”, would lead individuals to abnormally direct their attention when exposed to stimuli perceived as threatening (MacLeod et al., 1986; Mogg et al., 2004). Studies in samples of adults with high MA have shown how exposing a math stimulus versus a neutral one would lead subjects to show vigilance patterns toward the stimulus itself (Cohen et al., 2017; Eidlin Levy & Rubinsten, 2021; Rubinsten et al., 2015). Other evidence seems to show that anxious adults exhibit attentional avoidance patterns toward numerical stimuli (Pizzie & Kraemer, 2017). However, to date, this phenomenon has not been investigated in the developmental age, a period when the first negative attitudes toward discipline would be formed. Second, the evidence seems mixed regarding the behavioral patterns (i.e., vigilance and avoidance) that individuals would exhibit after being exposed to math stimuli perceived as threatening. Therefore, further investigation on developmental samples is needed, including considering motivational constructs that in the literature appear to play a role in influencing individuals' attentional biases (Karademas et al., 2007; Walsh et al., 2018).

#### ***1.2.4 Motivational factors***

It is widely recognized in the literature that several motivational factors influence students' attitudes toward math (Bandura, 1993). Among the most influential in learning would be self-

efficacy (SE), which refers to beliefs about one's perceived ability to organize and perform specific activities necessary to achieve certain goals while controlling one's own behavior, motivation, and emotions (Bandura 1994). Typically, self-efficacy is assessed by asking the individual about his or her proficiency in performing specific tasks, differing from constructs such as self-concept, which investigate an individual's perceived ability with respect to a broad domain of knowledge (Lee, 2009; Marsh et al., 2019). Studies have shown that SE would develop as early as primary school (Arslan, 2012; Joët et al., 2011; Živković et al., 2023), playing a crucial role even in middle school (Skaalvik et al., 2015) and in later educational pathways (Akin & Kurbanoglu, 2011; Pajares & Kranzler, 1995).

The development of SE beliefs would be influenced by many factors (Bandura, 1997; Fast et al., 2010; Schunk & Pajares, 2002; Usher & Pajares, 2009), which, according to Bandura (1997), would be mainly four. The first indicates how SE is strongly based on current and past experiences of success and failure within a specific discipline (Li et al., 2021). Another key aspect is vicarious experiences, where students observe and compare themselves with significant figures in their learning environment, such as peers, parents, and teachers (Ahn et al., 2017; Skaalvik et al., 2015). A third source of efficacy concerns the sociocultural context of individuals, that is, the set of norms and expectations shared by society (Ahn et al., 2016; Oettingen, 1995; Usher & Weidner, 2018). Finally, students would also be influenced by the emotional states and physiological activation experienced during academic activities (Joët et al., 2015; Usher & Pajares, 2008).

SE would influence how people feel, think, motivate, and behave during math tasks (Bandura, 1977). In fact, students with higher SE show greater interest in the discipline (Rottinghaus et al., 2003; Zhang & Wang, 2020), greater persistence (Czocher et al., 2020; Geisler et al., 2023), greater emotional and social involvement (Martin & Rimm-Kaufman, 2015), greater

effort (Galla et al., 2014; Multon et al., 1991), less procrastination (Klassen et al., 2008), and lower levels of MA (Li et al., 2021). In this context, numerous studies have shown that individuals with high SE tend to have better math performance compared to their peers (Galla et al., 2014; Schöber et al., 2018; Skaalvik et al., 2015; Živković et al., 2023). This is often accompanied by positive emotional states and an increased interest in the subject (Du et al., 2021). Regarding STEM choices, evidence suggests that higher SE in adults is linked to a stronger preference for pursuing educational and career paths in STEM fields (Cribbs et al., 2021; Wang, 2013).

However, the literature still presents several gaps regarding the role of SE beliefs in math. Firstly, evidence suggests that motivational factors, as in the case of MA (e.g., Rubinsten et al., 2015), may play a role in creating an attentional bias towards information perceived as threatening (Karademas et al., 2007; Walsh et al., 2018). This would indicate the potential influence of SE on attentional biases, specifically towards math stimuli. Secondly, while there is evidence linking SE with STEM choices in adulthood (e.g., Cribbs et al., 2021; Wang, 2013), there has been limited exploration of this relationship considering middle school students.

### **1.3 The present dissertation**

From the theoretical framework described, it seems that attitudes toward math do not operate in isolation but are rather part of a complex system that, interacting with cognitive factors, collectively influences learning outcomes (Ahmed, 2018; Justicia-Galiano et al., 2017; Ramirez et al., 2016; Rubinsten et al., 2015). Despite this understanding, numerous questions remain regarding the complexities of this system and how these factors interplay in shaping students' learning processes and their STEM school choices. More research is needed to understand how GA and MA interact with WM to affect students' academic performance in math. To date, only a few studies have examined the role of GA in early math learning (Cargnelutti et al., 2017;

Rubinsten et al., 2018; Wang et al., 2014), while also considering WM's potential impact on math performance (Ramirez et al., 2016; Soltanlou et al., 2019; Vukovic et al., 2013). Additionally, there have been limited studies in developmental samples investigating how MA might interfere with other cognitive processes, specifically focusing on attentional bias (e.g., Pizzie & Kraemer, 2017; Rubinsten et al., 2015). Another underexplored research area is the influence of affective-motivational factors, namely MA and SE, on predicting STEM school choices at the end of middle school, a critical period for the development of negative attitudes toward math (e.g., Caviola et al., 2022; Namkung et al., 2019) and for the emergence of an occupational identity (Ahmed, 2018; Porfeli & Lee, 2012). To address these gaps, this dissertation introduces novel findings from four distinct studies, offering valuable insights into how students' attitudes and cognitive abilities impact math performance and STEM school choices from primary through middle school.

In line with the theoretical framework, the first study (Chapter 2) focuses on how the interplay between GA, MA, and WM longitudinally predicts 3<sup>rd</sup> and 4<sup>th</sup> grade math performance. This investigation is based on the bio-psycho-social model proposed by Rubinsten and colleagues (2018), in which it is hypothesized that GA is a risk factor that can influence learning and the establishment of math-specific anxieties such as MA (Cargnelutti et al., 2017; Rubinsten et al., 2018; Wang et al., 2014). In addition, the study also builds on the theoretical assumptions of PET (Eyseneck & Calvo, 1992), which state that forms of anxiety would contribute to interfering with individuals' WM, leading to less accurate and cognitively burdensome performance (Justicia-Galiano et al., 2017; Soltanlou et al., 2019). With the aim of expanding the reference literature, a developmental approach was adopted to examine the pathways through which GA and MA would influence students' math performance. In doing so, we hypothesized some path models that

examine the mediating role of WM in the relationship between different forms of anxiety and math performance.

The second study (Chapter 3) aims to explore the relationship between MA and math performance by assessing how it may change according to different levels of WM. Specifically, by deepening the theoretical framework of PET (Eysenck & Calvo, 1992), we evaluate how the interaction between MA and WM may affect different types of math tasks by assessing students in the last three years of primary school. In fact, studies have shown conflicting results on who may suffer more from the negative effects of MA among high- and low-WM individuals (e.g., Ramirez et al., 2013, 2016; Soltanlou et al., 2019). In an effort to expand the existing literature, a comprehensive assessment was conducted using different math tasks, including arithmetic operations and math reasoning tasks. This approach enabled a nuanced examination of the interplay between MA and WM across specific math tasks, moving beyond the limitations of previous studies that primarily employed batteries to assess general math performance (Ramirez et al., 2013, 2016). In addition, we decided to focus on participants attending the last three years of primary school, a period in which there would be a gradual increase in disciplinary demands and a developmental period scarcely explored by previous investigations (e.g., Soltanlou et al., 2019).

Chapter 4 focuses on the influence of MA, SE, and math abilities on individuals' attentional bias towards math stimuli. This investigation aligns with the findings of Chapters 2 and 3, further elucidating the mechanisms through which children's attitudes could influence their cognitive processes. Previous studies have shown that high MA subjects process numerical stimuli abnormally, exhibiting avoidance or vigilance behaviors toward math stimuli in a rapid timeframe (e.g., Pizzie & Kraemer, 2017; Rubinsten et al., 2015). However, most studies have been conducted

on adult samples (Cohen et al., 2017; Pizzie et al., 2017; Rubinsten et al., 2015), leaving the age range between primary and middle school unexplored. Moreover, there are conflicting findings in the literature about whether individuals with high MA exposed to math stimuli exhibit patterns of vigilance or avoidance (Rubinsten et al., 2015; Pizzie et al., 2017). In this context, we also decided to evaluate the contribution of SE in predicting attentional bias, since motivational factors may play a role in influencing these processes (Karademas et al., 2007; Walsh et al., 2018).

Finally, the fourth study (Chapter 5) aimed to assess how attitudes toward math, gender, and math performance are associated with STEM school choices. Specifically, this study adopted a three-year longitudinal design to examine how MA, SE, math performance, and gender may influence STEM school choices in middle school students transitioning to high school. Much of the studies to date in the literature have focused on predicting academic and occupational STEM choices after high school (e.g., Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021; Wang, 2013), while no study has examined how attitudes may influence STEM choices immediately after middle school. Indeed, middle school represents a crucial period for the development of negative attitudes towards math as a consequence of increasing curricular demands (e.g., Namkung et al., 2019), and for the establishment of an occupational identity (Ahmed, 2018; Porfeli & Lee, 2012).

To summarize, the studies have the common goal of assessing how attitudes toward math can influence cognitive processes, math performance, and the students' STEM school choices. The dissertation spans a developmental period critical to the formation of attitudes toward math, from primary school through middle school. The results aim to offer both theoretical and practical insights, deepening our understanding of the dynamics related to attitudes toward math. Additionally, the findings provide useful indications for developing interventions to engage

students more effectively in learning and prepare them to face the challenges posed by our increasingly “mathematized” society.

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## **2. The interplay between math anxiety and working memory on math performance: A longitudinal study.<sup>1</sup>**

### **Abstract**

Mathematical skills are essential to mastering everyday activities, making professional choices, and exercising citizenship in a numerate society. There is extensive evidence of the relationship between math anxiety (MA) and working memory (WM) influencing math attainment. Studies have mainly considered adult samples, however, leaving primary school children almost unexplored. This study is a first attempt to examine how the complex interplay between MA and WM affects math achievement from a developmental perspective. A total of 148 third graders were assessed with WM, general anxiety (GA), MA, and math tasks. Anxiety and WM were assessed at the beginning of the school year when children started attending grade 3, while math achievement was tested twice at the start of grades 3 and 4. The findings seem to confirm that GA has both a direct and an indirect effect (mediated by WM) on math performance in third and fourth graders. MA has a direct effect on math performance in grade 4, but only an indirect effect in grade 3, suggesting MA has a developmental trajectory, becoming stronger over time. The implications in the educational setting are discussed, pointing to the importance of a combined intervention on MA and WM.

### **2.1 Introduction**

Numbers are an essential part of our lives and daily activities (in cooking, shopping, managing money, and reading the clock). Numerical abilities assessed at an early age predict

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<sup>1</sup> Pellizzoni, S., Cargnelutti, E., Cuder, A., & Passolunghi, M. C. (2022). The interplay between math anxiety and working memory on math performance: A longitudinal study. *Annals of the New York Academy of Sciences*, 1510(1), 132-144.

crucial life factors, such as academic success (Odic et al., 2016), employment opportunities (Bynner, 1997; Rivera-Batiz, 1992), salary size (Dougherty, 2003), socioeconomic status (Gerardi et al., 2013; Gross et al., 2009), and personal and social well-being (Furlong et al., 2016; Gross et al., 2009), and they are fundamental to an informed and active citizenship.

Given the importance of numerical abilities, it is crucial to elucidate the factors that can promote or hinder the process involved in learning this school subject. The literature on the topic has extensively investigated the general cognitive abilities required, with working memory (WM) emerging as one of the most important factors for academic success (Gathercole et al., 2004; St Clair-Thompson & Gathercole, 2006). In addition to such general cognitive abilities, emotional factors also seem to have a role in math attainment, and math anxiety (MA) has been the object of in-depth studies over the last 60 years (Carey et al., 2016; Dowker et al., 2016; Peng et al., 2019). Being aware of the importance of cognitive and other factors to math attainment, researchers are now focusing on their ability to predict math achievement (Fonteyne et al., 2017; Higbee & Thomas, 1999; Lu et al., 2011) and the influence of their complex interaction on learning (Devine et al., 2018; Lee et al., 2014; Passolunghi et al., 2019). That said, only a few contributions to date have focused on how WM and emotional factors mutually affect math proficiency, especially in younger students (Cargnelutti et al., 2017a; Justicia-Galiano et al., 2017; Ramirez et al., 2013; Vukovic et al., 2013).

This study is thus one of the first attempts to conduct a longitudinal study on the interplay between one of most robust cognitive math precursors (WM) and relevant emotional factors (general anxiety (GA) and MA) and to examine their specific contribution to math achievement with reliable tools. The aim is to extend the knowledge gained from previous work on this theme (Cargnelutti et al., 2017a).

### ***2.1.1 Working memory and math abilities***

WM is a limited-capacity system that enables information to be stored temporarily and manipulated (Baddeley, 1996; Baddeley, 2003). Multiple learning processes rely on WM. One of the best-known theorizations of WM is the tripartite model in which there is a central executive responsible for data storage, processing, and monitoring, and two other modality-dependent systems devoted to processing verbal or visuospatial information (Baddeley & Hitch, 1974). Although researchers have proposed alternative models to explain how WM functions such as modality-independent (Kane et al., 2004) or -dependent (Shah & Miyake, 1996) models, studies in developmental psychology indicate that the tripartite model can explain it best (Gathercole et al., 2004; Giofrè et al., 2017).

WM has a well-established effect on a variety of math domains, such as geometry (Giofrè et al., 2014; Giofrè et al., 2013), mental addition and subtraction (Caviola et al., 2014; Mammarella et al., 2013), and problem solving (Passolunghi et al., 2019; Passolunghi & Mammarella, 2010). It is well-known that children with a poor WM are also weak in mathematics (Hitch & McAuley, 1991; Passolunghi & Pazzaglia, 2005; Passolunghi & Siegel, 2004; Siegel & Ryan, 1989). Recent studies have shown that the relative contributions of memory components (verbal linguistic and nonverbal visuospatial) to general mathematic learning change as children grow older (Giofrè et al., 2018). When learning and remembering arithmetic, preschoolers seem to rely on visuospatial memory more than on verbal memory (McKenzie et al., 2003; Simmons et al., 2008). Later, in primary school, learning depends more on verbal rehearsal to store information in memory and, therefore, engages the phonological loop (Hitch et al., 1988; Rasmussen & Bisanz, 2005). This change seems to be due to verbally mediated strategies: children start to use verbal code to label symbols and numbers (Geary et al., 1996; Logie et al., 1994). On the basis of the study on primary

school children by Soltanlou and colleagues (2015) and preliminary correlational analysis of our data, we decided to focus specifically on verbal WM, which seems to be used more extensively when third and fourth graders experience and practice with math tasks.

### **2.1.2 General anxiety and math anxiety**

Anxiety is defined as a “*dispositional and dysfunctional response to a situation perceived as threatening*” (Lewis, 1970). At school, 10% of children experience this condition, which can be seen already in kindergarten (Egger & Angold, 2006). High levels of anxiety have been observed in children with learning difficulties or disabilities, who are typically described as more anxious than their classmates (Fisher et al., 1996). While the detrimental effect of emotional factors, such as anxiety, on children has been acknowledged, their influence on children's academic performance has been underexplored, in particular, if compared with the literature that focused on the cognitive abilities (Alloway & Passolunghi, 2011; Rohde & Thompson, 2007; St Clair-Thompson & Gathercole, 2006).

How to measure GA in young children remains a critical issue. Self-assessments are scarcely reliable, probably due to the complexity of the construct. Teachers' assessments have proved a better indicator of children's emotional states (e.g., Kendall et al., 2007; Lyneham et al., 2008; Salbach-Andrae et al., 2009) and could also predict their math achievement (e.g., Cargnelutti et al., 2017a). Teachers' ratings can, therefore, be taken as a useful measure of children's anxiety (Cargnelutti et al., 2017b).

If this dysfunctional response is aroused by a particular stimulus, then we can speak of a particular type of anxiety. MA is “*a feeling of tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in ordinary life and academic situations*” (Richardson & Suinn, 1972). At school, the prevalence of MA is in the range of 2–17%

(Chinn, 2009; Richardson & Suinn, 1972), depending on the student population considered and the criteria used to define the condition.

Recent meta-analytic investigations confirm a significant negative correlation between MA and mathematics performance (range:  $-0.30 < r < -0.34$ ), and this connection starts to take root early in a child's school career (Caviola et al., 2022; Namkung et al., 2019; Zhang et al., 2019). A crucial question in the debate on the emergence of MA concerns whether it is a cause or a consequence of math difficulties. In 77% of cases, children with severe MA have a typical or better mathematics performance, suggesting that the cognitive and emotional problems relating to mathematics are largely dissociated. However, the mechanisms underlying this relationship between cognitive and emotional factors shaping children's math achievements remain to be clarified.

### ***2.1.3 The link between WM and MA***

As mentioned earlier, there is extensive evidence of the relationship between MA and WM influencing math attainment. A recent meta-analysis found a moderate negative association between anxiety and WM (Moran, 2016). To date, WM has been the factor most often studied with a view to explaining the relationship between MA and math performance. One of the theories advanced to do so is called the Processing Efficiency Theory (PET; Eysenck & Calvo, 1992), developed from Baddeley's model of WM, which suggests that anxious thoughts (e.g., worries) influence WM by reducing its capacity. Several studies demonstrated that MA had a detrimental effect on math achievement because it reduced the individual's WM resources (Ashcraft & Kirk, 2001; Beilock & Carr, 2005; Young et al., 2012). There are two different hypotheses regarding the type of person who would be more exposed to this effect. Ashcraft and Kirk (2001) claimed that adults more gifted in relation to WM could manage both math tasks and

anxiety-driven thoughts more successfully and would seem to be unaffected by such a connection. An alternative view is that people with a better WM are more likely to experience math difficulties caused by MA, especially when coping with math tasks in more stressful situations (“choking under pressure”, see Beilock & Carr, 2005).

In undergraduate students experiencing severe MA, a recent fMRI experiment (Pizzie et al., 2020) showed an exaggerated response even to easy math problems across series of trials, and their reaction times were longer. This increase in processing time could be the sign of a greater WM load across all levels of task difficulty (Beilock, 2008), supporting the PET.

From a developmental perspective, the literature indicate that MA interferes with different WM components. In a sample of 11- to 15-year-old students, Passolunghi and colleagues (2016) found that children with a better verbal WM exhibited less MA. The relationship between MA and math performance seems to exist even in very young children on applied problems (Ramirez et al., 2013) and mathematical application (Vukovic et al., 2013). Furthermore, a recent meta-analysis (Caviola et al., 2022) found that WM mediated the relationship between MA and mathematics. Particularly, the authors found that this relationship did not change according to the WM type or the degree of cognitive control required by the WM task. Some studies examined the role of WM in the relationship between trait anxiety (not MA) and math performance using a mediation approach (Ganley & Vasilyeva, 2014; Ng & Lee, 2015; Owens et al., 2012). Justicia-Galiano and colleagues (2017) recently investigated the role of verbal WM and math self-concept as possible mechanisms mediating between MA and math performance in 8- to 12-year olds. They found that verbal WM mediated the relationship between MA and various math outcomes. This pattern emerged for both teacher-assessed trait anxiety and children's self-assessed MA.

#### **2.1.4 The present study**

To date, WM has been the most often studied potential mediator accounting for the relationship between MA and math performance, but data referring to younger students are still particularly scant. We consequently deemed it crucial to further address these themes to (1) investigate both MA and GA (the latter using both self and teacher ratings) using tools with a good reliability index, and to identify their specific contribution to math achievement; (2) examine the developmental link between math performance, cognitive ability (WM), and GA and MA from a longitudinal perspective, in an effort to shed some light on the origins of the link between these factors; and (3) identify a specific developmental trajectory that could connect math with anxiety in a crucial period of a child's schooling. To achieve these goals, we tested primary school children in third and fourth grade—school years that are fundamental both to their math acquisition and to the development of an awareness of their own inner emotional state (Cargnelutti et al., 2017a).

We aimed to extend the results of previous studies in several ways:

1. By further examining MA. Given the importance of how children are assessed on this complex factor, we used the “Abbreviated Math Anxiety Scale” (AMAS; Hopko et al., 2003) in this study. This is a self-report questionnaire on MA that focuses especially on the emotional aspect of this condition, with good reliability. We wanted to reinforce previous findings (Ramirez et al., 2012) obtained when MA was assessed with a less reliable scale. The AMAS also differs from the scale used by Cargnelutti *et al.*, (2017a) so it enabled us to explore the generalizability of previous findings by adopting different assessment tools.
2. By further examining GA. Using both self- and teacher-report questionnaires, and thereby extending previous studies (e.g., Justicia-Galiano et al., 2017; Vukovic et

al., 2013), we investigated whether math performance is influenced by anxiety specific to math, over and above the effect of GA. Unlike Justitia-Galiano and colleagues (2017a) we compared students' self-assessments on GA with teachers' assessments, considering complex psychological factors. Here again, we used a highly reliable questionnaire for self-assessed GA that differs from the one chosen by Cargnelutti *et al.* (2017) to see whether their finding of no significant influence of self-rated anxiety on math achievement was confirmed.

3. By investigating the developmental link between MA and math ability. We considered it crucial to focus on a specific period in children's academic careers, from third to fourth grade. This is when mathematical tasks become more demanding, and any prior negative experiences with math can make children feel anxious about the subject (Cargnelutti *et al.*, 2017b). Many studies have underscored the importance of considering the association between math performance and anxiety from a developmental perspective (Dowker, 2005; Ma & Kishor, 1997; Mata *et al.*, 2012). Some reports suggest that this association can emerge at some point during primary school and possibly around third grade (e.g., Cargnelutti *et al.*, 2017b). We consequently followed our students longitudinally up to grade 4.
4. By exploring the interplay between WM and MA, and how it affects math attainment, again from a developmental perspective. This topic has been partially studied in children, drawing on the literature regarding adults and in connection with math acquisition (Ashcraft & Kirk, 2001; Ramirez *et al.*, 2013; Vukovic *et al.*, 2013). The findings are limited and often contradictory in adult samples (see



Ashcraft & Kirk, 2001; Beilock & Carr, 2005), however, making further investigation is necessary. To this end, we tested two main assumptions: (1) that WM acts as a mediator between anxiety and math (in other words, anxiety affects WM, which, in turn, affects mathematics); or (2) that anxiety acts as a mediator between WM and math attainment, meaning that the level of WM influences the amount of anxiety, which, in turn, affects math performance. In testing these two alternative hypotheses, we also examined whether these variables can each have a direct effect on math as well.

To reach these goals, children were assessed in two phases. During the first, at the start of their third primary school year, children's cognitive and affective factors were tested, together with their math ability. In the second phase, at the beginning of their fourth year, their math ability was tested again. We used path analysis models to explore the relationships between the variables of interest (i.e., anxiety, WM, and math achievement).

We hypothesized that both GA and MA could have a significant negative effect on math performance. Concerning our two alternative assumptions, we expected the one identifying WM as a mediator between anxiety and math to be the more likely. We also predicted that anxiety would have a direct effect as well as the one mediated by WM. We envisaged a robust relationship between GA and both WM and math performance already at the beginning of grade 3, while we expected the involvement of MA to become stronger over time.

## **2.2 Methods**

### ***2.2.1 Participants***

A total of 158 children in grade 3 were enrolled in the study, but 12 were subsequently excluded for various reasons: five did not obtain their parents' permission to participate; two had

been diagnosed with a specific learning disability; three had a general developmental delay; and two were absent on the day of at least one of the two testing phases. The final sample thus consisted of 146 children (85 females). All participants were Caucasian, came from a middle socioeconomic background (judging from the school records), were native speakers of Italian, and had an average intelligence quotient (as measured with the Vocabulary and Block Design subtests from the WISC-IV, Wechsler, 2003; Italian edition by Orsini & Pezzuti, 2012). They were attending 10 different classes at primary schools in northern Italy. At the beginning of the study, children's mean age was 8 years, 4 months ( $SD = 4$ ). In accordance with the Declaration of Helsinki, a written informed consent form was signed by each child's parents and by the school principals. This study was conducted in compliance with the ethical guidelines of the Italian Association of Psychology and the ethical code of the Italian Register of Professional Psychologists.

### ***2.2.2 Procedure***

Children were tested at two different phases. The first, Time 1 (at the start of grade 3) was devoted to assessing anxiety (children's self-rated GA and MA and teachers' ratings of their GA), WM, and math attainment. Then Time 2 (at the start of grade 4) children's math attainment was tested again.

### ***2.2.3 Tasks***

**2.2.3.1 WM (verbal WM).** The listening span (LS) task we administered was an Italian adaptation of the test devised by Daneman and Carpenter (Daneman & Carpenter, 1980) used in previous studies (see also Passolunghi et al., 1999). It was chosen as the WM task to include in our model after preliminary analysis showed that it correlated more strongly with the math performance and anxiety measures than other tasks assessing verbal and visuospatial WM (the backward word span, backward digit span, or backward corsi). The task included different levels

of difficulty, numbered from 2 to 5 (with Level 2 consisting of two sets of two sentences, Level 3 consisting of two sets of three sentences, and so on), and children were asked to judge the sentences as true or false. Examples of the sentences are: “A and B are the first two letters of the alphabet,” or “The hen is a mammal that lives in the sea.” At the end of each set of sentences, children were asked to recall the last word of each sentence in the order of presentation (“alphabet” and “sea” in the above-mentioned examples).

**2.2.3.2 General anxiety.** The Revised Children's Manifest Anxiety Scale–Second Edition (RCMAS-2; Italian edition by Reynolds et al., 2012) is a self-report questionnaire used to identify the source and level of GA in children aged 6–19. We used the short form consisting of 10 items with a simple *yes* (1 point) or *no* (0 points) response format. The teacher's version of the anxiety subscale of the Depression and Anxiety in Youth Scale (DAYS; Italian edition; Newcomer et al., 1995) was administered as an additional measure of children's GA (given the previously reported high reliability of teachers' reports; e.g., Kendall et al., 2007; Lyneham et al., 2008; Newcomer et al., 1995). This subscale consists of seven items with a *yes* (1 point) or *no* (0 points) response format.

**2.2.3.3 Math anxiety.** The AMAS (Hopko et al., 2003) is a 9-item self-report questionnaire for assessing MA. Using a 5-point Likert-type scale (1 = low anxiety to 5 = high anxiety), participants indicated how anxious they would feel during situations involving math.

**2.2.3.4 Math abilities.** At the beginning of grade 3, we tested children's math performance using the Number module of the standardized MAT-2 test (Amoretti et al., 2007) developed for children in grade 2 or early in grade 3 (hereafter called MAT-3), which has a time limit of 20 minutes. The module consists of 11 tasks (e.g., ranking numbers from the smallest to the largest and breaking down composite numbers), each scoring 1 point, if completed correctly. For the

assessment at the beginning of grade 4, we used the same number module in the version developed for children in grade 3 or early in grade 4 (hereafter MAT-4). This module consists of 13 tasks (e.g., writing down numbers in the range 1–1000 and solving problems involving the concepts of expenses and profits) to be solved within 20 min and each scoring 1 point for correct answers.

### 2.3 Results

Our data analyses were run using the IBM® SPSS® Statistics 21 software and our path analyses with IBM AMOS. Preliminary analyses revealed no significant differences in math performance across the classes at either of the assessment times:  $F(9,136) = 1.22, p = 0.29$ , partial  $\eta^2 = 0.007$ , for MAT-3;  $F(9,136) = 1.79, p = 0.08$ , partial  $\eta^2 = 0.006$ , for MAT-4.

Descriptive statistics, including task reliability and correlation values between all the tasks, are given in Table 2.1.

		Min	Max	Mean (SD)	Reliability	1	2	3	4	5
1	MAT-3	4.00	11.00	7.82 (1.71)	0.74	–				
2	MAT-4	1.00	10.00	6.19 (2.08)	0.80	0.47***	–			
3	LS	0.00	4.00	2.21 (.85)	0.86	0.33**	0.45***	–		
4	RCMAS	0.00	6.00	3.97 (1.10)	0.60	–0.20*	–0.32**	–0.20*	–	
5	AMAS	9.00	39.00	20.34 (7.40)	0.90	–0.22**	–0.41***	–0.21*	0.44**	–
6	DAYS_T	0.00	6.00	1.73 (1.80)	0.66	–0.47***	–0.51***	–0.39***	0.33**	0.15

Table 2.1. Descriptive statistics and bivariate zero-order correlation. AMAS = Abbreviated Math Anxiety Scale; DAYS\_T = Depression and Anxiety in Youth Scale, assessed by teachers; LS = listening span; Max = maximum; Min = minimum; RCMAS = Revised Children's Manifest Anxiety Scale; SD = standard deviation. \*  $p \leq .05$ , \*\*  $p \leq .01$ , \*\*\*  $p \leq .001$ .

#### 2.3.1 Models with WM as a mediator between anxiety and math performance

We tested different path analysis models addressing both direct and indirect (mediating) effects by applying a bootstrapping procedure (1000 bootstrap samples). To see which

relationships between the variables of interest better explained math performance, we first ran a series of models with the WM measure (i.e., LS) as a mediator. In these models, we tested the different directionality of the link between MAT-3 and the anxiety measures, but without changing the directionality with MAT-4 in order to avoid retrospective models. Table 2.2 shows the statistical fit parameters of these models.

Model	Description	CMIN	d.f.	CMIN/d.f.	<i>p</i>	CFI	NFI	TLI	RMSEA	AIC	BCC
WM as a mediator											
1a	AMAS→MAT-3 DAYS_T→MAT_3	0.95	4	0.70	0.99	1.00	1.00	1.07	<0.001	46.3	48.63
1b	MAT-3→AMAS (n.s.) MAT-3→DAYS_T	5.38	4	1.35	0.25	0.99	0.97	0.97	0.05	51.38	53.72
1c	AMAS→MAT-3 MAT-3→DAYS_T	2.35	4	0.59	0.67	1.00	0.99	1.03	<0.001	48.35	50.68
1d	MAT-3→AMAS (n.s.) DAYS_T→MAT-3	1.13	4	0.28	0.89	1.00	1.00	1.06	<0.001	47.14	49.47
Anxiety as a mediator											
2a	AMAS→MAT3 DAYS_T→MAT-3	9.29	5	1.86	0.10	0.98	0.96	0.93	0.08	53.29	55.53
2b	MAT-3→AMAS MAT-3→DAYS_T	12.02	5	2.40	0.04	0.96	0.94	0.89	0.10	56.02	58.25
2c	AMAS→MAT-3 MAT-3→DAYS_T	11.33	5	2.27	0.05	0.97	0.95	0.90	0.09	55.37	57.60
2d	MAT-3→AMAS DAYS_T→MAT-3	9.22	5	1.84	0.10	0.98	0.96	0.93	0.08	53.22	55.45

Table 2.2. Statistical fit parameters of the tested models. AIC = Akaike information criterion; BCC = Browne-Cudeck criterion.

Model 1a (see Figure 2.1) had the best statistical fit and a robust theoretical validity, so it was chosen as the best model to compare with the models in which anxiety was the mediator. In this model, the directionality of the link went from anxiety to MAT-3, as we tested for the effect of both GA and MA on math performance. Both GA assessed by teachers (DAYS\_T,  $\beta = -0.39, p < 0.001$ ) and AMAS ( $\beta = -0.13, p = 0.06$ ) were negatively associated with math performance, although the latter association did not survive the threshold we set for statistical significance. LS as well had a significant effect on MAT-3 ( $\beta = 0.15, p = 0.05$ ) and was also negatively associated with both DAYS\_T ( $\beta = -0.37, p < 0.001$ ) and AMAS ( $\beta = -0.15, p = 0.04$ ). As for the remaining relationships, it is worth noting that DAYS\_T was also strongly and negatively associated with performance in MAT-4 ( $\beta = -0.29, p < 0.001$ ), and so was AMAS ( $\beta = -0.28, p < 0.001$ ). The anxiety measures thus predicted not only concurrent, but also future math performance in much the same way as previous math achievement predicted subsequent attainment in this subject. With regard to WM, LS was also associated with performance in MAT-4 ( $\beta = -0.21, p < 0.01$ ).

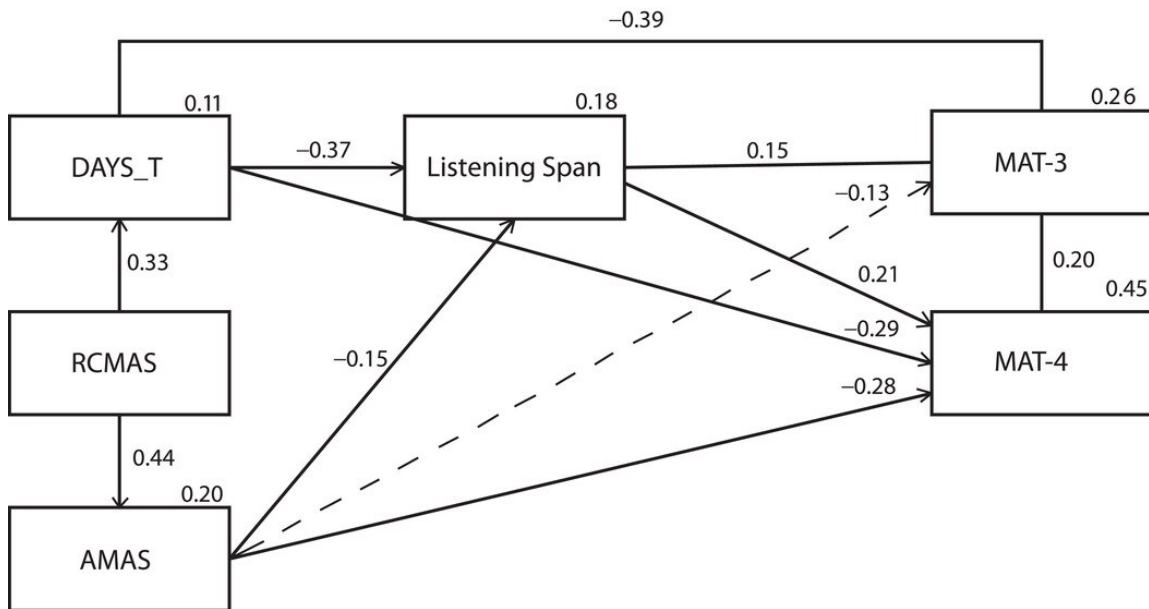


Figure 2.1. Standardized Model 1a. The dotted line represents a link not surviving the threshold we set for statistical significance ( $p > 0.05$ ).

### 2.3.2 Models with anxiety as a mediator between WM and math performance

In the second series of models, we tested the likelihood of WM (LS) influencing anxiety levels and, as a consequence, the relationship between the latter and math performance (which was only direct in this case). Here again, we examined the different directionality of the relationship between the anxiety measures and MAT-3, but the link AMAS  $\rightarrow$  LS was weak and not significant in any of the models ( $\beta = -0.11, p = 0.09$ ), so it was omitted. Table 2.2 shows the statistical fit indices for the model.

These models generally had a poor statistical fit, the strongest being Model 2a (see Figure 2.2), which was used for a comparison with Model 1a. In Model 2a, DAYS\_T had a strong negative association with MAT-3 ( $\beta = -0.38, p < 0.001$ ), while the negative association with AMAS did not survive the threshold we set for statistical significance ( $\beta = -0.13, p = 0.06$ ). LS had a significant association with MAT-3 ( $\beta = 0.15, p = 0.05$ ), and it was also negatively associated with GA ( $\beta = -0.35, p < 0.001$ ).

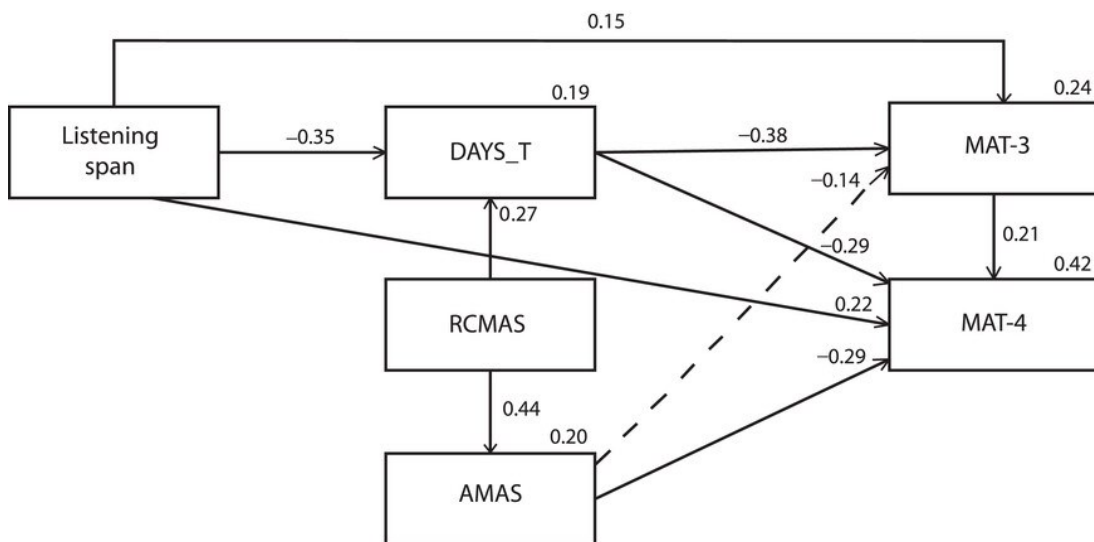


Figure 2.2. Standardized Model 2a. The dotted line represents a link not surviving the threshold we set for statistical significance ( $p > 0.05$ ).

### 2.3.3 Comparison between the two series of models and description of the model selected

Fit indices for the two series of models that we ran show that the models with anxiety as a mediator had a poor fit, whereas the fit for the models with WM as a mediator ranged from good (Model 1b) to very good (Models 1a, 1c, and 1d). In particular, lower values for AIC, BCC, and RMSEA for the latter more than the former models suggest that it is more reasonable, in statistical terms, too, for anxiety to negatively affect WM than vice versa. The percentage of explained variance of the MAT measures is also slightly higher for Model 1a ( $R^2 = 0.26$  versus  $R^2 = 0.24$  for MAT-3;  $R^2 = 0.45$  versus  $R^2 = 0.42$  for MAT-4), indicating an optimal pattern of relationships between the variables tested in this model for the purpose of explaining math performance. Additional details of Model 1a are given in Table 2.3.

Outcome variables	Predictor variables	Direct effects	Scalar estimates	Indirect effects	Total effects	$R^2$
MAT-3	LS	0.15*	0.076	-0.22**	0.15*	0.26
	RCMAS	-0.13	0.072	-0.02*	-0.22**	
	AMAS	-0.39**	0.078	-0.06*	-0.15*	
	DAYS_T				-0.44**	
MAT-4	MAT-3	0.20**	0.150	0.03*	0.20*	0.45
	LS	0.21**	0.143	-0.30**	-0.24*	
	RCMAS	-0.28***	0.132	-0.07**	-0.30	
	AMAS	-0.29***	0.152	-0.17*	-0.35**	
	DAYS_T				-0.46**	
LS	RCMAS	-0.15*	0.076	-0.19**	-0.19**	0.54
	AMAS	-0.37***	0.076		-0.15*	



	DAYS_T			-0.37	
AMAS	RCMAS	0.44***	0.074	0.44**	0.20
DAYS_T	RCMAS	0.33***	0.078	0.33**	0.11

Table 2.3. Standardized values of Model 1a. Significance levels for indirect and total effects correspond to the two-tailed  $P$  values derived from the bias-corrected percentile bootstrapping at 95% CI. \* $p \leq .05$ , \*\* $p \leq .01$ , and \*\*\* $p \leq .001$ .

## 2.4 Discussion

In a numerate and high-technology world, mathematics rules are fundamental to an individual's personal, educational, and economic success. That is why it is so important to better investigate the complex interplay between emotional and cognitive factors influencing math abilities, both in a prevention and a promotion perspective (Pellizzoni et al., 2020). In this study, we aimed to (1) assess MA and GA (from children's and their teachers' perspective) using tools with a good reliability index, and identify their specific contribution to math performance; (2) investigate the interplay between WM and anxiety (both GA and MA) on math achievement; and (3) follow the developmental trajectory that could connect math performance with GA and MA, in the third and fourth years of primary school.

We first evaluated, across the primary school classes sampled, both statistical significance and effect size of all the possible links between MA and math performance. We concurrently took the impact of GA into account to see whether MA could have a specific role beyond that of GA. We also explored whether anxiety significantly affected math performance directly, even after taking such a strong cognitive math precursor as WM into account. Anxiety and WM were tested at the start of grade 3, whereas math ability was assessed twice, at the start of grades 3 and 4.

We tested several models that differed in the relationship between anxiety and WM, and in their association with math achievement. In the first type of model, WM mediated the relationship between math achievement and anxiety; in the second, anxiety mediated the relationship between math achievement and WM. On comparing the best models (from the statistical and theoretical standpoints) of these two alternative hypotheses, the former—Model 1, with WM as a mediator—was stronger and is discussed below.

It emerged from this model that anxiety had a strong overall impact on math performance at both assessment times, but with important differences. The most relevant measure was children's GA as assessed by their teachers: it negatively affected their concurrent math performance but also predicted that of that assessed a year later, even after accounting for the indirect contribution of previous scores for math achievement. This finding confirms the crucial role of GA in this setting, as already seen in older children (e.g., Owens et al., 2012).

On the other hand, the effect of MA on concurrent math performance in grade 3 did not reach the threshold we set for statistical significance, but MA affected directly and significantly subsequent math performance in early grade 4. This finding seems to confirm, while using different assessment tools, the results of previous studies tracking the onset of a significant link between MA and math performance between grades 3 and 4 (e.g., Cargnelutti et al., 2017a Thomas & Dowker, 2000). This period could be crucial because (1) the demands of math learning increase and children have to make an effort to keep up; and (2) any prior negative experiences with math learning and achievement may have accumulated enough to undermine their further learning. In short, a vicious cycle can develop, with consequent mutually negative effects on anxiety and performance. Rated at the start of grade 3, MA did not significantly relate to our children's concurrent math performance, but it did predict their performance early in grade 4.

We hypothesize that this earlier lack of a significant relationship between MA and math achievement is attributable not to children's inability to rate their own MA, but to other factors having a more important role at the time. For instance, results of a previous study using latent profile analysis (Carey et al., 2017) found that younger students' MA could be driven by a general tendency toward anxiety, and only older students seem to exhibit more specific forms of anxiety. Similarly, in a study of Mammarella and colleagues (Mammarella et al., 2018) on children attending grades 3–6, the authors found no clear difference between general and academic forms of anxiety. For this reason, it is unlikely that results are influenced by children's inability to assess their own MA, rather results seem to suggest a developmental stage where the boundaries between general and specific anxiety are still vague.

The situation could be different for GA. Our study showed that teachers' ratings of this variable had a relevant role, whereas children's self-ratings were not directly related to math achievement at either of the assessment times. Unlike MA, which develops in very specific situations and children can be aware of it from a very early age (e.g., Ramirez et al., 2013, 2016; Wu et al., 2012; Wu et al., 2014), GA and its manifestations are less clearly defined and could, therefore, be harder for young children to detect and measure (e.g., White et al., 2009). Teachers' ratings of GA have already proved reliable and useful even for identifying clinically relevant conditions (e.g., Kendall et al., 2007; Lyneham et al., 2008; Tripp et al., 2006). In line with the above considerations, and even administering a different questionnaire (Hopko et al., 2003), children's self-rated GA was not related to their math performance at the start of grades 3 or 4.

Although previous studies showed that MA has a stronger impact on math performance compared with GA (e.g., Justicia-Galiano et al., 2017; Caviola et al., 2022; Mammarella et al., 2018), our results suggest that GA has concurrent (grade 3) and future (early in grade 4) effects on

mathematical performance. The results anyway indicate that the most relevant measure was children's GA as assessed by their teachers, whereas children's self-ratings were not directly related to math achievement at either of the assessment times, confirming previous studies. We believe that, as observed in other studies (Cargnelutti et al., 2019a), the teacher's rate could synthesize a risk factor that may contribute to the development of a more specific form of anxiety, MA, and, therefore, be indirectly related to mathematical performance that, at this developmental stage, is not captured by self-evaluation in younger students.

The second aim of our study was to clarify aspects of the role of WM in predicting math performance, and especially its link to anxiety. A single measure of verbal WM capacity (LS) was found positively and directly related to math learning at the beginning of grades 3 and 4. This result confirms the fundamental role of verbal WM as a math precursor (see meta-analysis in Friso-Van den Bos et al., 2013). On the other hand, it came as a surprise when our preliminary analyses revealed no significant impact of the visuospatial component of WM (not included in our path model), as this contradicts previous robust findings (e.g., Jarvis & Gathercole, 2003; Passolunghi & Mammarella, 2010; Reuhkala, 2001). A possible explanation may lie in the type of the math test we used, which is comprehensive of various math skills, but could demand little visuospatial WM processes. Our findings can also be interpreted from a developmental perspective, in that the contribution of the various WM components may differ at different ages, depending on the skills learned in a given developmental stage (see meta-analysis in Peng et al., 2016).

Our third aim focused on the relationship between WM and anxiety. Here again, it was the teachers' ratings of GA that showed an association with WM. GA was found to undermine performance in a WM task, in line with previous reports of a detrimental effect of anxiety on WM. It also emerged that WM mediated the indirect association between teachers' ratings of GA and

concurrent and future math performance; in other words, math attainment was also negatively affected by a decrease in WM resources caused by anxiety (e.g., Beilock, 2008). It is noteworthy that WM also mediated the indirect relationship between MA and both concurrent and future math achievement.

This study has some limitations. First of all, it is necessary to underline that, in path analyses, the definition of the effect directionality can be questionable, and it should be theoretically established rather than statistically provided. Furthermore, the small sample size prevented us from testing more complex models that included additional variables.

Second, it is crucial to note that reliability for DAYS\_T, specifically referred to the anxiety scale observed in the students, is not particularly high. Future studies are necessary to replicate our findings with more reliable tools.

Third, a broader evaluation on different forms of negative attitudes to learning (anxiety or depression) and personal assets, such as self-evaluation and ego resilience (Donolato et al., 2019; Donolato et al., 2020), are needed to better understand how the co-occurrence of a negative attitude and a positive approach may shape the learning process. Linked to this aspect, different questionnaires to measure GA, test anxiety, and MA are needed in an effort to shed more light on the reliability of both self and observer ratings on younger students.

Furthermore, in order to overcome the limits associated with self-report questionnaires on the developmental sample, future studies should use neurophysiological measures and implicit tasks. Such a comprehensive approach would be needed across all school years to look for any developmental changes in the predictive power of the relationship between anxiety and both cognitive precursors and math performance. Longitudinal models should also be used to

investigate a possible feedback effect, with a worse math performance causing more anxiety in a vicious cycle (e.g., Ashcraft & Moore, 2009).

### **2.4.1 Conclusion**

The interest of the findings of the present longitudinal study lies in that they show a combined effect of emotional and cognitive factors in predicting both concurrent and future math achievement. They suggest a crucial influence of anxiety as a variable that can consistently impair math attainment. GA was found to have an impact from a very early age, when it also undermined WM, whereas the role of MA appeared to emerge later on.

The findings of this study have important implications in the educational setting. They underscore the teacher's essential role in assessing the emotional complexities of the learning process. The data suggest that children with math difficulties can benefit from early intervention to help them contain and cope with their related anxiety. Such intervention can be run in parallel with more specific math training, as rehabilitation programs that focus only on improving math skills and their cognitive precursors might be ineffective if children do not learn how to handle their negative emotional states at the same time (Passolunghi et al., 2020).

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### 3. The relationship between math anxiety and math performance: The moderating role of visuospatial working memory.<sup>2</sup>

#### Abstract

According to the processing efficiency theory (PET), math anxiety would interfere with working memory resources, negatively affecting mathematical abilities. To date, few studies have explored how the interaction between math anxiety and working memory would affect different types of math tasks, especially in primary school children. Therefore, the purpose of this study was to explore whether the interplay between math anxiety and working memory would influence performance in numerical operations (i.e., math fluency task) and mathematical reasoning (i.e., math reasoning task) in a group of primary school children ( $N = 202$ ). Results showed that visuospatial working memory appeared to moderate the relationship between math anxiety and math performance when the math fluency task was considered, indicating that participants with higher levels of working memory were more negatively affected by math anxiety. No interaction effect was found for the math reasoning task in which students' scores were explained only by visuospatial working memory. The findings suggest that math anxiety and visuospatial working memory interact to influence performance in the math fluency task and that this effect may vary depending on the strategies used to complete the task. On the other hand, results on the math reasoning task showed that visuospatial working memory continues to have a positive effect on the math performance independently of math anxiety. The implications in the educational setting

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<sup>2</sup> Cuder, A., Živković, M., Doz, E., Pellizzoni, S., & Passolunghi, M. C. (2023). The relationship between math anxiety and math performance: The moderating role of visuospatial working memory. *Journal of Experimental Child Psychology*, 233, 105688.

are discussed, pointing to the importance of monitoring and intervention studies on affective factors.

### **3.1 Introduction**

In an increasingly number-based society, mathematical skills are essential for individuals' development at a personal level (Furlong et al., 2016; Gross et al., 2009), academic and occupational levels (Bynner, 1997; Dougherty, 2003; Gerardi et al., 2013; Gross et al., 2009; Rivera-Batiz, 1992), but also at collective and social levels (Foley et al., 2017; Pellizzoni et al., 2020; Peterson et al., 2011). Furthermore, national and international reports show that 36% of students struggle to achieve the basic level of math proficiency and 31% of students report negative emotions toward math activities (OECD, 2013). Given the importance of these abilities, researchers are now focusing on understanding the predictive role of the factors involved in math achievement (Fonteyne et al., 2017; Higbee & Thomas, 1999; Lu et al., 2011). The literature has extensively investigated the cognitive abilities (general cognitive precursors) that prompt math learning, including working memory (WM) that has been widely researched in the field (Fuchs et al., 2010; Passolunghi et al., 2014). Similarly, other studies have evaluated the contribution of emotional factors (e.g., general or specific anxiety) to math performance (e.g., Dowker et al., 2016). Nonetheless, few studies have focused on the mutual influence of cognitive and emotional factors in determining math proficiency, particularly in young children (Cargnelutti et al., 2017; Justicia-Galiano et al., 2017; Lee et al., 2014; Pellizzoni et al., 2022; Živković et al., 2022).

In light of the developmental sample, this study could be considered one of the first attempts to explore the unique contribution of emotional and cognitive factors, as well as their interaction, in predicting math learning. In particular, we evaluated how diverse visuospatial working memory (VSWM) profiles would be affected by math anxiety (MA) on arithmetic

operations (i.e., numerical skills involving number knowledge, numerical manipulations, and mental arithmetic; Geary et al., 2007) and mathematical reasoning (i.e., performing inferences, deductions, inductions, and associations in the domain of numerical knowledge; Thompson, 1996). In doing so, we evaluated which group of children is most susceptible to VSWM disruption as a result of a high level of MA, disambiguating between different models proposed in the adult literature (Ashcraft & Kirk, 2001; Beilock & Carr, 2005) and providing important insight into math learning and education.

### ***3.1.1 Affective and cognitive factors and their interplay in the learning process***

The role of emotional and cognitive factors in mathematical learning has been extensively studied in the literature, with a particular emphasis on their distinct impacts on learning (e.g., De Smedt et al., 2009; Donolato et al., 2020; Maehler and Schuchardt, 2016; Sorvo et al., 2022; Wu et al., 2012). Concerning emotional factors, several studies have highlighted the important role of math anxiety (Caviola et al., 2022; Namkung et al., 2019; Zhang et al., 2019).

**3.1.1.1 Math anxiety.** MA has several definitions that underpin different understandings of the construct, ranging from a personality trait to a clinical condition (Cipora et al., 2022). According to Richardson and Suinn (1972), MA is defined as a feeling of tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in ordinary life and academic situations. In this context, MA refers to a trait or state attitude that varies between individuals, resulting in avoidant behavior, less practice and competence, underachievement, and disruption of cognitive resources needed to accomplish the tasks (Cipora et al., 2022; Van Ameringen et al., 2003; Woodward & Fergusson, 2001). According to meta-analytic evidence, MA has a moderately negative effect on mathematical performance (ranging from  $r = -.34$  to  $r = -.32$ ) and starts to take root early in childhood (Caviola et al., 2022; Namkung et al., 2019; Zhang et al.,

2019). Although the association between MA and math achievements is well established, it is not clear whether MA is a cause or consequence of math underachievement (Carey et al., 2016; Cohen & Rubinsten, 2021; Rubinsten et al., 2018). In 77% of cases, children with severe MA have typical or better mathematics performance (Devine et al., 2018). These data suggest that other factors besides MA should be taken into account when considering math difficulties and that the cognitive and emotional problems related to mathematics are largely dissociated (Devine et al., 2018). Therefore, considering cognitive aspects could help to clarify the role of affective factors and their complex interaction in math learning.

**3.1.1.2 Working memory.** Within general cognitive precursors, WM has a prime role in predicting math achievement (Berg, 2008; Bull et al., 2008; De Smedt et al., 2009; Gathercole et al., 2004; Giofrè et al., 2017). WM is defined as a limited capacity system that holds information for brief periods of time while processing it (Baddeley & Hitch, 1974). The most popular theorization is the tripartite model of WM that is composed of a central executive responsible for data storage, processing, and monitoring and two modality-dependent systems that handle verbal working memory (VWM) and VSWM information (Baddeley & Hitch, 1974; Gathercole et al., 2004; Giofrè et al., 2017). WM has a well-established positive effect on a variety of math domains (Caviola et al., 2014; Giofrè et al., 2013; Giofrè et al., 2014; Mammarella et al., 2013; Passolunghi et al., 2019; Passolunghi & Mammarella, 2010). Furthermore, there is ample evidence that children with a higher WM capacity have an advantage in mathematics (Friso-van den Bos et al., 2013; Raghubar et al., 2010), whereas those with poor WM are weak in mathematics (Hitch & McAuley, 1991; Passolunghi & Pazzaglia, 2005; Passolunghi & Siegel, 2004; Siegel & Ryan, 1989).

Recently, research has focused on an intriguing debate on the modality-dependent (verbal or visuospatial) component of WM in math learning. Some studies indicated a substantial



correlation between the VWM and VSWM domains (Kane et al., 2004), whereas others found this distinction in some ages but not in others (Swanson, 2008). According to recent studies, VWM is more likely to be related to reading attainment, whereas VSWM is more likely to be related to math performance (Giofrè et al., 2018). Furthermore, during primary school the VSWM component is especially important in solving new and complex math tasks (e.g., Ashkenazi et al., 2013; Li & Geary, 2013; Szűcs et al., 2014), acting as a reliable predictor of math performance (Allen & Giofrè, 2021; Liang et al., 2022) and having a similar influence on numerical operations and mathematical reasoning domains (for systematic reviews, see Allen et al., 2019; Alloway et al., 2009; Meyer et al., 2010). Given the above-mentioned evidence, in the current study we decided to focus on the VSWM component, taking into account two tasks involving both numerical operations (i.e., math fluency task) and mathematical reasoning (i.e., math reasoning task).

### ***3.1.2 The interplay between MA and WM***

In several studies, MA was described as having a detrimental effect on math achievement by reducing WM resources (Ashcraft & Kirk, 2001; Beilock & Carr, 2005; Beilock & DeCaro, 2007; DeCaro et al., 2010; Miller & Bichsel, 2004; Young et al., 2012). Indeed, it has been suggested that one mechanism by which anxiety would lead to poor math achievement is the disruption of cognitive resources required to complete the task (e.g., Justicia-Galiano et al., 2017; Živković et al., 2022). One explanation for these findings is proposed by the processing efficiency theory (PET; Eysenck & Calvo, 1992). This theory has been developed on Baddeley's model of WM (Baddeley & Hitch, 1974) and suggests that anxiety would interfere with WM resources via intrusive negative thoughts, leading to poor performance effectiveness (i.e., a decrease in performance accuracy) and processing efficiency (i.e., lower task processing speed). In this

context, MA would have a detrimental impact on WM resources, causing people to display performances that are more mistake prone and effortful.

Although the impact of the interplay between WM and MA on math learning is well established, it is still not clear whether high- or low-WM capacity individuals would suffer more from the effects of MA (Ramirez et al., 2016; Sidney et al., 2019; Soltanlou et al., 2019). Indeed, there are two main accounts of how MA and WM interact in the context of math learning. According to some studies, low-WM-capacity individuals would suffer more from the negative effects of anxiety because they would have fewer resources to deal with the tasks and the anxious state, whereas high-WM-capacity individuals would have more possibility to simultaneously deal with anxious thoughts and math tasks' requirements (Ashcraft & Kirk, 2001; Miller & Bichsel, 2004; Owens et al., 2008; Owens et al., 2012; Owens et al., 2014; Soltanlou et al., 2019). For instance, Ashcraft and Kirk (2001) found that adults with higher WM were able to manage both math tasks and anxiety-driven thoughts more successfully. Similarly, Miller and Bichsel (2004) found that adults with high MA performed better in calculation and problem solving when they were high in WM. Recently, a study by Soltanlou and colleagues (2019) conducted on primary school children showed that multiplication learning was greatly impaired by MA in students with low VSWM.

In contrast, some studies (Beilock & Carr, 2005; Beilock et al., 2004) observed a phenomenon labeled “choking under pressure.” The research indicates that, especially when solving tasks under pressure, people who rely more heavily on WM when solving the math tasks perform worse, whereas people who rely less on WM are less affected by MA (Mattarella-Micke et al., 2011). In this regard, it has been proposed that high-WM individuals who rely more on memory-based math resolution strategies may be hampered by the concurrent presence of MA,

resulting in poor mathematical outcomes (Beilock & Carr, 2005). Interestingly, some studies involving young primary school children found that MA negatively affected their math performance on applied problems (Ramirez et al., 2013) and mathematical applications (Vukovic et al., 2013), particularly in those pupils with high levels of WM. Indeed, math tasks, differently from general cognitive ones, necessitate both specific knowledge and strategies that may be depleted by the concurrent presence of MA (Allen et al., 2020; Caviola et al., 2014; Cragg et al., 2017). For instance, in a study by Ramirez and colleagues (2016) that assessed children's math strategies, it was found that students with high WM capacity avoided using advanced WM-consuming strategies when high in MA.

Both these two lines of findings, despite inconsistencies, seem to support the PET given that anxiety would act on an individual's cognitive resources, either by interfering with WM resources (e.g., Soltanlou et al., 2019) or by interfering with correlates of WM, that is, advanced resolution strategies (e.g., Ramirez et al., 2016). Inconsistencies in the literature on the interplay between MA and WM could depend on methodological differences between studies. For example, studies that found those with high levels of WM to be more affected by MA (e.g., Ramirez et al., 2016) employed cross-sectional designs, capturing the impact of affective and cognitive factors on concurrent performance. On the other hand, the study by Soltanlou et al., (2019) assessed the role of these variables in learning, showing that those with lower WM appear to learn less when simultaneously influenced by MA. This could be because participants with higher levels of WM show greater progress in mathematical learning (Tomasetto et al., 2021). Another aspect that might have influenced the results in the literature is the type of task used in the studies. Indeed, recent meta-analyses showed that the variability in results could be partially attributed to the characteristics of the math task (Caviola et al., 2022; Zhang et al., 2019). For instance, performance

on arithmetic operations and numerical reasoning tasks, besides being commonly assumed to be two theoretically distinct subdomains of mathematical achievement (Allen et al., 2019; Cornoldi et al., 2020; Wechsler, 2017), also seem to be differentially influenced by affective factors (Caviola et al., 2022; Wu et al., 2017; Zhang et al., 2019; Živković et al., 2022). In particular, performance on school-based tasks such as arithmetic operations may be particularly affected by MA (Ashkenazi & Danan, 2017; Caviola et al., 2022) compared with numerical reasoning tasks (Živković et al., 2022). In addition, it is reported in the literature that greater experience and familiarity with the task may promote the use of more complex strategies (Laski et al., 2014). Thus, in the case of school-based tasks (i.e., arithmetic operations), children may develop advanced solving strategies with more ease than in numerical reasoning tasks, and this may explain some mixed results both between studies (Soltanlou et al., 2019) and within the same study (Vukovic et al., 2013). Assessing these two subdomains of mathematical learning separately would allow us to delve into specific interactions between affective and cognitive aspects, going beyond what cannot be revealed through the use of aggregate assessments (e.g., Ramirez et al., 2013, 2016). Furthermore, even though the PET suggests that anxiety affects both performance accuracy and speed, studies have not examined how the interaction between MA and WM affects timed math tasks. In addition, considering developmental samples, evidence has been gathered from samples of first, second, and third graders (Ramirez et al., 2013, 2016; Vukovic et al., 2013), whereas the last years of primary school are rather underexplored (Soltanlou et al., 2019). Finally, even though general anxiety is a significant factor in primary school math achievement (Cargnelutti et al., 2017; Pellizzoni et al., 2022) and interacts with WM in affecting children's cognitive performance (Owens et al., 2014), previous studies have never controlled it as a confounding variable.

### ***3.1.3 The current study***

Given the sparse and contradictory results of the literature, in the current study we sought to deepen the understanding of the complex interplay between cognitive and emotional factors and math achievement in a sample of late primary school students in the following ways:

1. Evaluating the specific contributions of VSWM and MA on numerical operations and math reasoning tasks retrieved from a standardized math achievement battery after controlling for age and general anxiety;
2. Examining the interaction between VSWM and MA by running a simple slopes analysis to explore how math performance is influenced by MA at different levels of VSWM.

We considered only the role of the VSWM component because, first, MA seems to display a stronger negative association with VSWM compared with VWM (Moran, 2016; Shackman et al., 2006; Soltanlou et al., 2015; Živković et al., 2022) and has stable effects during the primary school years (Allen & Giofrè, 2021; Liang et al., 2022); second, this component plays an important role in math learning, especially at the end of primary school (e.g., Li & Geary; 2013); and, third, tasks presented in a written format can inherently engage the visual components, influencing strategies that participants choose (Wong & Szücs, 2013).

We hypothesized that both VSWM and MA would affect performance on both numerical operations and math reasoning (Allen et al., 2019; Alloway et al., 2009; Meyer et al., 2010). With respect to the second aim, we predicted that VSWM would moderate the relationship between MA and math performance on the two different tasks. In particular, we aimed to explore how low-, average-, and high-VSWM-capacity individuals' math performance was affected by MA considering math fluency and a math reasoning task. These two math tasks were selected because

they required students to solve numerical operations and mathematical reasoning tasks that are well known to be specifically influenced by VSWM (see Allen et al., 2019; Alloway et al., 2009; Meyer et al., 2010).

The novelty of the current research is that we sought to evaluate the complex interplay between MA and WM when administering different timed math tasks. Previous studies have mainly considered aggregate measures of math achievement, finding that high-WM individuals suffer more from MA (Ramirez et al., 2013, 2016; Vukovic et al., 2013), whereas few studies have considered different math tasks (Sidney et al., 2019; Soltanlou et al., 2019). For instance, considering developmental samples, Soltanlou et al. (2019) found opposite results using a single arithmetic task. Hence, we assessed children with two tasks (i.e., arithmetic and numerical reasoning tasks) to test whether different instruments could lead to variable findings. Another novel aspect of our study is that we used timed tasks given that previous studies in the field have mainly employed tasks without time limits (e.g., Ramirez et al., 2013, 2016; Vukovic et al., 2013). Timed tasks are suitable in this context because they could assess both accuracy and participants' speed. This is of prime importance given that, according to the PET, MA would interfere with WM resources via negative intrusive thoughts, which could lead to poor performance affecting both accuracy and processing speed while solving the task (Eysenck and Calvo, 1992; Eysenck et al., 2007; Núñez-Peña & Suárez-Pellicioni, 2014; Young et al., 2012).

Furthermore, it is important to note that the current study focused on a sample of late primary school children, a developmental period relatively unexplored by previous studies on MA and WM (Soltanlou et al., 2019). Several studies considering early primary school children (Ramirez et al., 2013, 2016; Vukovic et al., 2013) found that high-WM individuals suffer more from MA. On the other hand, Soltanlou et al., (2019) found opposite results when considering

children in their last years of primary school. Therefore, it is clear that further research, employing different developmental samples, is necessary.

One last consideration must be made regarding the methods. In the current study, we strengthened our methods both with an adequately powered sample and by controlling for general anxiety, which was typically not controlled in previous studies despite the fact that (a) it is a predictor of math proficiency in primary school (Cargnelutti et al., 2017; Pellizzoni et al., 2022) and (b) several studies have found that low-WM individuals could be more influenced by general anxiety while solving a cognitive task (Owens et al., 2014).

## **3.2 Method**

### ***3.2.1 Participants***

Participants in the study were 210 students attending the last 3 years of primary school in northern Italy. Participants with a diagnosis or ongoing assessment of a neurodevelopmental disorder or a specific learning disorder, or who had been in Italian school for less than 4 years were not included in the sample. Before starting the study, 8 children were excluded from the sample because they had an ongoing neuropsychiatric diagnosis or assessment, and 6 children were excluded because they were in the Italian school system for less than 4 years. Multiple imputations were used to handle missing data from 5 participants using the predictive mean matching method, replacing missingness by plausible data values and using five imputed datasets to estimate pooled regression parameters (see Van Buuren & Groothuis-Oudshoorn, 2011). A total of 8 participants produced outlier scores on the math tasks and were handled with listwise deletion and removed from the analysis. Thus, the final sample consisted of 202 children (102 male and 100 female) with a mean age of 9.68 years ( $SD = 1.20$ ). All participants were typically developing children who

were not diagnosed with any learning or neurodevelopmental disability and did not attend any special needs curriculum. Students were Caucasian, and the socioeconomic status of the sample was primarily middle class and established on the basis of school records. In line with government data on the migration background of Italian pupils (MIUR, 2022), the composition of our sample was 91% composed of citizens born in Italy, 6% of European Union (EU) citizens born outside Italy, and the remainder of non-EU citizens.

After the approval from school principals to take part in the research project, parents gave written consent for their children to participate in the study. Students were informed that their participation was voluntary and that they could withdraw from the study at any time. The study was conducted in accordance with the Declaration of Helsinki and in compliance with the ethical guidelines of the Italian Association of Psychology and the ethical code of the Italian Register of Professional Psychologists. The research was approved by the ethical committee of the University of Trieste.

### ***3.2.2 Measures***

Children were tested in two phases. The first assessment session occurred at the beginning of the school year when students' affective (math and general anxiety) and cognitive (VSWM) factors were evaluated. After 5 months from the first session, we evaluated children's math performance employing two different tasks (i.e., math fluency and math reasoning tasks).

**3.2.2.1 Math anxiety.** The Abbreviated Math Anxiety Scale (AMAS; Hopko et al., 2003; Italian version adapted by Caviola et al., 2017) is a self-report questionnaire composed of 9 items used to identify children's trait MA level. Participants were asked to indicate, on a 5-point Likert scale (1 = a little, 5 = extremely), how anxious they would feel in different situations that involve math activities (e.g., "Learn a new topic in math class"). The final score on the AMAS was



calculated as the sum of the scores on each item (ranging from 9 to 45), with higher scores corresponding to higher levels of MA.

**3.2.2.2 General anxiety.** The Revised Children’s Manifest Anxiety Scale (RCMAS-2; Reynolds et al., 2012; Italian edition) is a self-report questionnaire used to measure the level of general anxiety in individuals aged 6 to 19 years. We used the short form composed of 10 items and asked children to judge whether the statements reflected their everyday experience in a binary “yes” (1 point) or “no” (0 points) response format. The total score could range from 0 to 10, with higher scores corresponding to higher levels of general anxiety.

**3.2.2.3 Visuospatial working memory.** VSWM was measured employing a computerized version of the Dot Memory task (adaption by Miyake et al., 2001). Participants were asked to remember the sequence and positions of Xs inside a  $5 \times 5$  matrix that later disappeared. After that, they needed to recall and indicate the sequence and positions of these Xs in a new empty matrix. The test was administered adopting a self-terminating procedure, starting with a simple matrix with two randomly positioned Xs. Participants continued as long as they were able to solve at least one of two matrices for a given level, and no feedback was provided. The total score was the sum of correctly recalled positions and sequences and could range from 0 to 70.

**3.2.2.4 Math performance.** To assess math performance, we administrated two paper-and-pencil subtests of the AC-MT-3 (Test di Valutazione delle Abilità di Calcolo e del Ragionamento Matematico) 6–14 battery (Cornoldi et al., 2020) that evaluated calculation skills: the math fluency and math reasoning tasks (see Figure 3.1).

A) Math fluency task

$$\begin{array}{r} 37+ \\ 34= \\ \hline 71 \end{array}$$

$$\begin{array}{r} 86- \\ 53= \\ \hline 33 \end{array}$$
  

$$\begin{array}{r} 63+ \\ 79= \\ \hline 142 \end{array}$$

$$\begin{array}{r} 94- \\ 36= \\ \hline 58 \end{array}$$

B) Math reasoning task

21	19	20	16
15	13	12	8

24	32	9	18
26	34	27	36

Figure 3.1. Some examples of the math fluency (A) and math reasoning (B) task items used in the current study are shown. The solutions for items are shown in red.

The math fluency subtest evaluates students' arithmetic skills and requires solving 15 arithmetic operations (additions and subtractions) as quickly as possible in 1 min. The numbers of addition and subtraction tasks all were composed of two-digit numbers. Furthermore, in 4 additions and 3 subtractions, children were required to perform carrying and borrowing procedures. Children were instructed to complete a series of additions and subtractions as quickly as possible before the test started. Next, children were shown 2 examples (1 addition and 1 subtraction), and then asked to perform a third example on their own. The final score was the number of operations solved correctly, ranging from 0 to 15. The math reasoning subtest assesses children's arithmetical skills and reasoning ability using numerical series. Before beginning this test, children were told that their task was to find, through the identification of a rule, the correct number to fit inside the empty cell in the table. The correct rule was to be inferred from the number sequence in the first row of the table and applied to the row below. Children were then shown two examples of solving the

task and asked to solve a third example on their own. Participants had 2 min to solve 12 incomplete numerical matrices with the correct number. Responses were awarded a score of 0 or 1 depending on whether they were incorrect or correct, respectively. The total score could range from 0 to 12.

### 3.3 Results

Descriptive statistics (means and standard deviations), reliability of the measures, and bivariate correlations are shown in Table 3.1.

	<i>M</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>	<i>R</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1. MA</b>	23.18	7.89	9	44	.90	–			
<b>2. General anxiety</b>	3.81	2.61	0	10	.82	.31**	–		
<b>3. VSWM</b>	17.06	11.29	2	49	.85	-.15*	.06	–	
<b>4. Math fluency task</b>	7.05	2.55	0	10	.77	-.18*	-.08	.20**	–
<b>5. Math reasoning task</b>	4.22	3.39	0	9	.80	-.05	.05	.22**	.08

Table 3.1. Descriptive statistics (means and standard deviations), reliability of the measures according to the literature, and bivariate correlations. *Note.* MA, math anxiety; VSWM, visuospatial working memory. \* $p < .05$ ; \*\*  $p < .01$

#### 3.3.1 Moderation analysis

To assess the specific contributions of VSWM and MA and their interplay on the math fluency and math reasoning task, we performed two multiple regression analyses, one for each considered math task (Figure 3.2).

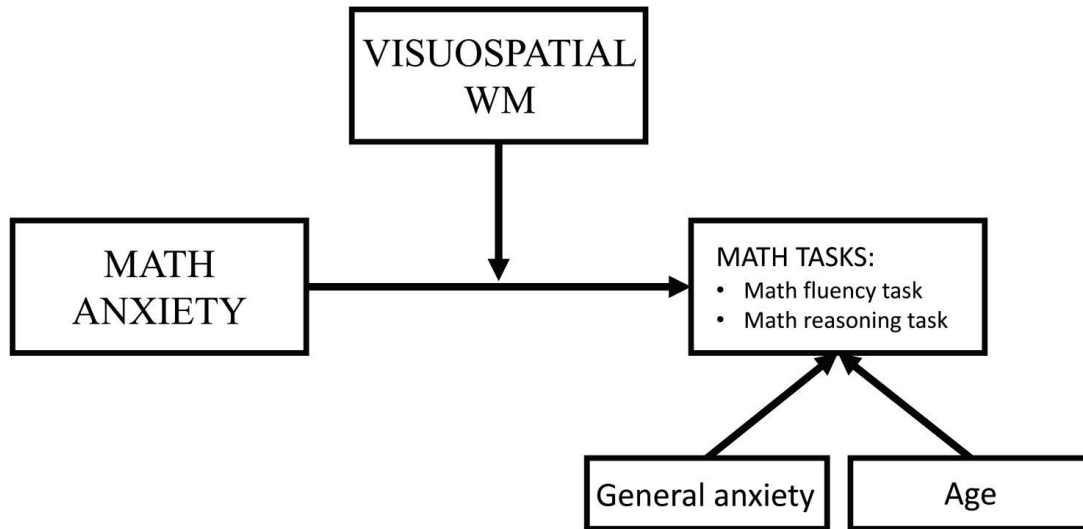


Figure 3.2. Path model with the predictor (math anxiety), the moderator (visuospatial WM), the dependent variables (math fluency task and math reasoning task), and the covariates (age and general anxiety).

MA, VSWM, the interaction term  $MA \times VSWM$ , and the covariates (general anxiety and age) all were regressed on the two math tasks separately (Table 3.2). All variables were included as continuous predictors and centered before conducting the regression analyses. The beta effects ( $\beta$ ) reported in the tables and the text refer to standardized regression coefficients; that is, for each standard deviation increase in the predictor variable, the beta effects show how many standard deviations the dependent variable (i.e., the math fluency or math reasoning task) will change. Cohen's (1988) criteria were used to classify the effect size as small effect ( $.10 < \beta < .29$ ), medium effect ( $.30 < \beta < .49$ ), or large effect ( $\beta > .50$ ).

	$\beta$	<i>SE</i>	<i>t</i>	<i>df</i>	<i>p</i>	95% CI
Math fluency task						
Constant	-.028	.068	-0.421	196	.674	[-.162, .105]
MA	-.154	.072	-2.124	196	.034*	[-.297, -.011]
VSWM	.153	.074	2.058	196	.041*	[.006, .299]

MA × VSWM	-.190	.063	-2.977	196	.003**	[-.316, -.064]
Age	-.133	.072	-1.847	196	.66	[-.274, .009]
General anxiety	-.007	.073	-0.091	196	.927	[-.150, .137]
Math reasoning task						
Constant	-.001	.070	-0.018	196	.985	[-.139, .136]
MA	-.035	.074	-0.475	196	.635	[-.181, .110]
VSWM	.152	.076	1.999	196	.047*	[.002, .302]
MA × VSWM	-.028	.066	-0.429	196	.796	[-.158, .101]
Age	.177	.073	2.403	196	.017*	[.032, .322]
General anxiety	.019	.074	0.259	196	.796	[-.127, .101]

Table 3.2. Regression analysis considering math fluency task and math reasoning task as dependent variables. Math anxiety (MA), visuospatial working memory (VSWM), and the interaction between math anxiety and visuospatial working memory (MA × VSWM) were set as predictors. Age and general anxiety were considered as covariates. CI = confidence interval. \* $p < .05$ . \*\* $p < .01$ .

In the first multiple regression model (Table 3.2), we used a moderation analysis to evaluate the specific contributions of VSWM and MA and their interaction. First, a statistically significant effect of both MA [ $\beta = -.154, t(196) = -2.124, p = .034$ ] and VSWM [ $\beta = .153, t(196) = 2.058, p = .041$ ] was found on the math fluency task. In particular, MA negatively predicted scores on the task, whereas VSWM positively predicted them. Results also showed a significant main effect of the interaction term MA × VSWM [ $\beta = -.19, t(196) = -2.977, p = .003$ ]. Specifically, the simple slope analysis (Figure 3.3) revealed that participants with both high VSWM capacity ( $\beta = -.345, 95\%$  confidence interval (CI) [-.542, -.011]) and medium VSWM capacity ( $\beta = -.154, 95\%$  CI [-.298, -.148]) were significantly and negatively affected by MA in the math fluency task. However, MA did not seem to affect participants with low VSWM capacity ( $\beta = .036, 95\%$  CI [-.148, .220]).

### Simple slopes: math fluency task

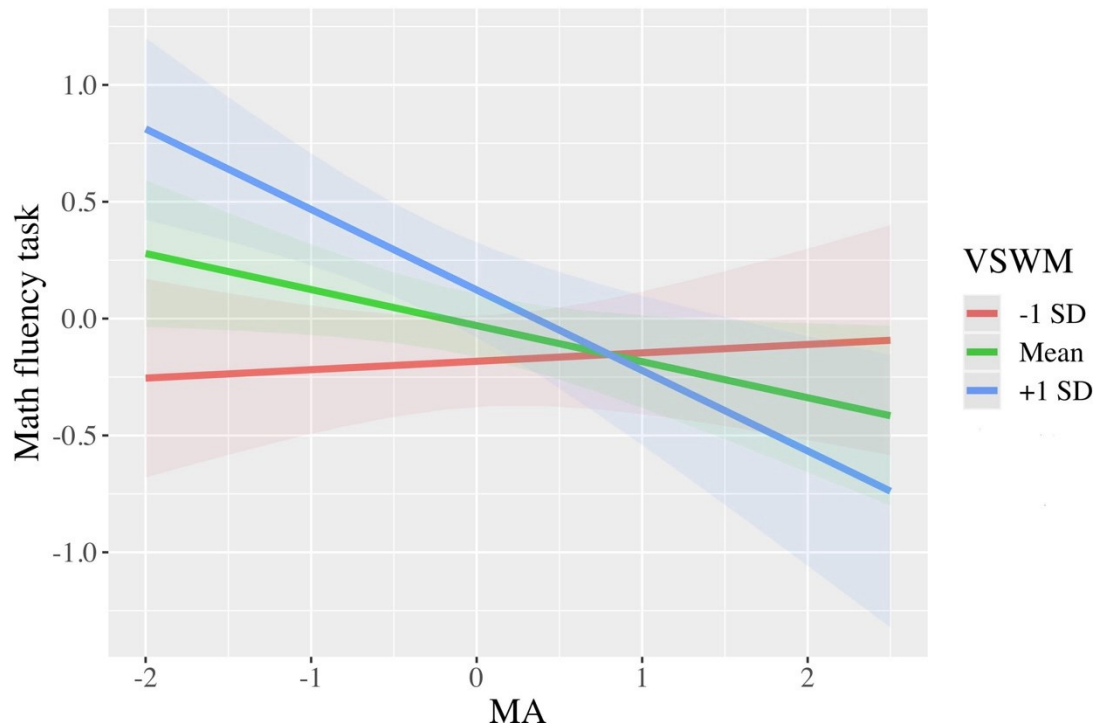


Figure 3.3. Simple slope analysis considering visuospatial working memory (VSWM) as a moderator, math anxiety (MA) as a focal predictor, and math fluency scores as the dependent variable. General anxiety and age were set as covariates.

In the second multiple regression model (Table 3.2), we evaluated the specific contributions of MA and VSWM and their interaction on the math reasoning task. Regression analyses found a positive effect of VSWM on the math reasoning task [ $\beta = .152, t(196) = 1.999, p = .047$ ], whereas MA did not reach significance [ $\beta = -.035, t(196) = -0.475, p = .635$ ]. Moreover, results revealed that the interaction term MA  $\times$  VSWM was not significant [ $\beta = -.028, t(196) = -0.429, p = .796$ ], indicating that VSWM capacity did not moderate the relationship between MA and the math reasoning task. We also examined whether age would interact with MA (MA  $\times$  Age) and the interaction term MA  $\times$  VSWM (MA  $\times$  VSWM  $\times$  Age) in the matrix reasoning task given that participants' age had a statistically significant influence on that task [ $\beta = .177, t(196) = 2.403, p = .017$ ]. Results for

both interaction terms ( $MA \times Age$  and  $MA \times VSWM \times Age$ ) showed a marginal statistical effect; therefore, we did not further investigate performing a simple slope analysis.

### **3.4 Discussion**

Given the importance of math skills at both the individual and collective levels, it is critical to deepen the understanding of the interplay between MA and VSWM in math learning, as well as to better comprehend which students are most affected by these factors, in order to support the learning process during the development stage (e.g., Ashcraft & Kirk, 2001; Miller & Bichsel, 2004; Owens et al., 2014; Soltanlou et al., 2019). According to the PET (Eysenck & Calvo, 1992), anxiety is assumed to interfere with WM resources, leading to poor performance in math, but it is less clear who are the most affected individuals based on specific task types and age range. In fact, on the one hand, some studies reported that low-WM-capacity individuals would suffer more from the detrimental effects of anxiety due to limited resources, leading to poor performance on cognitive and mathematical tasks (e.g., Ashcraft & Kirk, 2001; Miller & Bichsel, 2004; Owens et al., 2014; Soltanlou et al., 2019). On the other hand, some findings suggested that MA would specifically interfere with advanced memory-based resolution strategies used by high-WM individuals to accomplish math tasks. As a result, individuals with high WM capacity would suffer more from the detrimental effects of MA (Ramirez et al., 2013, 2016; Vukovic et al., 2013).

Given this state of the art, the first aim of the current study was to examine the specific contributions of MA and VSWM in a sample attending the last years of primary school by measuring performance on two separate math tasks, namely the fluency task and math reasoning task. As expected, our data revealed that VSWM was a positive predictor for both tasks. Our results confirm and extend previous research asserting that VSWM is a relevant component in numerical operations and math reasoning (Allen et al., 2019; Alloway et al., 2009; Green et al., 2017; Harari

et al., 2013; Meyer et al., 2010), especially in late primary education (e.g., Li & Geary, 2013; Pellizzoni et al., 2022). Partially in accordance with our starting hypothesis, MA negatively predicted students' performance on the math fluency task but not their achievement on the math reasoning task. This finding is in accordance with a previous study of Harari and colleagues (2013), which found that MA did not correlate with a measure similar to the math reasoning task administered in the current study. The inconsistent impact of MA on different math tasks could depend on earlier negative experiences with the specific math tasks we proposed. Indeed, solving arithmetic operations is a commonly evaluated skill in the school context, and children might have perceived the task as threatening based on their previous assessment experiences. In contrast, the math reasoning task is less used in children's math school curricula to assess their math performance and, therefore, may have failed to elicit negative affective reactions. When investigating the role of MA in math performance, future studies should pay closer attention to the tasks.

The second aim of the study was to evaluate the interaction between MA and VSWM, exploring how low-, average-, and high-VSWM-capacity individuals' math performance was affected by MA when considering math fluency and math reasoning tasks. Results on the math fluency task revealed a statistically significant interaction between MA and VSWM, which confirmed our initial hypothesis. In particular, we observed that individuals with high WM capacity were more impaired by MA. Previous studies on children (Ramirez et al., 2013, 2016; Vukovic et al., 2013) and adults (Beilock & Carr, 2005) found a similar pattern of results, where it was hypothesized that MA would interfere with WM-based resolution strategies, resulting in poor performances in children with higher WM capacity (Ramirez et al., 2016). Indeed, solving arithmetic operations necessitates the use of several VSWM-consuming strategies such as the



application of specific procedural rules involving the decomposition of the operands in digits, their alignment in columns, the ability to apply carrying–borrowing rules, and the elaboration of partial results (Allen et al., 2020; Caviola et al., 2014; Cragg et al., 2017). Furthermore, the written format could inherently engage the visual components, influencing the strategies chosen by participants (Wong & Szücs, 2013). Our results are in contrast to some studies involving adults (Ashcraft and Kirk, 2001; Miller and Bichsel, 2004) and primary school children (Soltanlou et al., 2019), which found that low-WM individuals suffer more from MA given their fewer resources. Considering developmental samples, Soltanlou et al. (2019) found, contrary to our study, that low-WM individuals were more negatively affected by MA compared with high-WM ones. It must be noted that the authors considered a multiplication learning task that required children to solve one- and two-digit operations. One main difference with our study is that the authors evaluated children’s learning rather than task performance; thus, their findings could reflect the fact that high-WM individuals learn more math despite being affected by MA. Studies that found a similar pattern to ours (Ramirez et al., 2013, 2016; Vukovic et al., 2013) mainly evaluated math competence through aggregate scores of math performance that included tasks such as verbal math problems, probability understanding, and geometry. Despite the possibility that aggregate measures could hide how task characteristics influence the interplay between MA and WM, these results highlight that high-WM individuals suffer more from MA on average. On the other hand, in contrast to the starting hypothesis, the relationship between MA and performance was not moderated by different levels of VSWM in the math reasoning task. This could be because MA had no effect on task scores and, thus, had no effect on the performance associated with the different VSWM profiles.

Our results could be interpreted theoretically in the context of strategies that students use when solving mathematical tasks. It is well established in the literature that knowing a variety of

math strategies is beneficial for math learning and that using advanced memory-based strategies posits high demands on WM while solving math tasks (Cho et al., 2011; Geary et al., 2004; Laski et al., 2013; Ramirez et al., 2016). As pointed out by Ramirez et al. (2016), suffering from MA would hinder the use of those advanced memory-based strategies, leading high-WM students to display worse math performance. Despite the fact that in our study we did not directly assess math strategies, the pattern of results suggests their likely involvement when considering profile differences in MA, WM, and math performance. Indeed, when considering the math fluency task, high-WM individuals were more affected by MA compared with low-WM individuals. Whether the WM task we considered could influence the results of the current study remains an open question. Indeed, previous studies have used different WM tasks with a wide range of content, including numbers (Ramirez et al., 2013), letters (Ramirez et al., 2016), and visuospatial information (Soltanlou et al., 2019; Vukovic et al., 2013). Furthermore, research using verbal modality (Ramirez et al., 2013, 2016) appears to find greater agreement between findings, whereas research using visuospatial modality appears to have produced mixed findings when considering the interaction between MA and WM (Soltanlou et al., 2019; Vukovic et al., 2013). From this evidence pattern, it seems that the WM modality interacts with MA depending on the children's age. Indeed, studies that focused on verbal tasks have detected interactions with MA in the early grades of primary school (Ramirez et al., 2013, 2016), whereas VSWM seems to have a major role in second grade, third grade (Vukovic et al., 2013), and fifth grade (Soltanlou et al., 2019). In this context, our results may also depend on the central role of VSWM in the last years of primary school when math learning becomes more complex (Ashkenazi et al., 2013; Li & Geary, 2013; Szűcs et al., 2014). Future studies should examine how the interplay between MA and WM modality could vary depending on the considered developmental period.

Taken together, these findings seem to shed some new light on the debate surrounding the interplay between MA and WM in the last years of primary school, a developmental period that has received little attention in the literature. In this context, our results demonstrate that cognitive and emotional factors appear to interact differently depending on the features of the math task. Indeed, children's performance was affected differently by MA depending on VSWM levels. In particular, high-VSWM-capacity students were more negatively affected by MA in a task involving numerical operations but not number reasoning. As a result, tasks' features may explain incongruent findings in the literature, and future studies should take into account different tasks when investigating how MA and WM interplay in math performance. Furthermore, we found that the VSWM component positively affected performance in both the numerical operations and math reasoning tasks, indicating that MA does not entirely drain the protective role of WM resources. This pattern of results suggests that WM, rather than MA, is a better predictor of disciplinary outcomes, and our findings may explain seemingly contradictory evidence in the literature. For instance, a recent study conducted by Soltanlou and colleagues (2019) found that high-WM individuals were less influenced by MA in a multiplication learning intervention. In discussing their results, the authors stated that high-WM individuals would have more resources to deal with math learning and MA. However, it also could be that WM resources represent a stronger predictor of learning outcomes per se compared with MA (Soltanlou et al., 2019). In addition to prior studies, general anxiety was evaluated as a covariate, and it was found that general anxiety does not have a significant influence on math performance. Indeed, past research has shown that the influence of general anxiety is more prevalent in earlier grades of primary school, whereas more specific forms of anxiety (e.g., MA) emerge later (Cargnelutti et al., 2017; Pellizzoni et al., 2022).

### ***3.4.1 Limitations***

There are some limitations associated with our study that should be acknowledged and addressed by future research. First, we employed correlational data that could make it difficult to state causal relationships between the examined variables, and for this reason future studies should consider using longitudinal or experimental methods. Furthermore, we evaluated a limited set of variables, and so future research should consider investigating other cognitive factors (Pelegrina et al., 2020) and including an assessment of students' math strategies, as was done in a prior study (Ramirez et al., 2016). Our study also did not test whether the complexity of the task or participants' prior knowledge (Chan et al., 2022; Laski et al., 2014) may have affected the results, aspects that will need to be controlled in future studies. In addition, we did not assess the interaction between different WM modalities and MA in the context of math learning. Indeed, MA appears to interact with the verbal WM modality when it comes to very young children in primary school (Ramirez et al., 2013, 2016), whereas VSWM appears to be more important when older students are considered (Soltanlou et al., 2019; Vukovic et al., 2013). For this reason, future research should take into account the unique contributions of different WM modalities while also exploring their role during development. Given the characteristics of our sample, it is plausible that our results could be more easily generalized to samples of average socioeconomic status and educational background similar to that of Italy. Therefore, the generalizability of our results could be reduced in countries with different methods of organizing mathematics curricula, different language and cultural backgrounds, or educational poverty or an absence of formal scholarization (Pellizzoni et al., 2020).

### **3.4.2 Conclusions**

General mathematics assessments often include a broad variety of problem types, requiring children to switch between operations, strategies, and mental models. However, the relationships between different WM components, MA, and mathematics performance are found to vary depending on the type of mathematics tests used. Our findings shed new light on the interplay between MA, VSWM, and math tasks, showing that high-WM individuals would be more affected by MA for specific types of tasks (e.g., math fluency) but not for others (e.g., math reasoning). However, both tasks were positively predicted by VSWM, indicating that its supporting role in math performance is not completely flattened by MA. Our study depicts how a combined interplay of cognitive and emotional factors influences math performance as well as how interindividual differences and task characteristics can explain students' outcomes in learning.

These findings emphasize the importance of considering the effects of anxiety in the context of individuals' cognitive profiles and have important implications in educational settings. We showed that the presence of MA could also hamper the performance of those students who are high in WM capacity, preventing them from reaching their full potential. In this regard, early detection and prevention of negative affective reactions toward math would result in positive outcomes not only in cognitive and mathematical aspects but also in individuals' future academic and occupational success (Passolunghi et al., 2020).

Furthermore, data suggest the need to modulate interventions for specific profiles, considering not only emotional components but also their interaction with cognitive components and specific types of tasks. For this reason, future research should focus on a more targeted intervention, considering different types of children's profiles and learning trajectories, to promote

math achievement and empower children and future citizens with appropriate tools to understand the world around them.

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## 4. Attentional bias and math avoidance: insights from a developmental sample<sup>3</sup>

### Abstract

Stimuli perceived as threatening subtly influence how individuals orient their attention, a phenomenon labelled as attentional bias. According to literature, individuals with negative attitudes toward math would exhibit attentional bias when presented with math-related stimuli. However, attentional bias and its relationships with math anxiety, math self-efficacy, and math skills are understudied, particularly when considering developmental samples. For this reason, the aim of the present study was to assess the attentional bias toward math stimuli (i.e., math vs. neutral words) and to evaluate its relationship with math anxiety, math self-efficacy and math skills in fifth and sixth grade students ( $M_{\text{months}} = 135.84$ ;  $SD_{\text{months}} = 7.53$ ). The findings indicated that children who were more anxious and had low levels of math self-efficacy and math skills appeared to avoid math stimuli. Math self-efficacy also seemed to mediate the link between math anxiety and attentional bias, suggesting that motivational constructs may play a role in regulating emotional arousal after exposure to math stimuli. The results provide new insight into how avoidance behaviors, even for stimuli that are not purely numerical, would influence children's attentional processes rapidly and automatically, posing a risk factor for maintaining negative attitudes toward the discipline.

### 4.1 Introduction

In an increasingly technological and data-driven world, mathematical knowledge is an interpretive tool that guides individuals and societies to understand and keep up with the technological and scientific developments of today's times (Gellert & Jablonka, 2007). A decades-

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<sup>3</sup> Cuder, A., Pellizzoni, S., Doz, E., Rubinsten, O., & Passolunghi, M. C. Attentional bias and math avoidance: insights from a developmental sample. Submitted to: *Cognition & Emotion*. (Brief report)

long strand of research in mathematical learning has shown how affective-motivational factors and disciplinary performance play a main role in shaping individuals' attitudes towards mathematics and future academic and career choices (Eccles & Wigfield, 2020). Among affective factors, mathematical anxiety (MA) is defined as a feeling of tension that interferes with the manipulation of numbers and the solving of arithmetical problems (Richardson & Suinn, 1972), affecting learning as early as primary school. Mathematical self-efficacy, on the other hand, indicates a set of beliefs about one's perceived competence with respect to solving mathematical tasks and succeeding in the discipline (Bandura, 1996; Di Giunta et al., 2013). Along with disciplinary skills, affective and motivational factors interplay in influencing broad aspects related to mathematics such as engagement, interest, perseverance in the discipline, and career choices. In this context, having high MA, low self-efficacy and poor mathematical performance represents a risk factor for the development of negative attitudes towards maths (Eccles & Wigfield, 2020).

Only recently, scientific debate has pointed out how individuals' negative attitudes toward math would also result in a subtle alteration of attentional processes fundamental to the processing of mathematical information (Pizzie & Kraemer, 2017; Rubinsten et al., 2015), phenomenon that goes by the name of attentional bias (MacLeod et al., 1986; Mogg et al., 2004). The present study represents one of the first attempts to investigate how affective-motivational factors and math skills would modulate attentional biases toward mathematical information in children attending primary and middle school.

#### ***4.1.1 The attentional bias***

Several studies have shown how attentional processes can be altered when the individual is exposed to threatening information (MacLeod et al., 1986; Mogg et al., 2004). From a theoretical point of view, attentional bias would occur with a time course (Abado et al., 2020; Mogg et al.,



2004). Specifically, individuals would exhibit an immediate pattern of vigilance when exposed to threatening stimuli as opposed to neutral stimuli. Following this rapid engagement, individuals would shift their attention away from the threatening stimulus showing an avoidance pattern. In this context, it is argued that the evaluation of the threatening stimulus could be guided at first by bottom-up processes, which would allow rapid identification of the threat. Subsequently, the threatening stimulus would be processed by regulatory processes that would lead individuals to manifest avoidance patterns (Cisler & Koster, 2010). In this context, it has been proposed that vigilance and avoidance patterns would be functional in quickly detecting a threat and then pursuing emotional regulation strategies (Cisler & Koster, 2010).

The etiology and maintenance of anxiety disorders have been shown to be significantly influenced by attentional bias toward negative stimuli (for review, see Abado et al., 2020; Okon-Singer, 2018). Although it also exists in healthy populations, attentional bias is more pronounced in clinical and subclinical populations (for a review, see Abado et al., 2020; Aue & Okon-Singer, 2015). For instance, attentional bias has been observed in association with various anxiety-related disorders (Salum et al., 2013); but also in relation to motivational constructs (Karademas et al., 2007; Walsh et al., 2018). When it comes to math learning, individuals with high MA would exhibit attentional bias toward mathematical information perceived as threatening (Cohen & Rubinsten, 2017) showing vigilance (e.g., Rubinsten et al., 2015) and avoidance (Pizzie & Kraemer, 2017) patterns. In addition, the investigation of attentional bias towards mathematical information remains limited concerning its connection to influential factors like motivation. Existing literature provides some evidence indicating that dispositional self-efficacy (Karademas et al., 2007) and contingent motivation (Walsh et al., 2018) can affect individuals' attention towards emotional stimuli. In other words, motivational factors, such as mathematical self-efficacy, may have a role

in shaping attentional bias by motivating individuals to avoid mathematical information as part of an emotional regulation process (see Cisler & Koster, 2010).

Considering developmental samples, several investigations suggest that attentional biases may occur for various phobic and distress disorders (see Salum et al., 2013) but also in children with specific learning disorders (Haft et al., 2019). However, to date, it remains unclear whether attentional bias toward mathematical information may occur in school-age children. Indeed, starting in primary school, children may begin to develop negative attitudes toward mathematics (e.g., Pellizzoni et al., 2022) that would affect the way mathematical stimuli are processed at the attentional level.

#### ***4.1.2 The present study***

In light of the theoretical framework, it is relevant to investigate whether children's affective-motivational factors and mathematical skills may influence attentional bias toward mathematical stimuli. As a result, the aims of the present study were twofold: 1) evaluate how MA, self-efficacy and math skills influence attentional bias in the form of vigilance and avoidance patterns toward math words (vs. neutral) in a sample of primary and middle school students; and 2) explore the contribution of MA and self-efficacy on attentional bias toward mathematical information.

Regarding the assessment of attentional bias, we made no specific assumptions about its directionality (i.e., patterns of vigilance-avoidance to threat information) given that the literature is unclear on whether individuals would show vigilance (e.g., Rubinsten et al., 2015) or avoidance (Pizzie & Kraemer, 2017) patterns toward math information. We hypothesized that children's attentional bias toward mathematical words would be influenced by MA and math skills. Indeed, previous research on adult populations showed that MA and math skills are related to attentional

bias toward math stimuli (Pizzie & Kraemer, 2017; Rubinsten et al., 2015). We also expected to find an effect of math self-efficacy on attentional bias toward math information. Indeed, motivational factors appear to be linked to attentional bias, influencing how individuals focus on positive and negative stimuli (Karademas et al., 2007; Padmala et al., 2017; Pourtois et al., 2013; Vogt et al., 2020; Walsh et al., 2018). Within this context, math self-efficacy can serve as a motivational component that plays a role in regulating the impact of MA on attentional bias (Cisler & Koster, 2010). If participants exhibit a vigilance pattern, we expect to find a direct effect of MA on attentional bias, as vigilance responses have been associated with rapid threat detection in anxious individuals (Mogg et al., 2004). Conversely, if an avoidance pattern is detected, we hypothesize that the effect of MA on attentional bias will be indirect, mediated by math self-efficacy. In this case, math self-efficacy may play a role in regulating individuals' arousal, leading to avoidance behaviours (Cisler & Koster, 2010; Pourtois et al., 2013; Walsh et al., 2018).

The present study aimed at expanding previous literature by introducing some theoretical and methodological novelties. First, we considered within the same study the contribution of both affective-motivational aspects (i.e., MA and self-efficacy) and mathematical abilities on attentional bias to math information. To the best of our knowledge, this represents the first attempt to investigate the relationship between math self-efficacy and attentional bias toward math information. Secondly, the current study advances existing literature by investigating the attentional bias toward math stimuli in primary and middle school students. In fact, previous studies mainly focused on older students and adults (Cohen & Rubinsten, 2017; Pizzie et al., 2017; Rubinsten et al., 2015), neglecting however younger students (i.e., primary and middle school students) who are still in the process of learning mathematics. Finally, since some evidence

indicated that general forms of anxiety may influence attentional bias (e.g., Salum et al., 2013), we controlled for general anxiety to avoid possible confound effects in our analyses.

## **4.2 Methods**

### **4.2.1 Participants**

A sample of 66 students from the fifth grade of primary school and first grade of middle school were recruited into the study. Subsequently, three students were excluded from the analyses for exhibiting poor accuracy in the Dot-Probe task (n=1 for accuracy below 80% in probe identification; n=2 for accuracy below 80% in rhymes), and two for having outlier math skills. Thus, the final sample consisted of 61 children ( $M_{\text{months}}=135.84$ ;  $SD_{\text{months}}=7.53$ ; age range = 117-151 months; F=27; M=34) attending the 5<sup>th</sup> (n=25) and 6<sup>th</sup> grade (n=36). Following the approval of the principal and teachers to participate in the research project, parents gave written consent for their children to participate in the study. Students were informed that their participation was voluntary and that they could withdraw at any time. The study was approved by the ethics committee of the University of Trieste. The study was conducted in line with the Declaration of Helsinki and the ethical guidelines of the Italian Association of Psychology.

### **4.2.2 Procedure**

The tests were administered in two sessions close in times. In the first session conducted collectively in the classroom, students were administered the questionnaires and the math tasks. In the second session, conducted individually with each student in a quiet space within the school, the Dot-Probe task was administered in computerized form.

### **4.2.3 Materials**

**4.2.3.1 Dot probe task.** An adaptation of the Dot-Probe task (MacLeod et al., 1986; Rubinsten et al., 2015) was used to measure attentional bias toward mathematical words (see

Figure 4.1). The instrument was adapted from a paradigm originally designed for adult participants (Rubinsten et al., 2015). Following the method used by Rubinsten et al. (2015), the word stimuli used in the study were selected based on a pilot study conducted on an independent sample of primary and middle school students ( $n = 105$ ). Specifically, we first selected a list of 16 mathematical words and a list of 16 neutral words using a frequency lexicon of the Italian language. Next, we checked that the selected words did not differ in number of syllables and letters. Finally, we constructed a self-report questionnaire, in which we asked each child to rate the degree of perceived familiarity with respect to the words (i.e., math and neutral words). The results showed that mathematical and neutral words did not differ in degree of perceived familiarity. In this task, each trial began with a fixation point presented for 740ms followed by a blank screen presented for 100ms. Next, a word stimulus semantically associated with mathematics (e.g., "addition") or neutral (e.g., "balcony") was presented in the central left or central right part of the screen for 1000ms. This was followed by an inter-stimulus interval that could randomly range from 100ms to 150ms. The random duration of the inter-stimulus interval prevented participants from predicting the temporal appearance of the probe. Next, a probe was presented (either one "\*" or two asterisks "\*\*") that appeared in the same portion of the screen as the word stimulus (congruent condition) or opposite (incongruent condition). Participants had to respond on a QWERTY keyboard with "1" if there was only one asterisk and "2" if there were two. The probe remained on the screen for 3000ms or until the participant provided the answer. To ensure that children had processed the prime correctly, a second word would appear after the probe, which may or may not rhyme with the previously presented prime word. In case it rhymed, the participant had to respond with "1" otherwise with "2." After the answer or 4000ms a blank screen would appear for 1500ms, and the next trial would begin. There was a one-minute break between the three evaluation blocks.

Before calculating the Dot-Probe task scores, trials in which the participant responded incorrectly to the probes or to the rhymes were removed from the analyses.

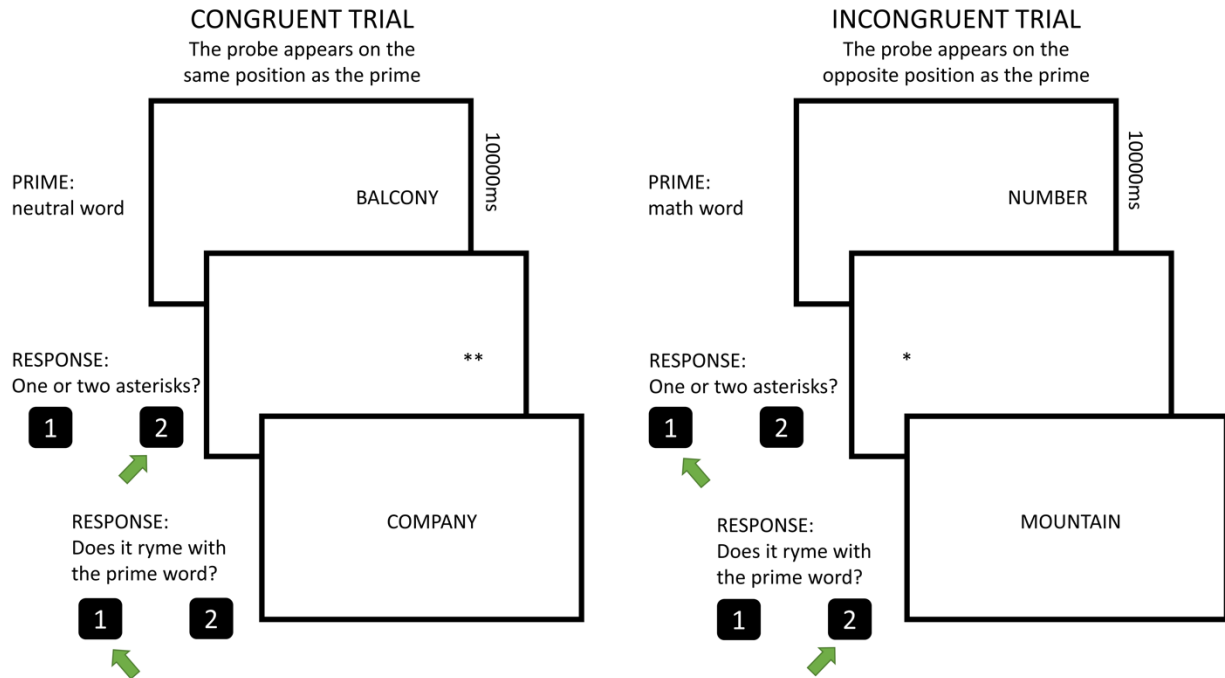


Figure 4.1. Illustration of the Dot-Probe task (adapted from Rubinsten et al., 2015).

**4.2.3.2 Math anxiety.** The Abbreviated Math Anxiety Scale (AMAS, Caviola et al., 2017) was used to measure math anxiety. The questionnaire consisted of nine self-report items, in which students were asked to rate the degree of fear they felt in certain situations involving math. The response was given on a Likert scale from 1 (i.e., "very little fear") to 5 (i.e., "very much fear"). The total score was equal to the sum of the points given on the Likert scale (score range: 10-45). The instrument shows good test-retest reliability ( $r = .85$ ).

**4.2.3.3 Math self-efficacy.** To measure mathematical self-efficacy, we administered a 5-item self-report questionnaire (adapted from Di Giunta et al., 2013) asking students to rate their ability to deal with various situations involving mathematics. The scale was developed to measure

academic self-efficacy, i.e., perceived ability to cope with mathematical tasks. Participants responded using a 5-point Likert scale, where 1 corresponds to low perceived effectiveness (i.e., “Not good at all”) and 5 to high perceived effectiveness (i.e., “Very good”). The total score was the sum of all scores (score range: 10-50). Test reliability is good showing a coefficient of *Alpha* = .86.

**4.2.3.4 Math abilities.** Regarding the assessment of mathematical skills, several tasks of the AC-MT battery (AC-MT-3 6-14, Cornoldi et al., 2020) were used. In particular, three paper-and-pencil subtests were selected: approximate calculation, mathematical fluency, and inferences. In the approximate calculation test, students were asked to mentally solve 15 mathematical operations in an approximate manner, indicating among three alternatives the one that was closest to the correct result. Participants were instructed not to perform the operation but to estimate its result and find the value that came closest to it. In the fluency task, students had to solve 15 mathematical operations presented in columns (i.e., addition, subtraction and multiplication) as fast as possible. In the inference task, the participant was asked to perform three different tasks each consisting of four items. The first, required the student to perform operations presented as symbol-number equivalences. For example, operations as "scissors + scissors = 4" were presented and participants were asked to identify the numerical value corresponding to the scissors symbol. In the second task, operations were presented in Arabic format. These were composed of the addends and the result but with the operator missing. The participants' task was to correctly enter the sign of the operation, which corresponded to the presented result. Finally, the third task presented pairs of operations, one complete and one with no result. The two operations were very similar to each other, and the complete operation provided a useful clue for solving the incomplete one. In other words, participants were required to solve the incomplete operation, not by doing the

calculation in their heads, but by helping themselves with the operation already performed. All tasks were timed and the duration was one and a half minutes for the approximate calculation task; one minute for the math fluency task and two minutes for the inference task. One point was awarded for each correctly solved item, resulting in a final score that could range from 0 to 42 points. Reliability of the instrument was good (ranging from  $r = .69$  to  $r = .89$ ).

**4.2.3.5 General anxiety.** General anxiety was measured with the Revised Children's Manifest Anxiety Scale (RCMAS-2, Reynolds et al., 2012; Italian Edition). The assessment instrument is self-report and involves 10 items with a binary response, yes or no. In responding to the items, students were asked whether the proposed situation describes their daily life experience. The total score corresponds to the sum of all affirmative answer (scoring range: 0-10). Reliability of the instrument is good showing a coefficient of  $Alpha = .82$ .

### 4.3 Results

Descriptive statistics and bivariate correlations are shown in Table 4.1.

Variable	M	SD	Skewness	Kurtosis	1	2	3	4	5
1. MA	20.48	5.23	0.42	-0.29	-	-	-	-	-
2. General anxiety	4.05	2.62	0.50	-0.84	.36**	-	-	-	-
3. Self-efficacy	19.02	3.46	-0.51	-0.68	-.68**	-.25	-	-	-
4. Dot-Probe task (congruent)	-0.01	0.11	-0.41	1.08	-.27*	-.03	.42***	-	-



5. Dot-Probe task (incongruent)	-0.01	0.12	0.03	1.13	.17	.19	-.14	-.19	-
6. Math skills	20.84	7.81	-0.02	-0.20	-.42**	-.15	.47**	.28*	-.11

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Table 4.1. Descriptive statistics (mean; standard deviations; skewness and kurtosis) and bivariate correlations of the measures. M = mean; SD = standard deviation. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ .

No correlation between Dot-Probe task scores in the incongruent condition and MA ( $r = .17, p = .177$ ), self-efficacy ( $r = -.14, p = .264$ ) or disciplinary skills ( $r = -.11, p = .379$ ) has been found, therefore we did not further consider this condition in the analyses. Indeed, in the congruent condition it is easier to verify the avoidance patterns associated with slower RTs presumably due to the shift of attention to other spatial positions, whereas in the incongruent condition it may not have been possible to detect this pattern. In particular, the probe appeared on the other side of the screen and the experimental paradigm adopted did not allow us to detect whether the participant had directed attention exactly where the probe would appear (see Limitations).

#### 4.3.1 Regression analysis

In order to evaluate the contribution of affective-motivational factors and math skills on attentional bias processes, three different multiple regression models were conducted (Table 4.2), placing Dot-Probe scores as the dependent variable and age and general anxiety as covariates. In each regression model, MA (Model 1), self-efficacy (Model 2) and math skills (Model 3) were placed as predictors. All predictors were included as continuous predictors and centered before conducting the regression analyses. We report the Bayes factor (BF) for each predictor, which we interpreted as supporting the alternative hypothesis over the null hypothesis.

		$\beta$	SE	$t$	$p$	$BF_{10}$
Model 1	Intercept	-0.008	0.014	-0.599	.552	
	Age	0.008	0.014	0.561	.577	0.35
	General anxiety	0.010	0.015	0.677	.501	0.26
	MA	-0.032	0.015	-2.140	.036*	1.87
Model 2	Intercept	-0.008	0.013	-0.638	.526	
	Age	0.010	0.013	0.767	.446	0.35
	General anxiety	0.011	0.014	0.825	.413	0.26
	Self-efficacy	0.049	0.014	3.607	<.001***	45.32
Model 3	Intercept	-0.008	0.014	-0.598	.552	
	Age	0.007	0.014	0.507	.614	0.35
	General anxiety	0.003	0.014	0.207	.836	0.26
	Math skills	0.032	0.014	2.128	.038*	2.20

Table 4.2. Regression analysis considering the Dot-Probe task scores as dependent variable. In each model, either math anxiety (MA), math self-efficacy or math skills were placed as predictors. Age and general anxiety were considered as covariates. \*  $p < .05$ , \*\*\*  $p < .001$ .

The results showed higher levels of MA were negatively associated with Dot-Probe task scores ( $\beta = -0.032$ ,  $t = -2.140$ ,  $p = .036$ ,  $BF_{10} = 1.87$ ), indicating that more anxious subjects tended

to respond more slowly to the probe, subsequent to exposure at the same screen location of a mathematical word compared to a neutral one. In addition, the results showed that Dot-Probe task scores were positively predicted by self-efficacy ( $\beta = .049, t = 3.607, p < .001, BF_{10} = 45.32$ ) and math skills ( $\beta = .032, t = 2.128, p = .038, BF_{10} = 2.20$ ). In other words, subjects with lower self-efficacy and lower math ability tended to respond more slowly to the probe preceded by a math word than a neutral one.

#### 4.2.2 Mediation model

In order to test the mediating role of self-efficacy in the relationship between MA and Dot-Probe scores (congruent condition) a mediation model was proposed (see Figure 4.2). Specifically, MA was placed as the focal variable, math self-efficacy as the mediating variable and the dot-probe task as the dependent variable. Bootstrap samples ( $n = 1000$ ) were used to generate 95% bias-corrected confidence intervals.

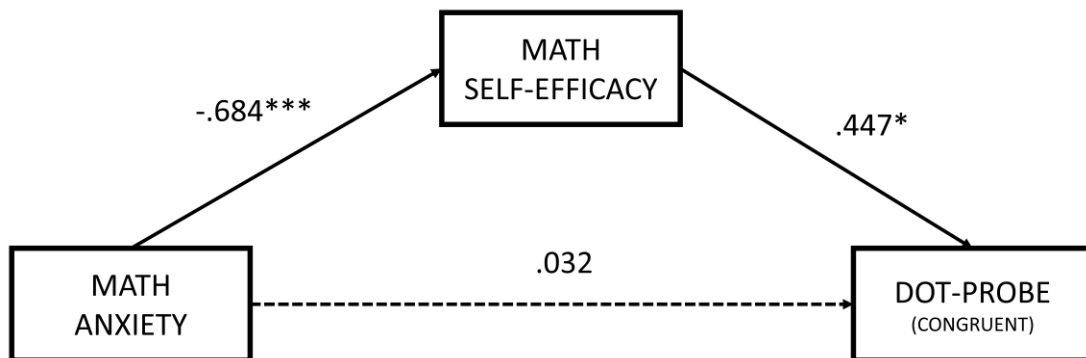


Figure 4.2. Mediation model in which math anxiety was placed as the focal variable, math self-efficacy as the mediating variable and Dot-Probe score as the dependent variable.  $*p < .05, ***p < .001$ .

The results showed a negative effect of MA on math self-efficacy ( $\beta = -.684, s.e. = 0.080, p < .001$ ), but not on the Dot-Probe task ( $\beta = .032, s.e. = 0.208, p = .880$ ). In addition, the results

showed that math self-efficacy had a positive effect on Dot-Probe task scores ( $\beta = .447$ , *s.e.* = 0.211,  $p = .035$ ). The indirect effect of MA on the Dot-Probe task through the mediation of math self-efficacy was found to be statistically significant ( $\beta = -.306$ , bootstrap *s.e.* = .146, bootstrap 95% CI [-0.579, -0.031]). In other words, the mediation analysis suggests that self-efficacy mediates the relationship between MA and Dot-Probe task scores.

#### **4.4 Discussion**

Mathematical skills are essential in an increasingly mathematical, technological and engineered society. However, many people feel uncomfortable when they have to face math related concepts. Importantly, these negative attitudes toward mathematics are present already in the first years of primary school (e.g., Pellizzoni et al., 2022) and seem to manifest also behaviourally in the way individuals process threatening information (MacLeod et al., 1986; Mogg et al., 2004). Numerous studies have confirmed attentional bias toward math stimuli in adults (Pizzie & Kraemer, 2017; Rubinsten et al., 2015) leaving almost unexplored this process in school-age students. For this reason, the aim of the present study was to comprehend the role of emotional-motivational factors (i.e., MA and self-efficacy) and math skills on attentional bias toward math related words in a sample of primary and middle school students.

According to our initial hypotheses, results revealed that participants' mathematical anxiety (MA), self-efficacy, math skills are associated to an attentional bias toward math-related words. These findings agree with previous studies among adults that investigated the association between MA (Pizzie & Kraemer, 2017; Rubinsten et al., 2015), math performance (Cohen & Rubinsten, 2017), and attentional bias. Moreover, as suggested by previous investigations (Karademas et al., 2007; Walsh et al., 2018), our results seem to show that motivational aspects such as mathematical self-efficacy also have an influence on attentional bias.

Findings also showed that participants took longer to identify the probe's identity when it was preceded by a math word compared to a neutral word, indicating the presence of an avoidance pattern. This pattern is consistent with studies (e.g., Pizzie & Kraemer, 2017) that also observed an avoidance pattern towards math stimuli in adult samples. However, it is important to note that our results are in contrast with some previous findings (e.g., Cohen & Rubinsten, 2017; Rubinsten et al., 2015) in which an opposite pattern emerged. In those studies, individuals with high MA exhibited vigilance towards the threat and displayed faster reaction times when probes appeared in the same location as the math stimulus. One possible explanation for these inconsistencies could be the duration of exposure to the prime stimuli. According to the vigilance-avoidance theory (e.g., Mogg et al., 2004), the longer the exposure to the threatening stimuli, the more likely it is for the child to be influenced by arousal regulatory processes (Cisler & Koster, 2010; Haft et al., 2019), which could lead to threat avoidance. In other words, our task may have captured a snapshot of the late time course processes of attentional bias. A second possible explanation for these inconsistencies is methodological. As suggested by Pizzie and Kraemer (2017), the studies that found robust vigilance to math stimuli (e.g., Cohen & Rubinsten, 2017; Rubinsten et al., 2015) employed the Dot-Probe task with more complex cognitive demands, such as two- or three-digit mathematical operations in the prime that needed to be solved by the participants. In contrast, in our study, we used a simplified version of the Dot-Probe task with words (mathematical vs. neutral) to specifically investigate whether children's attentional bias would be influenced by the mathematical semantic context itself.

Our results also suggest that math self-efficacy may be a mediator in the relationship between MA and attentional bias avoidance patterns, constituting the strongest predictor of attentional bias. Our findings could be framed considering the vigilance-avoidance theory (Cisler

& Koster, 2010; Mogg et al., 2004), which posits that anxiety may initially lead the individual to rapidly detect the threat, and subsequently, regulatory processes may evoke avoidant behavioural responses to threatening words. In other words, the avoidance patterns we observed may be associated to motivational regulatory processes aimed at reducing anxiety towards the threatening information (Cisler & Koster, 2010; Haft et al., 2019). Indeed, prior research has indicated that attention can be influenced by motivational constructs, which may also contribute to the orientation of attention towards emotionally evocative stimuli (Karademas et al., 2007; Walsh et al., 2018). The results of our mediation analysis also showed that MA did not have a direct effect on attentional bias. In fact, anxiety would affect attentional processes in the first moments when the threatening stimulus is presented, leading the subject to show vigilance patterns (Abado et al., 2020; Cisler & Koster, 2010; Mogg et al., 2004). The Dot-Probe task in our study could have detected specific avoidance patterns, helping regulate the child's behaviour when facing the threatening information. In this context, mathematical self-efficacy may have a role in shaping attentional bias by motivating individuals to avoid mathematical information as part of an emotional regulation strategy (Cisler & Koster, 2010).

#### ***4.4.1 Limitations***

Our research has some limitations. First, our study was cross-sectional and future studies should evaluate the observed effects also using longitudinal designs. These approaches would help to understand the directionality of effects among the examined constructs and assess whether attentional biases affect affective-motivational constructs and mathematical performance over time. Second, we exposed the prime words for a specific time (i.e., 1000ms) in the Dot-Probe task, which may have captured only certain aspects of attentional bias. Future studies will need to look more broadly at the time course of attentional processes to assess how individuals exhibit

attentional bias in earlier and later stages. Furthermore, in the incongruent condition of the Dot-Probe task, the score was not related to either explicit MA or math self-efficacy or mathematical skills. This finding indicates that the participants neither engaged nor diverted attention from the prime word (i.e., neutral or mathematical word) thus affecting the response time to the probe. This result may depend on the limitations of the task, which methodologically could not accurately capture the spatial orientation of the participant's attention. Finally, caution must be exercised in generalizing the results, since emotional manifestations may vary when considering clinical populations or other age groups (Abado et al., 2020). Future studies should replicate the present findings on children with high math anxiety, as has been done on adults (e.g., Rubinsten et al., 2015), or on children diagnosed with Specific Learning Disorders (e.g., Haft et al., 2017).

#### Conclusion

To summarize, our study investigated how attentional bias toward mathematical information can be influenced by affective, motivational aspects and math skills, advancing literature both from theoretical and practical perspectives. First of all, results showed that besides math anxiety, self-efficacy and math skills were also associated with an avoidance response toward threatening information in a sample of primary and middle school children. Furthermore, it appears that disciplinary self-efficacy has the most robust contribution in predicting attentional bias, suggesting its primary role in explaining threatening information avoidance strategies. The attentional bias would occur rapidly and outside the individual's awareness and, from a clinical perspective, could be a foundational risk factor for the maintenance of avoidance behaviours toward the discipline. So far, a variety of activities are proposed in the literature to decrease negative emotions evoked by mathematics. However, our results suggest that simple exposure to mathematical stimuli can also evoke attentional bias toward the threatening stimuli. For this

reason, mere exposure to mathematical stimuli may not be the optimal choice to reduce negative attitudes towards the discipline. Previous investigation on different math trainings seem to underline exactly this point (Passolunghi et al., 2020). In this context, making children more aware of mathematical strategies could be more effective in decreasing negative attitudes towards mathematics. Therefore, future works should investigate attentional biases toward mathematical information more deeply, designing interventions aimed at their modulation with the goal of tempering negative attitudes toward the discipline.

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## **5. The Impact of Math Anxiety And Self-Efficacy In Middle-School Stem Choices: A Three-Years Longitudinal Study<sup>4</sup>**

### **Abstract**

In today's world, which is progressively oriented towards science and technology and facing a growing demand for skilled professionals, it becomes essential to identify the factors that encourage individuals to pursue careers in STEM fields (Science, Technology, Engineering, and Mathematics). Previous research has showed that affective-motivational factors, math performance, and gender influence STEM occupational and academic choices in adulthood. However, few studies examined how these factors may influence STEM choices as early as middle school. This study aims to assess how math anxiety, math self-efficacy, math performance and gender influence STEM school choices during middle school. We longitudinally assessed a group of 109 students (Year 6) over three school years, with measurements taken at three different occasions. Results indicated that individuals who made a STEM school choice experienced lower math anxiety, higher self-efficacy and math performance, and were predominantly male. Furthermore, the results indicated that both math anxiety in Year 7 and self-efficacy in Year 6 made the most substantial unique contributions to the STEM school choice. The findings shed new light on the factors involved in middle school students' STEM choices, introducing significant theoretical, practical, and interventional implications.

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<sup>4</sup> Cuder, A., Pellizzoni, S., Di Marco, M., Blason, C., Doz, E., Passolunghi, M.C. The Impact of Math Anxiety And Self-Efficacy In Middle-School Stem Choices: A Three-Years Longitudinal Study. Submitted to: British Journal of Educational Psychology.

## 5.1 Introduction

In our increasingly "*mathematized*" society, mathematical thinking plays a crucial role in supporting technical and scientific progress and understanding their dynamics (Keitel et al., 1993). Unsurprisingly, math performance is closely associated with improved educational and occupational outcomes (Bynner, 1997; Rivera-Batiz, 1992), economic status (Gerardi et al., 2013; Gross, 2006), as well as individuals' physical and mental health (Furlong et al., 2016; Gross, 2006). Moreover, individuals with a strong mathematical education significantly contribute to the economic and social development of countries (Foley et al., 2017; Peterson et al., 2011). STEM (Science, Technology, Engineering, and Mathematics) education is critical for enhancing a country's economy by preparing individuals and societies to confront future challenges. However, there is a noticeable shortage of trained professionals in STEM disciplines, as underscored by researchers and governments (Beilock & Maloney, 2015; European Commission, 2015; Henriksen, 2015). Furthermore, international reports indicate a decline in math performance following the COVID-19 pandemic, potentially impacting students' future STEM careers (Betthäuser et al., 2023; OECD, 2023).

Given the central role of STEM education in individual and societal development, understanding the factors that influence students' choices in STEM education and careers is fundamental. Several authors highlighted the importance of math attitudes, math performance, and gender in shaping career and academic STEM choices (Ahmed, 2018; Cribbs et al., 2021; Hembree, 1990). Yet, few studies longitudinally examined the influence of these factors on STEM school choices during middle school years, which is a critical period for developing negative attitudes towards math and for defining individuals' occupational identity (Ahmed, 2018; Caviola et al., 2022; Namkung et al., 2019; Porfeli & Lee, 2012). In this context, the present study

represents one of the first attempts to assess the role of affective-motivational factors (i.e., math anxiety and math self-efficacy), along with math performance and gender, in influencing the STEM school choices of middle school students.

### **5.1.1 Math anxiety**

Several studies highlighted the central role of affective-motivational factors in shaping individuals' learning experiences (Li et al., 2021; Namkung et al., 2019; Pizzie & Kraemer, 2017). Among these emotional factors, math anxiety (MA) has received an extensive attention. MA can be defined as a specific form of anxiety towards math, namely "*a feeling of tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in everyday life and academic situations*" (Richardson & Suinn, 1972). In other words, MA can be described as a set of feelings encompassing tension, worry, and apprehension on current and future situations involving mathematics (Ashcraft & Moore, 2009; Carey et al., 2016; Peña et al., 2013).

Research indicates that the development of MA is multifactorial (Rubinsten et al., 2018), with its onset occurring as early as primary school (e.g., Cargnelutti et al., 2017; Ramirez et al., 2016; Tomasetto et al., 2021). Several studies have shown how MA negatively impacts math performance, beginning in primary school (Pellizzoni et al., 2022) and peaking during middle school (Caviola et al., 2022; Namkung et al., 2019). Higher levels of MA are linked with lower self-efficacy (Ahmed et al., 2012; Li et al., 2021), and avoidance behaviors towards math (Ashcraft et al., 2007; Pizzie & Kraemer, 2017). Higher levels of MA seem also to interfere with cognitive processes (Cuder et al., 2023; Rubinsten et al., 2015). Recent evidence has indicated that MA is often associated with a lower sense of efficacy among students in mathematics (e.g., Justicia-Galiano et al., 2017; Živković et al., 2023), emphasizing the importance of investigating affective and motivational factors.

### **5.1.2 Math self-efficacy**

Motivational factors play a central role in influencing student' learning experience (Usher & Pajares, 2008; Živković et al., 2023). One of the core motivational factors in math learning is math self-efficacy (SE), which influences how individuals feel, think, motivate themselves, and behave during math-related tasks (Bandura, 1977; Usher & Pajares, 2008). SE is typically measured by asking students about their confidence in performing specific math tasks. This construct is typically distinct from self-concept, which assesses individuals' proficiency in a broader domain of knowledge (Lee, 2009; Marsh et al., 2019).

The development of self-efficacy beliefs begins as early as primary school (Joët et al., 2011; Živković et al., 2023), and is influenced by experiences with the discipline (Li et al, 2021), relationships with caregivers and peers (Ahn et al., 2017; Skaalvik et al., 2015), cultural context (Ahn et al., 2016; Giofrè et al., 2020; Pellizzoni et al., 2020; Usher & Weidner, 2018), and negative emotions related to learning (Usher & Pajares, 2008). Students with higher self-efficacy tend to have better math performance (Galla et al., 2014; Schöber et al., 2018; Skaalvik et al., 2015) and experience more positive emotional states (Du et al., 2021). Furthermore, higher SE is linked to greater engagement in the discipline (Martin & Rimm-Kaufman, 2015; Rottinghaus et al., 2003; Zhang & Wang, 2020), increased persistence (Czocher et al., 2019; Galla et al., 2014; Geisler et al., 2023; Multon et al., 1991), and less procrastination (Klassen et al., 2008). In other words, SE is a central construct in sustaining positive attitudes toward math, making it a potential factor linked to STEM choices.

### **5.1.2 STEM choices**

The aforementioned literature seems to indicate that negative attitudes toward math can lead to math avoidance (Ashcraft et al., 2007; Huang et al., 2018; Eidlin-Levy et al., 2021; Martin

& Rimm-Kaufman, 2015; Meece et al., 1990; Pizzie & Kraemer, 2017). Indeed, several studies indicate that MA and SE can influence interests in pursuing math courses (Betz & Hackett, 1983; Hembree, 1990; Huang et al., 2019) or future career aspirations in STEM fields (Chan, 2022; Eidilin-Levy et al., 2021). However, a limited number of studies evaluated how MA and SE can influence STEM educational and occupational choices (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021; Wang et al., 2013). For instance, a longitudinal study (Ahmed, 2018) showed that MA is negatively associated with STEM career choices (Ahmed, 2018). Similarly, a study conducted on college students by Daker and collaborators (2021) indicated that MA was associated with the number of STEM courses the student chose to take, controlling for math performance. A study by Wang (2013) revealed that SE, assessed in high school, has an indirect role in influencing entry into college STEM courses. Recently, a study by Cribbs and collaborators (2021) showed that both MA and SE were associated with STEM career choices in college students. In other words, evidence indicates that MA and SE play a role in influencing career and educational choices among young adults.

Another relevant factor to consider when evaluating STEM pathway choices is gender. Currently, females appear to be underrepresented in college courses and jobs in science, showing a negative trend over time (Breda et al., 2023; Halpern et al., 2007). Recent evidence has also shown that females tend not to choose careers in STEM fields (LeFevre et al., 1992; Huang et al., 2019; OECD, 2013). At the same time, a large body of research has indicated that girls typically report higher MA than boys (e.g., Devine et al., 2012; Doz et al., 2023; Hill et al., 2016). A recent international report (OECD, 2023) has also revealed a gender gap in math performance to the disadvantage of girls in Italy, which is the highest among all OECD countries. Therefore, further



studies are needed to assess the unique contributions of affective-motivational factors, math performance, and gender to STEM choices.

To sum up, the current literature suggests that affective-motivational constructs play a crucial role in predicting future occupational and college choices in STEM in adults (Ahmed, 2018; Cribbs et al., 2021; Wang, 2013). However, few studies assessed the role of MA and SE, along with math performance and gender on STEM school choices in middle school students. In this context, the Italian educational system offers an interesting opportunity to investigate how affective-motivational factors can shape students' school choices. During the last year of middle school, Italian students must choose which high school to enrol in for the following year. High schools in Italy are characterized by five-year curricula that aim to prepare students for specific university courses and career paths (MIUR, 2023). For instance, national reports have shown that students in science-oriented high schools have better math performance (INVALSI, 2023) and are more inclined to pursue STEM university courses (AlmaLaurea, 2022). Focusing on middle school students is crucial, since these students are particularly prone to developing negative attitudes toward math (e.g., Caviola et al., 2022; Namkung et al., 2019) and occupational identity begins to emerge (Ahmed, 2018; Porfeli & Lee, 2012). For these reasons, exploring the Italian educational context could be particularly important to comprehend the role of affective-motivational aspects and math performance in STEM choices as early as middle school. This significance is heightened in a country where gender differences in math performance are among the largest in the world (OECD, 2023).

### ***5.1.3 Aims***

The main aim of the present study was to assess the role of MA, SE, math performance and gender in STEM school choices of students transitioning to high school, examining their unique

contribution. Focusing on a longitudinal sample of middle school students assessed in Year 6, Year 7, and Year 8, we hypothesized that MA, SE, math performance and gender were associated to future STEM school choices. Indeed, several studies in the literature, seem to indicate that affective (Ahmed, 2018; Cribbs et al., 2021; Eidlin-Levy et al. 2021) motivational factors (Cribbs et al., 2021; Wang, 2013), and math performance (Huang et al., 2018; Eidlin-Levy et al., 2021) predict college and career STEM choices and aspirations. We also hypothesized that girls would be less likely than boys to choose STEM careers. Studies have shown that females tend to choose academic-work careers in this subject area less frequently (Huang et al., 2018; LeFevre et al., 1992; PISA, 2013). One possible explanation could stem from the fact that girls are more prone to experience MA and have lower performance in math than their male peers (Devine et al., 2012; Doz et al., 2023; PISA, 2023), especially in the Italian context (Giofrè et al., 2020; PISA, 2023). In this study, we aimed at testing whether gender effects persist even after controlling for the effects of affective-motivational factors and math performance.

The novelty of this study lies in its examination of STEM school choices during middle school, a period often overlooked in existing research. Prior studies have predominantly focused on the impact of MA and SE in students approaching critical decisions about college or careers (Ahmed, 2018; Cribbs et al., 2021; Wang, 2013) or have explored interests and vocational aspirations (Eidlin-Levy et al., 2021; Huang et al., 2019). Additionally, the longitudinal approach of the study over the course of three school years allows for capturing the contribution of affective-motivational aspects on STEM school choices over the first two years of middle school. Most of literature is in fact based on cross-sectional samples or, if longitudinal, considers a short time span (e.g., Cribbs et al., 2021; Eidlin-Levy et al., 2021). In this context, evidence has shown that middle school represents a critical period characterized by strong changes in emotional and motivational

experience, including the development of an occupational identity (Ahmed, 2018; Caviola et al., 2022; Huang et al., 2018; Namkung et al., 2019; Porfeli & Lee, 2012).

## **5.2 Methods**

### **5.2.1 Participants**

Participants in the study were students attending middle school who were longitudinally assessed on three measurement occasions (T1, T2, T3) one year apart. Children under observation for suspected or established neurodevelopmental or specific learning disorders, or those who had not been in Italian school for at least four years, were not included in the study. The initial sample consisted of 111 children who had provided their STEM school choices. One student was excluded for responding randomly at the questionnaires, while another student was excluded for being an outlier in the math performance tasks, with an extremely low performance in all tasks. This resulted in a sample to 109 participants. Among the remaining participants, due to school absences, we tested  $n = 97$  students at T1 ( $M_{\text{age}} = 11.81$ ;  $DS_{\text{age}} = 0.35$ ;  $F = 45.36\%$ ),  $n = 97$  students at T2 ( $M_{\text{age}} = 12.85$ ;  $DS_{\text{age}} = 0.35$ ;  $F = 44.33\%$ ) and  $n = 109$  children at T3 ( $M_{\text{age}} = 13.93$ ;  $DS_{\text{age}} = 0.36$ ;  $F = 45.87\%$ ). The gender of each participant was obtained through questionnaires.

The socioeconomic status of the participants' families was averaged using school records information. Participation in the research was bound by the approval of the project by the school principals of the schools involved. An informed consent and a data protection agreement form were signed by each parent or legal guardian, thereby authorizing their child's participation in the study. The study was approved by the Ethics Committee of the University of XXX.

### **5.2.2 Procedure**

The study was conducted over three longitudinal time periods (T1, T2, and T3), conducted in April and May of each middle school year through collective classroom assessments (see Figure

5.1). The initial assessment (T1) occurred in the first year of middle school. It is worth noting that in the Italian system primary school consists of five years (Year 1 to Year 5). After primary school students are enrolled in the so-called middle schools (Year 6 to Year 8), while high school start from Year 9 to Year 13. The administration of MA and SE questionnaires was conducted in a single session lasting approximately 20 minutes.

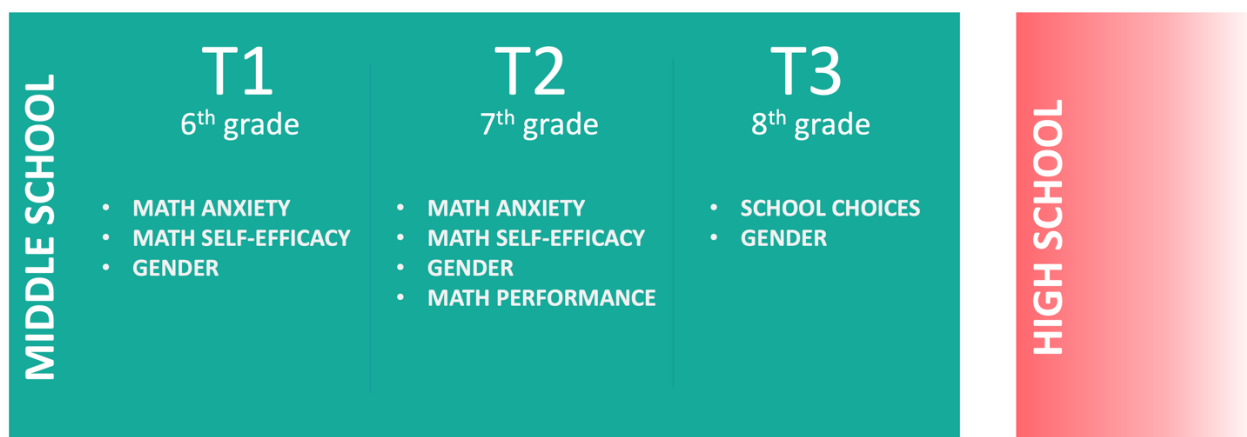


Figure 5.1. Graphical representation of the study procedure.

The second measurement occasion (T2) occurred one year later (Year 7), and consisted of two sessions, lasting 20 minutes each. In the first session, questionnaires were administered to measure MA and SE. The second session involved the evaluation of math performance and consisted of three tasks (i.e., the approximate calculation task, the math fluency task, and the math inference task) taken from a standardized battery.

The third measurement occasion (T3) took place in the last year of middle school (Year 8) and involved the completion of a questionnaire regarding the students' school choice. This was a five-minutes questionnaire administered by the teacher, following instructions from the research group.

### **5.2.3 Measures**

**5.2.3.1 Math anxiety.** To measure math anxiety (MA), we used the Abbreviated Math Anxiety Scale (AMAS, Hopko et al., 2003; Italian version adapted by Caviola et al., 2017), a self-report questionnaire comprising nine items. Children were asked to think of themselves in various math-related situations and to rate their level of fear for each described event (e.g., “thinking about the math test you will have to take tomorrow”). Responses were reported on a 5-point Likert scale (1 = very little fear, 5 = a lot of fear). The total score was calculated by summing the responses to the nine items, with scores ranging from a minimum of 9 to a maximum of 45. This instrument has demonstrated good internal consistency ( $\alpha = .90$ ).

**5.2.3.2 Math Self-efficacy.** Math self-efficacy (SE) was measured through the self-efficacy beliefs questionnaire (adapted from Di Giunta et al., 2013). The self-report questionnaire consists of five items in which participants are asked to indicate how good they feel they are at solving certain math tasks. Participants responded via a 5-point Likert scale (1 = not at all good, 5 = very good) and the total score was determined by the sum of the five items; thus, the minimum score obtainable could range from a minimum of 5 to a maximum of 25. The instrument appears to have good internal consistency ( $\alpha = .77$ ).

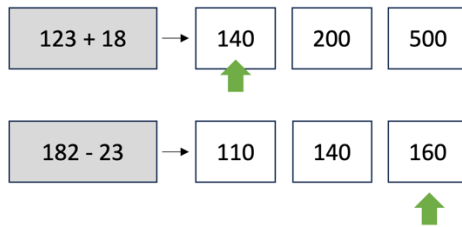
**5.2.3.4 Math performance.** Math performance was assessed through some tasks taken from the AC-MT-3 6-14 standardized battery (Cornoldi et al., 2020). Paper-and-pencil tests were administered collectively: the approximate calculation task, the math fluency task, and the math inference task (see Figure 5.2). In the approximate calculation task (Figure 5.2a), participants were presented with fifteen mathematical operations (additions, subtractions, and multiplications) on the left side of the sheet. They were required to solve these mentally and circle the number closest to the result, choosing from three options.

In the math fluency task (Figure 5.2b), participants were given column operations (seven additions, five subtractions, and three multiplications). They had to perform these operations (15 additions, 15 subtractions, and 15 multiplications) and write down the correct results.

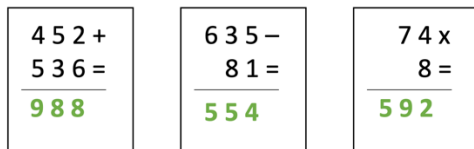
In the math inference task (Figure 5.2c), three different tasks were proposed. The first type involved operations (addition, subtraction, and multiplication) presented with symbols replacing the numbers. Students had to identify the number corresponding to each symbol to solve the equation. The second type required students to complete operations (addition, subtraction, multiplication, and division) that were presented with their results but missing the mathematical symbol (+, -, ×, ÷). They had to insert the correct symbol to complete the operation accurately. In the third type, for each item, two similar line operations (addition, subtraction, multiplication, and division) were presented; the first was missing the result, and the second was complete. Students needed to determine the result of the first operation using the second as a reference, without performing the actual calculation.

Each correctly solved item was awarded one point, and the total score could range from 0 to 42 points. The test-retest reliability of the three tests according to the authors of the battery (Cornoldi et al., 2020) is good for the approximate calculation task ( $r = .73$ ), the math fluency task ( $r = .89$ ) and the math inferences task ( $r = .69$ ).

a) Approximate calculation task

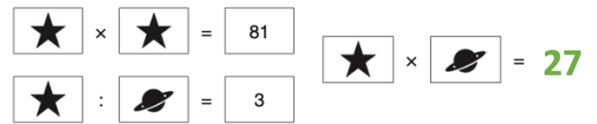


b) Math fluency task



c) Math inference task

Subtest 1:



Subtest 2:

$$1065 (+) 205 = 1270$$

Subtest 3:

$1152 : 6 = ?$ <b>192</b>	$192 \times 6 = 1152$
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Figure 5.2. Graphical representation of paper-pencil tests used to assess math performance: approximate calculation task, math fluency task and math inference task. Task solutions are shown in green.

**5.2.3.5 STEM school choices.** School choices were assessed through a self-report questionnaire administered to children in their last year of the middle school (Year 8). This questionnaire was given after children had already made their decisions to enrol in a specific high school. It is worth mentioning that all Italian children must make their decisions typically by the end of January. Students were asked to specify the name of the high school and the chosen educational curriculum. Subsequently, the educational programs provided by the schools were used to calculate the number of hours dedicated to STEM subjects (e.g., mathematics, physics, chemistry, science) for each individual schools; with higher scores corresponding to higher number of hours dedicated to STEM subjects throughout high school years. Here again is important to note that the number of hours dedicated to STEM subjects can vary greatly in Italian high schools.

## 5.3 Results

### 5.3.1 Preliminary analysis

Statistical analyses were conducted using *R* (R Core Team, 2023). Before examining the influence of affective-motivational factors, math performance and gender on STEM school choices, a cluster analysis was performed on the number of hours dedicated to STEM school subjects over the five years of high school. A clustering approach was selected because the literature lacks a clear definition of high schools that can be categorized as STEM. In the context of the Italian education system, high schools are known for their focus on either a more technical-scientific or a humanistic curriculum (MIUR, 2023). Furthermore, a preliminary analysis of the distribution of average weekly hours devoted to STEM subjects revealed a density approximating a bimodal, indicating a group of schools with higher STEM subject content and a group of schools with low STEM subject content (Hartigans' Dip test = 0.124;  $p < .001$ ). The *Mclust* library (Scrucca et al., 2023) was used to conduct cluster analysis which identified a two-cluster solution as optimal (log-likelihood = -397.198, BIC = -817.943, LCI = -821.028) compared to a solution without clusters (log-likelihood = -431.336, BIC = -872.091, LCI = -872.091). A point-biserial correlation between the number of hours devoted to STEM subjects and the clusters obtained was found to be positive and strong ( $r = .897$ ,  $p < .001$ ). Students were therefore subdivided in two clusters. The first cluster was composed of students who had chosen schools with fewer weekly hours of STEM subjects ( $n = 40$ ,  $M_{\text{hours}} = 5.38$ ,  $SD_{\text{hours}} = 0.52$ ) than the second cluster ( $n = 69$ ,  $M_{\text{hours}} = 9.78$ ,  $SD_{\text{hours}} = 1.26$ ).

### 5.3.2 Group comparisons

We used a Chi-square test to assess differences between males and females in STEM school choice. The results showed significant differences in STEM school choices frequencies,  $\chi^2(1) =$



6.019,  $p = .014$ , showing that 74% ( $n = 44$ ) of males chose STEM schools (vs. 25%,  $n = 15$ ). In contrast, females seemed to equally make STEM schools choices (50%,  $n=25$ ) as non-STEM school choices (50%,  $n=25$ ).

To assess differences in affective-motivational factors and math performance on students' STEM school choices, we initially conducted a linear discriminant analysis (LDA) and then we have evaluated model performance using ROC curves. Specifically, in the LDA, we considered the STEM school choice cluster as the response variable, and included MA (T1 and T2), SE (T1 and T2), math performance and gender as predictors. The coefficients of linear discriminants are presented in Table 5.1. The model's performance, using ROC curves, indicated a good predictive power ( $AUC = 0.811$ ,  $sensitivity = 0.824$ ,  $specificity = 0.576$ ). Afterwards, we conducted a multivariate analysis of covariance (MANCOVA), to assess differences in affective-motivational factors and math performance based on students' STEM school choices. We placed STEM school choice as the fixed factor, MA (T1 and T2), SE (T1 and T2) and math performance as the independent variables, and participants' gender as the covariate. We used Cohen's  $d$  to calculate the effect size related to the observed differences, using Cohen's (1988) criterion for its interpretation: small effect  $d = 0.20$ , medium effect  $d = 0.50$ , large effect  $d = 0.80$ . The MANCOVA showed a main effect of the STEM school choice factor, Wilks'  $\Lambda = 0.738$ ;  $F(1, 87) = 5.884$ ,  $p < .001$ . Specifically, univariate tests showed that there were statistically significant differences in SE measured at T1,  $F(1,87) = 17.34$ ,  $p < .001$ , Cohen's  $d = 1.00$ , in SE measured at T2,  $F(1,87) = 15.299$ ,  $p < .001$ , Cohen's  $d = 0.83$ , in MA measured at T2,  $F(1,87) = 16.912$ ,  $p < .001$ , Cohen's  $d = -0.92$ , and in math performance,  $F(1,87) = 5.807$ ,  $p = 0.018$ ,  $d = 0.44$ . No difference between groups was found in MA measured at T1,  $F(1,87) = 2.330$ ,  $p = 0.130$ , Cohen's  $d = -0.34$ .

	STEM school choice (n = 59)		non-STEM school choice (n = 31)		CLD	F	d
	M	SD	M	SD			
MA (T1)	21.22	4.38	22.77	4.90	0.376	2.330	- 0.34
MA (T2)	19.64	5.27	24.26	4.57	-0.658	16.912***	- 0.92
SE (T1)	19.20	2.25	17.03	2.50	0.599	17.344***	1.00
SE (T2)	19.25	3.02	16.87	2.06	0.275	15.299***	0.83
Math performance	45.47	10.40	39.94	10.13	0.042	5.807*	0.84

Table 5.1. Descriptive statistics of affective-motivational factors and math performance related to STEM school choices. Note: CLD = LDA coefficients;  $F$  = F-test of the MANCOVA;  $d$  = Cohens'  $d$  of the univariate test results of the MANCOVA. Note: \*\*\*  $p < .001$ ; \*  $p < .05$ .

### 5.3.3 Logistic regressions

To assess the unique contribution of affective-motivational factors, math performance, and gender on STEM school choice, we conducted five logistic regressions (Table 5.2) using STEM school choice as the dependent variable. The first two models (Model 1 and Model 2) aimed to separately assess the effects of gender and math performance on STEM school choices. Subsequently, in Model 3, gender and math performance were simultaneously regressed on the dependent variable to determine their unique contribution. In Model 4, MA and SE measured at T1 were introduced to assess their contributions while controlling for the effects of gender and performance. Finally, in Model 5, we introduced MA and SE measured at T2, while controlling for predictors at T1, gender, and math performance. Effect sizes were estimated using the Nagelkerke pseudo  $R^2$ , allowing us to estimate the variance explained by the model to that of a null model.

	Estimate	SE	z	p	Pseudo $R^2$
<i>Model 1</i>					
Intercept	0.000	0.283	0.000	1.000	0.086**

Gender	1.076	0.411	2.615	0.009**	
<i>Model 2</i>					
Intercept	0.596	0.217	2.743	0.006**	0.249***
Math performance	0.453	0.227	1.990	0.047*	
<i>Model 3</i>					
Intercept	0.139	0.311	0.447	0.655	0.291***
Gender	0.878	0.444	1.976	0.048*	
Math performance	0.484	0.233	2.076	0.038*	
<i>Model 4</i>					
Intercept	0.345	0.367	0.941	0.346	0.515***
MA (T1)	0.093	0.290	0.320	0.749	
SE (T1)	0.953	0.316	3.015	0.002**	
Math performance	0.378	0.268	1.408	0.159	
Gender	0.758	0.504	1.504	0.132	
<i>Model 5</i>					
Intercept	0.415	0.391	1.061	0.288	0.589***
MA (T1)	0.435	0.340	1.280	0.200	
SE (T1)	0.811	0.351	2.311	0.021*	
MA (T2)	-0.863	0.363	-2.377	0.017*	

SE (T2)	0.367	0.358	1.024	0.306
Math performance	0.053	0.310	0.172	0.863
Gender	0.860	0.541	1.590	0.112

Table 5.2. Logistic regressions models outputs considering STEM school choice as dependent variable. Note: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$

In Model 1 we included gender as the only predictor. The model was found to be statistically significant, but with limited in terms of predictive power,  $\chi^2(1) = 7.083$ ,  $p = .008$ ,  $R^2 = 0.086$ . Specifically, the result showed that gender had a significant positive effect,  $\beta = 1.076$ ,  $SE = 0.411$ ,  $p = .009$ , that is, males had a higher propensity to choose STEM schools.

In Model 2 we included math performance as the only predictor. The model was found to be statistically significant, with a moderate predictive power,  $\chi^2(1) = 20.714$ ,  $p < .001$ ,  $R^2 = 0.249$ . Specifically, the result showed that math performance had a significant positive effect on STEM school choices,  $\beta = 0.453$ ,  $SE = 0.227$ ,  $p = .047$ .

In Model 3 we entered gender and math performance simultaneously. The model was found to be statistically significant with moderate predictive power  $\chi^2(2) = 24.715$ ,  $p < .001$ ,  $R^2 = 0.291$ . In particular, the result showed that both gender,  $\beta = 0.878$ ,  $SE = 0.444$ ,  $p = .048$ , and math performance,  $\beta = 0.484$ ,  $SE = 0.233$ ,  $p = .0379$ , had a significant positive effect on the STEM school choice.

In Model 4 we included MA and SE measured at T1, math performance and gender in the model. The model was statistically significant with a good predictive power,  $\chi^2(4) = 47.547$ ,  $p < .001$ ,  $R^2 = 0.515$ . Results showed that SE measured at T1,  $\beta = 0.953$ ,  $SE = 0.316$ ,  $p = .002$ , but not

MA,  $\beta = 0.093$ ,  $SE = 0.290$ ,  $p = .749$ , was positively predictive of STEM school choice. Neither math performance,  $\beta = 0.378$ ,  $SE = 0.268$ ,  $p = .159$ , nor gender,  $\beta = 0.758$ ,  $SE = 0.504$ ,  $p = .132$ , predicted STEM school choice, after controlling for MA and SE at T1.

In Model 5, we also included MA and SE at T2, as well as all the other predictors included in previous models. The model was statistically significant with a good predictive power,  $\chi^2(6) = 57.06$ ,  $p < .001$ ,  $R^2 = 0.589$ , which was the highest as compared to all previous models. The results showed that only SE measured at T1,  $\beta = 0.811$ ,  $SE = 0.351$ ,  $p = .021$ , and MA measured at T2,  $\beta = -0.863$ ,  $SE = 0.363$ ,  $p = .017$ , were predictive of STEM school choice. No statistically significant effects were found for MA measured at T1,  $\beta = 0.435$ ,  $SE = 0.340$ ,  $p = .200$ , SE measured at T2,  $\beta = 0.367$ ,  $SE = 0.358$ ,  $p = .306$ , math performance,  $\beta = 0.053$ ,  $SE = 0.310$ ,  $p = .863$ , and gender,  $\beta = 0.860$ ,  $SE = 0.541$ ,  $p = .112$ .

#### **5.4 Discussion**

This study examines the impact of MA, SE, math performance, and gender on STEM school choices among middle school students. While prior research has primarily focused on high school students and adults, exploring the influence of affective and motivational factors (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021; Wang, 2013), as well as math performance and gender (Breda et al., 2023; Huang et al., 2019), this study provides fresh insights into the factors shaping STEM school choices during the transitioning from middle to high school (Years 6 to 8 in the Italian school system). This period is in fact critical period for the development of negative attitudes towards math (Caviola et al., 2022; Namkung et al., 2019) and for the formation of an occupational identity (Ahmed, 2018; Porfeli & Lee, 2012).

The results showed statistically significant differences in affective-motivational factors, math performance, and gender between those who made a STEM school choice compared with

those who did not. As for affective-motivational factors, children who made a STEM school choice tended to have a lower MA at T2, although no statistically significant differences were observed in MA measured at T1. This result aligns with other studies conducted on adults, suggesting that MA influence STEM choices (Ahmed, 2018; Cribbs et al., 2021), even after controlling for gender and math performance (Daker et al., 2021). Furthermore, this pattern of results also aligns with Ahmed's (2018) longitudinal study, which indicates that the effects of MA play a prominent role when evaluated in a time period closed to the STEM choice.

As for motivational aspects, our results showed that students who made a STEM school choice had statistically significant higher levels of SE at both T1 and T2. This outcome aligns with evidence indicating that SE is one of the most powerful predictors of STEM choices in college and future careers (Cribbs et al., 2021; Wang, 2013). Notably, SE seems to be associated with more positive performance in math (Galla et al., 2014; Skaalvik et al., 2015), higher levels of positive emotions (Du et al., 2021), and interest in the discipline (Martin & Rimm-Kaufman, 2015; Zhang & Wang, 2020), all of which could facilitate individuals' STEM choices. Additionally, results indicated that being male was positively associated with a STEM school choice. This finding is consistent with existing literature, which suggests that girls are less likely to make STEM choices (Huang et al., 2018; LeFevre et al., 1992; PISA, 2013). Not surprisingly, the results also showed that math performance was positively associated with STEM school choice. Our results seem to confirm previous evidence, showing that math performance plays a crucial role in predicting interest in math and future career choices in STEM fields (Huang et al., 2019; Eidlin-Levy et al., 2021).

Our study delved into the unique longitudinal contributions of affective-motivational factors, math performance, and gender on STEM school choices. The results from logistic models

unveiled that MA, measured at T2, and SE, measured at T1, were the main predictors of STEM school choice, while controlling for the effects of gender and math performance. These findings suggest intriguing developmental patterns linking affective-motivational factors in pursuing STEM schools. On the one hand, MA seems to play a crucial role when measured in temporal proximity to making the STEM school choice, aligning with the observation made by Ahmed (2018) in adults. Conversely, as early as the Year 6, SE appears to be a positive predictor of STEM school choice. In this sense, SE may be a central construct in fostering positive emotional states toward math (Du et al., 2021; Martin & Rimm-Kaufman, 2015; Usher & Pajares, 2008); however, future studies are needed to further investigate the role of this construct in STEM choices. Intriguingly, gender or math performance did not have any statistically significant impact on STEM school choice once accounting for the effects of all the other predictors (including MA and SE). This result aligns with a study by Daker and colleagues (2021), in which math performance and gender did not predict STEM course participation, after accounting for the effects of MA. Notably, MA and SE seem to be both important in determining middle school students' STEM school choices, offering new perspectives for early interventions aimed at promoting more informed future school choices.

#### ***5.4.1 Limitations***

Some limitations should be considered. For a start, a larger sample of children, encompassing different contexts and Italian regions, would enable the examination of interregional differences and variations between different cultures, enhancing the study's generalizability to a broader context. Also, affective-motivational and performance variables were only assessed in Years 6 and 7. Including a longer time frame, while also taking a longitudinal approach, could probably provide a better insight into the impact of these variables in the long run. Finally, the

study did not consider the influence of other factors such as parents, peers, and teachers; which can also have an impact on math performance (Semeraro et al., 2020) and on future career choices (Wang & Degol, 2013).

#### **5.4.2 Conclusions**

In a world increasingly shaped by mathematical knowledge and a growing demand for skilled professionals in technological-scientific fields, identifying factors that encourage educational pathways in STEM fields is crucial for an advanced society (Beilock & Maloney, 2015; European Commission, 2015; Henriksen, 2015; Keitel et al., 1993). To the best of our knowledge, this study is the first to investigate the combined role of affective-motivational factors, math performance and gender on STEM school choices. The results seem to indicate that affective-motivational factors, math performance and gender all contribute to students' choices in STEM education. However, when the unique contribution of these factors is considered, it becomes clear that MA and SE emerge as the crucial predictors of STEM school choices. Notably, our findings reveal that SE positively influences STEM career choices as early as in Year 6. From Year 7 onward, MA begins to have a detrimental impact in STEM school choices.

In light of these findings, future studies should delve into the role of affective-motivational factors in STEM choices, particularly in middle school years (Year 6 to 8 in the Italian school system). This period seems to be crucial for the establishment of occupational identity (Ahmed, 2018; Porfeli & Lee, 2012) and the emergence of negative attitudes toward math (Caviola et al., 2022; Namkung et al., 2019). A closer investigation should be dedicated to structuring interventions that carefully consider affective-motivational factors. As suggested by the results of the present study, these factors seem pivotal in influencing STEM choices, more so than other factors, including math performance and gender. Consequently, activities aimed at mitigating



negative attitudes toward math could prove beneficial (Passolunghi et al., 2020), making STEM educational pathways an accessible opportunity for a growing number of students.

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## 6. General discussion

In an increasingly technologically advanced society, developing positive attitudes toward math is critically important. Indeed, numerous studies indicate that strong math skills and positive attitudes toward math predict individual and collective economic growth, as well as individual well-being (Bynner, 1997; Gerardi et al., 2013; Gross et al., 2009; Hakkarainen et al., 2015; Rivera-Batiz, 1992). However, there has been a recent global decline in math performance (OECD, 2023), occurring concurrently with a growing demand for skilled STEM professionals (European Commission, 2015; Henriksen, 2015). Furthermore, within the Italian context, national and international reports highlight a gender gap in math disadvantageous to girls (Giofrè et al., 2020), which also appears to be among the widest on the international stage (OECD, 2023). For this reason, identifying factors that influence math performance and STEM choices is relevant both theoretically and practically, as understanding these factors is crucial for guiding the development of tailored interventions.

The theoretical framework suggests that attitudes toward math, in conjunction with cognitive factors (e.g., Ramirez et al., 2016; Soltanlou et al., 2019), are crucial in predicting students' math performance (Namkung et al., 2019; Živković et al., 2023) and their STEM choices (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021; Wang, 2013). In this doctoral thesis, different affective-motivational and cognitive factors have been studied in four different scientific works to shed some new light not only on their unique contributions but also on their interplay with math performance and STEM school choices. Specifically, a series of research questions raised in recent literature were addressed in this doctoral thesis:

1. What are the developmental patterns of general anxiety (GA) and math anxiety (MA) in influencing working memory (WM) and longitudinal math performance during primary school?
2. How can the relationship between MA and specific math tasks vary according to different levels of individuals' WM?
3. How can MA and math self-efficacy (SE) influence individuals' attentional bias towards math stimuli?
4. How can MA, SE, gender, and math performance longitudinally influence students' STEM school choices at the end of middle school?

## **6.1 Research findings**

The studies of this research thesis have been designed with the general aim of shedding some new light on how affective-motivational and cognitive factors interplay in influencing math performance and STEM school choices. The main highlights of this doctoral dissertation are:

1. Affective and cognitive factors interplay and longitudinally influence math performance;
2. MA prevents students from reaching their full potential, even considering individuals with high-WM resources;
3. MA and SE can influence basic processes such as attentional bias, leading students to avoid math stimuli;
4. MA and SE are the most robust longitudinal predictors of STEM school choices, controlling for gender and math performance.

The first study (Chapter 2) consisted of monitoring GA, MA, and WM by studying their contributions to math performance in a longitudinal design conducted in a period between 3<sup>rd</sup> and

4<sup>th</sup> grade. The results showed that GA (as evaluated by teachers) had a negative effect on concurrent and longitudinal math performance, while MA (self-evaluated by students) seemed to show a direct effect only on math performance measured when students attended 4<sup>th</sup> grade. These results appear to indicate that math performance during the period between 3<sup>rd</sup> and 4<sup>th</sup> grade is influenced by general forms of anxiety. Furthermore, the results of this research showed that the effects of GA and MA on math performance were both mediated by individuals' WM. Consistent with Processing Efficiency Theory (PET, Eysenck & Calvo, 1992), our results agree with studies showing that WM plays a mediating role in the relationship between MA and math performance (Justicia-Galiano et al., 2017; Soltanlou et al., 2019). In this research, longitudinal design is particularly salient because (1) we observe that teachers could early capture some emotional inner state that children are not completely aware of (especially using self-report scales); (2) the demands of math learning increase over time, and children have to make an effort to keep up, both at a cognitive and emotional level. In this sense, we believe that adopting a longitudinal approach is crucial, as it can aid in clarifying the developmental trajectories associated with math performance; and (3) GA and MA were found to undermine performance in a WM task, in line with previous reports of a detrimental effect of anxiety on WM. It also emerged that WM mediated the indirect association between teachers' ratings of GA and concurrent and future math performance (e.g., Beilock, 2008).

The second study (Chapter 3) aimed to further investigate the results observed in the first research work. Using an interaction analysis, we assessed the relationship between MA and different math tasks, and we tried to understand how this association varies across different levels of individuals' WM. Indeed, although several studies agree that forms of anxiety may interfere with individuals' WM, to date, it is unclear whether the effect of MA is more pronounced in individuals with low-WM (e.g., Soltanlou et al., 2019) or those with high-WM (Ramirez et al.,



2016). In this context, some authors have suggested that anxiety would interfere more with subjects who have few WM resources to manage anxious thoughts and task demands (e.g., Soltanlou et al., 2019), while other studies have shown that MA would interfere with strategies that make intensive use of WM, going to hinder high-WM subjects' math performance (e.g., Ramirez et al., 2016). While most research focused either on adults or children in the early primary school years, we chose to shift our focus to the later primary school years, as the impact of math anxiety tends to intensify in this age range. Furthermore, in continuity with the first study (Chapter 2), we used an interaction analysis that allowed us to examine in greater detail the effects of MA on math performance by considering different levels of WM (see Soltanlou et al., 2019). Findings revealed that high-WM subjects seemed to be more affected by MA when some tasks (i.e., math fluency task) but not others (i.e., math reasoning task) were considered. These results indicate that, for certain math tasks, MA may more severely impair performance in individuals with high WM. From a theoretical perspective, this would occur because individuals with high WM tend to use advanced problem-solving strategies more frequently, which could be more susceptible to the detrimental effects of anxiety (Ramirez et al., 2013, 2016). It should be noted that in the proposed models, WM consistently exhibited a positive effect on math performance, which was not entirely depleted by the presence of MA. This suggests that WM is a robust protective factor in learning and that MA can adversely affect even individuals with high WM, thereby hindering their ability to achieve their full potential.

Numerous studies in the literature have shown that anxiety, in addition to interfering with WM cognitive processes, is also able to influence the way individuals direct their attention towards stimuli perceived as threatening, a phenomenon that goes by the name of "attentional bias" (MacLeod et al., 1986; Mogg et al., 2004). The aim of the third study (Chapter 4) was to assess

the role of affective-motivational factors and math performance in influencing attentional bias toward mathematical stimuli, considering students at the end of primary school and the beginning of middle school. To date, the literature has mainly assessed attentional biases by considering adult populations and limiting analyses to MA (e.g., Pizzie & Kraemer, 2017; Rubinsten et al., 2015). In addition, evidence seems to show mixed results on behavioral patterns associated with attentional bias, and in particular, some evidence shows that subjects with high MA show vigilance patterns (Cohen & Rubinsten, 2017; Rubinsten et al., 2015), while others show avoidance patterns (Pizzie & Kraemer, 2017). Our results showed that participants with high MA, lower SE, and poor math performance exhibited an avoidance attentional bias toward math stimuli. In addition, the results showed how SE may be a mediator in the relationship between MA and attentional bias. In this context, our results can be interpreted in light of vigilance-avoidance theory (Cisler & Koster, 2010; Mogg et al., 2004), which argues that forms of anxiety can prompt rapid threat detection with vigilance behaviors (e.g., Rubinsten et al., 2015), whereas only later motivational aspects may intervene by evoking avoidance patterns of the threatening stimulus (Cisler & Koster, 2010; Haft et al., 2019). Indeed, our task may have detected avoidance of the math stimulus in a time window subsequent to vigilance behaviors (Haft et al., 2019). In other words, our results show how having negative attitudes toward math can undermine the way a student interfaces with math stimuli, acting in a rapid timeframe, out of awareness, and as early as primary school.

As emerged from the first three studies, investigating the role of attitudes (MA and SE) is of primary importance in understanding how they influence individuals' math performance and cognitive functioning. However, less evidence has shown how affective-motivational constructs are able to influence STEM school choices. Previous studies have shown that STEM choices are influenced by the attitudes that individuals show with respect to math (Ahmed, 2018; Breda et al.,

2023; Edilin-Levy et al., 2023). However, no study to date has focused on how these, controlling for gender and math performance, influence STEM school choices at the end of middle school. For this reason, the fourth study (Chapter 5), using three longitudinal evaluations over the three school years (6<sup>th</sup>, 7<sup>th</sup>, and 8<sup>th</sup> grade), aimed to assess how affective-motivational factors, gender, and math performance influenced STEM school choices of middle school students transitioning to high school. Findings revealed that students who made a STEM school choice had lower MA, higher SE, better math performance, and were predominantly male. Additionally, the results showed that SE in the 6<sup>th</sup> grade and MA in the 7<sup>th</sup> grade made unique contributions to STEM school choice, once controlling for the effects of all other predictors. In other words, MA, SE, gender, and math performance all seem to be associated with STEM choices. However, when their unique contributions are considered, only MA and SE seem to influence STEM school choice. These findings agree with other studies that have shown the contribution of MA and SE in influencing career aspirations (Edilin-Levi et al., 2023) and individuals' STEM choices (Ahmed, 2018; Cribbs et al., 2021; Daker et al., 2021). Furthermore, the results seem to align with the findings of Daker and colleagues (2021), where STEM choices were more strongly associated with affective-motivational factors than with gender and math performance.

## **6.2 Implications and future directions**

Affective and motivational factors can influence individuals' cognitive processes, affecting learning and preventing students from reaching their full potential. In this context, this dissertation has some crucial implications for educational settings:

1. Data suggest that children with math difficulties could benefit from early interventions to help them cope with anxiety and promote self-efficacy. Such

interventions should be run together with math skills and cognitive precursor training (Passolunghi et al., 2020);

2. Interventions on emotional aspects could also benefit students' cognitive functioning by freeing WM resources and preventing attentional biases toward math stimuli;
3. Developing positive attitudes toward math would help students make more informed school choices that also contemplate STEM disciplines.

The results outlined in Chapter 2 showed how forms of anxiety, such as GA and MA, can emerge as early as primary school, affecting students' math performance. In this context, it was found that GA influences both cross-sectional and longitudinal math performance while MA appears to play a greater role in predicting longitudinal performance when teachers' requests increase and the tasks are more challenging for students. This suggests a developmental pathway where the initial impacts of more general forms of anxiety, like GA, are followed by the influence of specific anxieties, such as MA on math performance (Rubinsten et al., 2018; Wang et al., 2014). Furthermore, this result pattern would emphasize that, with age, students become increasingly aware of the emotions experienced in relation to learning. Findings in Chapter 2 showed how the effects of GA and MA on math performance were mediated by WM. In other words, results suggest that anxiety would negatively affect math performance interfering with WM resources by making task execution more burdensome and susceptible to errors. In this regard, Chapter 3 sought to investigate more thoroughly how the relationship between MA and math performance might vary across different levels of individuals' WM. The results showed that primary school students with high levels of WM were particularly susceptible to the negative effects of MA on math performance. The results can be interpreted as an effect of MA on the advanced strategies that

high-WM subjects would use to solve math tasks (e.g., Ramirez et al., 2016), preventing them from reaching their full potential. For this reason, future studies should more carefully evaluate how the relationship between forms of anxiety and math performance takes shape during the early primary school years, also considering the cognitive factors involved. In this context, future studies should move beyond correlational models in favor of experimental paradigms that assess the effects of MA on WM while participants solve math tasks. Considering the practical implications, it could be beneficial to specifically target emotional aspects as the root of math difficulties and interference with cognitive resources. Particularly, enhancing learning by making it more engaging and aligned with the students' competence and increasing metacognitive abilities in math performance could reduce anxiety (Passolunghi et al., 2020). This approach would also include strategies to manage and mitigate feelings of anxiety (e.g., Passolunghi et al., 2020; Supekar et al., 2015; Zettle, 2003), making students more aware of their emotional reactions to math (Jamieson et al., 2010).

In Chapter 4, the study examined how affective-motivational constructs interact not only with WM but also with other basic cognitive factors related to math learning, specifically attentional bias (Pizzie & Kraemer, 2017; Rubinsten et al., 2015). The results indicated that negative attitudes towards math (i.e., higher MA and lower SE) and low math performance were associated with avoidance patterns toward math stimuli. Moreover, a mediation analysis revealed that the relationship between MA and attentional bias was mediated by participants' SE. In other words, motivational constructs may play a role in regulating emotional reactions in response to exposure to math stimuli perceived as threatening (Cisler & Koster, 2010; Haft et al., 2019). This highlights how attitudes towards the discipline can lead to avoidance behaviors that occur rapidly and outside individuals' awareness. These processes can potentially alter the way individuals

interact with the discipline, interfering with the execution of math tasks or leading to avoidant behaviors of math stimuli. Future research should investigate whether attentional bias toward math stimuli influence the development of negative attitudes towards math. Indeed, numerous studies suggest that attentional biases play a role in the etiology and maintenance of anxiety disorders, making them a clinically relevant risk factor (Abado et al., 2020; Okon-Singer, 2018; Putwain et al., 2020). Consequently, future studies should also explore whether interventions aimed at fostering positive attitudes towards math learning can also generalize to attentional bias.

The results presented in Chapter 5 showed how attitudes towards the discipline, math performance, and gender influence STEM school choices. The longitudinal study revealed that SE in 6<sup>th</sup> grade and MA in 7<sup>th</sup> grade have a significant and unique contribution to STEM school choices. Essentially, these results suggest that affective-motivational factors play a crucial role in shaping students' STEM school choices as early as the first two years of middle school. Various studies have shown that the middle school period is crucial for the development of negative attitudes (e.g., Caviola et al., 2021; Namkung et al., 2019) and for the emergence of an occupational identity (e.g., Ahmed, 2018; Porfeli & Lee, 2012). In this regard, since the data seem to support that affective-motivational aspects are prominent in predicting STEM school choices over math performance and gender, intervention studies should focus on specifically promoting positive attitudes towards math (e.g., Passolunghi et al., 2020). Furthermore, future studies should explore whether an affective-motivational intervention can also generalize to an increased propensity to make STEM school choices.

In conclusion, possessing strong math skills is crucial in an increasingly technological and mathematized world. Evidence indicates that proficiency in math is linked to improved occupational and academic outcomes, higher socioeconomic status, and well-being (Bynner, 1997;

Gerardi et al., 2013; Gross et al., 2009; Hakkarainen et al., 2015; Rivera-Batiz, 1992). For these reasons, we believe it is essential to equip the citizens of the future with the necessary tools to understand and navigate the world through a mathematical lens. This dissertation aimed to assess with robust and longitudinal studies how attitudes toward math, in conjunction with cognitive factors, can influence students' math performance and their STEM choices, spanning a developmental period from primary to middle school.

Overall, our findings highlight the role of attitudes toward math in understanding the mechanisms by which they influence students' learning experiences. The results presented in this thesis carry both theoretical and practical implications. Theoretically, it has been shown that attitudes, beginning in primary school, do not operate in isolation but interact with cognitive processes, influencing students' math performance. These attitudes also have tangible implications for critical life decisions, such as STEM school choices during the crucial transition from middle to high school. Practically, the outcomes of these studies provide valuable insights for designing targeted interventions to foster positive attitudes towards math. Early intervention in affective and motivational aspects could lead to not only improved academic performance but also enhanced well-being for students, offering them fairer opportunities to succeed in math.

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