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Individual differences in basic cognitive processes and self-regulated learning: Their interaction effects on math performance

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ABSTRACT

The study analyzes the relationships between working memory capacity, executive attention, and self-regulated learning (SRL) on math performance (MP), and more specifically on items with different levels of complexity and difficulty. Sample: 575 university students (female: 47.5%; 18–25 years old), first academic year. Instruments: Attention Network Test; Automated Operation Span; Mathematics Test; On-line Motivation Questionnaire, and Learning Strategies Questionnaire. Results confirm the crucial role of individual differences in WMC that impact directly on MP, mediated by subjective competence. Affective SRL contribute significantly as mediating variables but their positive effect depends on the availability of cognitive resources. Findings partially confirmed the differential contribution of cognitive processes in the prediction of performance in complex vs difficult items. We found support for a complex pattern of interactions between cognitive processes and components of SRL model at the strategy level, in their effect on MP, and given specific item characteristics.

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1. Introduction

Self-regulated learning (SRL) is a broad construct that involves the interaction between different control systems (cognition, attention, metacognition, emotions, motivation, and volition) (Boekaerts, 2011; De Corte, Mason, Depaepe, & Verschaffel, 2011; Schunk & Zimmerman, 2008; Zimmerman & Schunk, 2011). According to the literature, self-regulation involves a set of cognitive and affective processes that share a common characteristic: the coordination of information processing and control (Heyder, Suchan, & Daum, 2004).

Although there is substantial research which has investigated the influences of: (a) working memory (e.g. Pickering, 2006); (b) attentional systems (e. g. Rueda, Posner, & Rothbart, 2004); (c) motivational and affective factors, on math performance (Seegers & Boekaerts, 1996; Pekrun, Elliot, & Maier, 2006), we have little understanding about how these cognitive and non-cognitive variables interact among themselves. The assessment of individual differences in working memory capacity (WMC) and attentional resources as micro-processes of SRL is absent from most educational psychology research (Boekaerts, 2017). The cognitive literature has pointed out that WMC could explain how different resources are available in a specific learning situations according to the student's goal(s), while another function such as executive attention (EA) could help to maintain the focus on the task (Checa & Rueda, 2011; Kane, Conway, Hambrick, & Engle, 2008; Posner, Rothbart, Sheese, & Voelker, 2014). The main research question of this study focuses on the relationships between these cognitive processes and self-regulated learning factors in their effects on math performance in general, and specifically on the effect they have in the processing and therefore the outcome for different types of items (according to their complexity and difficulty characteristics).

2. Theoretical framework

2.1. Self-regulated learning

Several SRL models have been described in the educational literature (for a recent literature review see Panadero, 2017). The present

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study is based on two interrelated models of SRL: a structural model and a dynamic model, which have been shown to successfully describe many aspects of the learning process and academic outcomes (Boekaerts, 1993, 1997, 2002a, 2006, 2007, 2011).

The structural model describes the main components that are involved in the students' self-regulation of their learning (for a graphic representation see Panadero, 2017): 1) content domain, 2) cognitive strategies, 3) cognitive regulatory strategies, 4) meta-cognitive knowledge and motivational beliefs, 5) motivation strategies, and 6) motivational regulatory strategies (Boekaerts, 1997). Each component represents a certain type of prior knowledge that can be used when necessary and they are structured around two basic mechanisms of SRL: cognitive and affective/motivational self-regulation (Panadero, 2017).

The dynamic model explains how these components of the structural model interact and how information flows depending on the main purpose that guides the self-regulation process (for a graphic representation see Boekaerts, 2011; Panadero, 2017). The dynamic "dual processing self-regulation model" states that three purposes coexist and guide self-regulated learning: (1) the students' desire to increase their knowledge and skills, (2) their wish to maintain personal well-being, and (3) their wish to protect their commitment to the learning task. The first purpose defines top-down strategies where values, needs and personal goals guide the pursuit of task goals: the student is on a mastery/growth pathway. The second purpose activates bottom-up strategies which focus on the self and thus follows a well-being pathway. The last purpose refers to the redirection of the strategies from the well-being to the mastery/growth pathway via external or internal stimulus (Boekaerts, 2011). The appraisal construct has a central role in this model, consisting of a dynamic "working model" which is constantly fed information from three sources: 1) the perception of the learning situation including the task, instructions and the context; 2) declarative and procedural knowledge, cognitive strategies and metacognitive knowledge relevant to the learning situation; and 3) the self-system involving the self-concept, values, goals, and other motivational beliefs. It is assumed that positive appraisals are triggered by a primarily positive working model, either because cognitive resources and knowledge are available or because motivational control is possible, or both (Boekaerts, 2011). Different findings have supported this hypothesis revealing that the joint effect of positive and negative task judgments influences the students' intention to learn and their experiential state (e.g. Boekaerts, 1999).

This study also focuses on cognitive strategies related to the learning strategies (LS) construct that is those which involve any thoughts or behaviors that help students to acquire new information and to integrate it with their existing knowledge (Weinstein, 1987; Weinstein & Mayer, 1986; Weinstein, Palmer, & Schulte, 1987). In addition, this work examines the role of subjective competence which refers to the belief that students hold about their own ability in relation to a specific domain (Boekaerts, 2002b). Previous research supports the strong influence of self-efficacy beliefs on mathematics performance (De Corte et al., 2011; Fast et al., 2010; Hoffman & Schraw, 2009; Kingston & Lyddy, 2013; Marcou & Philippou, 2005; Wigfield, Battle, Keller, & Eccles, 2002).

2.2. Self-regulation, working memory capacity and executive attention

Working memory (WM) plays a fundamental role in several operations of self-regulation: a) maintaining an active mental representation of self-regulatory goals and standards (Hofmann, Schmeichel, & Baddeley, 2012; Kruglanski & Kopetz, 2009; Miller & Cohen, 2001); b) exercising a top-down control in direction to the goal-relevant information and away from tempting stimulus in different cognitive tasks (Kavanagh, Andrade, & May, 2005; Knudsen, 2007; Unsworth, Schrock, & Engle, 2004); c) shielding of goals and standards from interference because of the sustained attention following a goal (Dreisbach & Haider, 2009); d) having a primary role in providing an indirect way of inhibitory control; e) participating in the suppression of ruminative thoughts (Brewin & Smart, 2005); and f) exercising down-regulation of undesirable affect and impulses, providing a mental "workspace" for emotional regulation (Wranik, Barrett, & Salovey, 2007).

WM has been conceptualized as a limited capacity system that allows the short-term representation and manipulation of information. A large body of research shows that working memory capacity (WMC) plays a key role in many areas and it is central to the understanding of complex behaviors in a variety of cognitive activities such as problem solving, reasoning and comprehension (Engle, 2002). Previous research has demonstrated that both storage and processing components of working memory predict higher-order cognitive abilities (Unsworth, Redick, Heitz, Broadway, & Engle, 2009). WMC, as is measured by complex span tasks, requires to remember some type of items which are interspersed with some type of processing task unrelated to the retention of items. It has been shown that both recall scores from the storage component, and aspects of processing (speed and accuracy) provide an index of WMC (Unsworth et al., 2009). Therefore, these studies have highlighted the multifaceted nature of complex span tasks: they refer to multiple processes that underlie higher-order cognitive abilities (Unsworth et al., 2009).

According to an "executive attention" theory of WMC, there are domain-general executive attention processes that explain individual differences in the performance in a complex span task (Kane et al., 2008). Although some theories have explained WMC and attention as closely related processes, even considering them isomorphic (Cowan, 2005; McCabe, Roediger, McDaniel, Balota, & Hambrick, 2010; Rensink, 2002), there is evidence in the literature which suggests important differences (Fougnie, 2008; Shipstead, Redick, Hicks, & Engle, 2012). Some authors have suggested that the relationships between WMC and attention depend on the stage of attention involved and the kind of information maintained in WM (Awh, Vogel, & Oh, 2006). One exhaustive review by Fougnie (2008) has found strong evidence of the functional differences between attention and storage in WM. According to Fougnie's review, attention is mostly involved in the manipulation of information in WM, but it has minimal participation in WM maintenance (Fougnie, 2008).

Executive attention refers to a system that controls interference and solves conflicts between possible responses (Fan, McCandliss, Sommer, Raz, & Posner, 2002). Although WM span differences are related to the performance in a variety of attentional tasks, the interaction between WM span and executive attention is yet unclear (Friedman & Miyake, 2004; Heitz & Engle, 2007). Redick and Engle (2006) have found high WM participants perform significantly better in the executive control network but not in the orienting or alerting networks. However, the interaction effects between different levels of WMC and executive attention in performance tasks, such as math tasks, has still not been examined. In addition, several studies have confirmed two separate, but strongly correlated factors underlying WMC: the scope and the control of attention (Shipstead et al., 2012). "Scope" refers to the amount of information maintained in working memory, while "control" is the ability to direct attention to goal-relevant information, inhibiting irrelevant information (Shipstead et al., 2012).

In order to understand how these cognitive processes are integrated in a specific task, we adopted a conceptual framework of human cognitive-architecture, the Adaptive Control of Thought-Rational (ACT-R) (Anderson, 2007; Anderson & Lebiere, 1998). ACT-R assumes all tasks engage knowledge that can be described as the set of declarative and procedural knowledge relevant to the task. Declarative knowledge involves concepts, images, facts, and sounds, and is represented in terms of knowledge units or "chunks" (Anderson, Matessa, & Lebiere, 1997). Procedural knowledge is represented by production rules that specify the operations of how to bring declarative knowledge to solve a problem (Anderson et al., 1997).

According to ACT-R theory, WM can be defined in terms of two aspects. One is the content that is being maintained (e.g., the letters in a working memory task), and the other one is the process. WM in terms of the content involves the most highly activated part of declarative nodes where the actual processing takes place. Its internal structure, as represented in the production rules, guides the sequence of cognitive activity (Anderson, Reder, & Lebiere, 1996). The process-oriented definition considers WM as "the propagation of source activation from the current goal" (Lovett, Reder, & Lebiere, 1999; p. 143). In this cognitive architecture, there is a control or goal module that "keeps track of one's current intentions in solving the problem" (Anderson, 2005, p. 314). This goal module enables disengagement from basic or immediate goals and focuses on the means (Anderson, 2005, 2007; Beaman, 2010). Conceptually, executive attention could be considered as this functional module given that it reduces the interference allowing the cognitive system to focus on the relevant information. From a methodological perspective, the activation control conditions, whether of facilitation and/or inhibition involved in the executive attention measure, represent to a large extent the functions of this goal buffer of the ACT-R theory (Anderson, 2005; Fan et al., 2002).

2.3. Item characteristics: complexity and difficulty

Various studies have investigated the relationship between some characteristics of the task and performance (e.g. Campbell, 1988; Haerem & Rau, 2007; Mangos & Steele-Johnson, 2001). Perry, Phillips, and Dowler (2004) have found that complexity of the tasks was an important predictor of the opportunities to develop and engage in self-regulated learning. There is little consensus about the features of a complex and/or difficult task (Campbell, 1988). A difficult item can be defined in terms of the probability of correct response, as represented by the difficulty parameter in item response theory (IRT) (Hambleton, Swaminathan, & Rogers, 1991). However, this probability of correct response is not necessarily related to the complexity of the item (i.e., there could be an 'easy' item which involves a 'complex' cognitive process, such as compare-and-contrast; similarly, a simple 'recall' item could be very difficult with low probability of being correctly answered). Complexity is related to the processing demands of the task in terms of the multidimensional structure underlying the item (Boekaerts, 2017). This study refers to complexity in terms of the structure of the problem, with multiple paths to a solution and potentially multiple solutions, where expertise can help but may not be sufficient, and where an uncertainty of outcome remains (Glouberman & Zimmerman, 2002; Haerem & Rau, 2007).

A model of working memory developed from the perspective of the ACT-R cognitive architecture assumes that a limited attentional resource, focused on the current goal, increases the availability of goal-relevant knowledge compared to the availability of other knowledge elements. In a complex task (with more elements connected to each goal node) the limited source activation must be spread among the goal nodes, thus decreases the amount of source activation reaching any one linked node (Lovett et al., 1999). There are individual differences in this attentional resource which have an impact on the ability to access the most important information across domains (Lovett et al., 1999).

3. Present study

The main objective of this research was to study the effects of basic cognitive processes such as working memory capacity (WMC) and executive attention (EA) on mathematics performance (MP), and the mediating effects of specific self-regulated learning factors (SRL). In addition, we extend these analyses to understand the effect of those factors on math performance given certain item characteristics such as complexity and difficulty. Specifically, we address these questions: What amount of variance in mathematics performance is explained by all the variables considered? Which is the relative importance of each predictor?

Previous studies have found significant moderate correlations between WMC and MP (Ashcraft & Kirk, 2001; Peng, Namkung, Barnes, & Sun, 2016). However, there is still a certain amount of debate regarding the relationship of WMC with executive attention in their joint –and independent- contribution to math performance (e.g. Barkley, 1998; Fernandez-Castillo & Gutiérrez-Rojas, 2009; Redick & Engle, 2006), with some authors stating that the joint impact of these cognitive factors has not been sufficiently studied in the literature (e.g., Heitz & Engle, 2007). On the one hand, we consider WMC as the active part of declarative memory and EA as the goal module which reduces the interference allowing the focusing of the activation on the relevant information. On the other hand, when students solve math tasks they have to hold, manipulate, and update information in WM (Bull & Espy, 2006), thus it is expected that math performance will demand more involvement from WM than simply the goal-relevant module (EA), including the total area of activation for solving problems (Anderson, 2005; Lovett et al., 1999). We can expect:

Hypothesis 1. WMC will show a higher contribution than EA in predicting MP.

Previous studies have emphasized a mediating role of SRL on academic performance (Dupeyrat & Marine, 2005; Fenollar, Roman, & Cuestas, 2007; Simons, Dewitte, & Lens, 2004). Based on the motivational efficiency hypothesis which predicts that self-efficacy would facilitate focused effort and strategy use, thus increasing the efficiency of problem-solving (Hoffman & Schraw, 2009), we propose the following hypothesis:

Hypothesis 2. SRL components will mediate the relationship between cognitive processes (WMC & EA) and MP.

More specifically, and considering the fundamental role of self-efficacy beliefs on mathematics performance found in the literature as a major mechanism of motivation and self-directedness (Bandura, 1991; Bandura, Barbaranelli, Caprara, & Pastorelli, 2001; Locke & Latham, 1990), we should expect:

Hypothesis 3. Subjective competence (SC) will show a higher contribution than other SRL factors in predicting MP.

Given that in a complex task (with more pathways to each goal node) the limited source activation must be spread among the goal nodes, it is expected a decrease in the amount of source activation reaching any given linked node (Lovett et al., 1999). However, difficulty is related to the probability of a correct response (independently from complexity), so a low complexity-high difficulty item would not increase the workload for the cognitive system, and WMC in particular. Instead, this type of item would only require an inhibitory control of non-relevant information to select a correct response among several options, and with particular demands on the goal-maintaining elements (Shipstead et al., 2012). Thus, the following hypotheses were proposed:

Hypothesis 4. WMC will show a higher contribution to the prediction of performance in high complexity-low difficulty items than to the prediction of low complexity-high difficulty items.

Hypothesis 5. EA will show a higher contribution to the prediction of performance in low complexity-high difficulty items than to the prediction of high complexity-low difficulty items.

If we consider that cognitive strategies and affective components of SRL increase the efficiency of problem-solving through the use of strategies and of focused effort, then a more challenging task will demand the application of effortful strategies (Boekaerts, 2007; Boekaerts, 2011; Dunlosky & Kane, 2007; Dunlosky & Thiede, 2004; Dunning & Holmes, 2014; Fredrickson & Losada, 2005; Hoffman & Schraw, 2009). Then, we propose:

Hypothesis 6. SRL will have stronger mediation effects in their prediction of performance in high complexity-low difficulty items, than in low complexity-high difficulty items.

4. Material and methods

4.1. Participants

The total sample consisted of 848 university students (Female: 51%), 18 to 25 years old ($M = 20.16$; $SD = 3.19$), attending the first year in several disciplines (psychology, engineering, medicine, law, social communication, business and marketing) from private universities. A total of 109 participants were excluded because they had lower than 80% accuracy in the interference task of the Automated Operation Span test (WMC). In addition, we excluded 164 outliers as suggested by Kline (1998): extreme skew > 3; kurtosis > 10; and according to the Mahalanobis distance criterion (AMOS 21.0). The final sample consisted of 575 students (Female: 47.5%; M *age* = 20.13; $SD = 3.22$). Based on Graffar's modified scale (Méndez-Castellano & de Méndez, 1994) 69.1% of the sample belonged to stratum II or medium-high SES, while 26.2% of the sample corresponded to a medium-low SES (stratum III), and only 4.7% belonged to low SES (stratum IV).

4.2. Instruments and measures

Table 1 summarizes the measures and instruments used:

Attention Network Test (*ANT*) (Fan et al., 2002)**.** This test measures three attentional networks: alerting, orienting, and executive attention. Participants are asked to indicate when a central arrow points left or right, via two mouse buttons (left or right, respectively). (See Fan et al., 2002 for more detailed information about this task). Reliability studies have indicated a high reliability for total reaction times (RT) (0.87). The other conditions, determined by the previously described operations with the respective RT, show the following reliabilities: the executive control network has the highest reliability (0.77), the orienting network has a moderate reliability (0.61), and the alerting network has a test-retest reliability of 0.52 (Fan et al., 2002).

Automated Operation Span (*AOSPAN*). This is a computerized version of the Ospan task that measures WMC (Unsworth, Heitz, Schrock, & Engle, 2005). The participant is asked to remember a series of letters (3–7 letters) while he/she has to solve a simple math operation (See Unsworth et al., 2005, for a more detailed information about this task). Test-retest reliability for the absolute AOSPAN score is 0.77. Reliability studies indicated relatively small practice effects on the AOSPAN and the rank-ordering of individuals was stable across test sessions (Redick et al., 2012). As reported by Redick and Engle (2006), the analyses performed were carried out using the Absolute AOSPAN score (the sum of all perfectly recalled sets) and the processing time component (reaction times to solve math operations). Although the use of partial scores has been recommended from a measurement or psychometric perspective (Conway et al., 2005), we have decided to use the absolute score span for theoretical reasons. First, based on the WMC definition and the ACT-R theory as general framework, a WMC measure should be able to focus on the active maintenance component of the information, while a second task is being processed. Second, we consider that an absolute score is more consistent with our research question about the differential effects of maintenance and executive control component on math performance. A partial recall measure would not necessarily capture the cognitive capacity of the system required by a full recall, and it would therefore blur the distinction between the processes being studied (Anderson et al., 1996; Anderson et al., 1997; Redick & Engle, 2006). In addition, a high and significant correlation was found between the absolute score and the partial score in the sample of the four cognitive groups ($r = 0.91$; $p < .001$), and from a measurement perspective, the reliability of the absolute score is satisfactory (0.77).

Other studies have used an 85% (math) accuracy criterion for the interference task. This criterion is used in order to ensure that participants do not show a trade-off between solving the operations and remembering letters (Unsworth et al., 2005), and that they are actually performing both tasks to the best of their ability, thus ensuring that the simple arithmetic operations are actually interfering and taxing their cognitive capacity, therefore obtaining an accurate measure of their WMC. In this particular study, the revised criterion of 80% correct was used as a measure of their arithmetic “accuracy”. The decision to use this slightly revised accuracy requirement was taken after an analysis of the math test in this sample of students. The math test included items from the international Trends in International Mathematics and Science Study (Garden et al., 2006) study, which were used to equate the results with international norms. These results showed that the sample population from this study was performing at a significantly lower level of ability than the international test participants in basic mathematics operations. Results from the Item Response Theory (IRT) equating method used showed that the mean ability (Theta value) for this sample was 0.66 standard deviation lower than the international sample. Given the demonstrated significantly lower level of mathematical ability of this group, and after observing that an elevated number of errors were due to true arithmetic errors and not to distractions from the interfering task (as observed and controlled by the experimenter) we decided to slightly modify the cut-off criterion in order to more accurately reflect

Table 1
Summary of conceptual variables, measures and instruments.

Conceptual variable	Measure	Instrument
Cognitive variables	Absolute Span Score: sum of all perfectly recalled sets	AOSPAN
	Reaction Time Operation (Logarithm n)	AOSPAN
	Executive attention: mean RT of all congruent flanking conditions, summed across cue types, from the mean RT of incongruent flanking conditions (lower RT indicates better efficiency of the attentional network)	Attention Network Test
Self-regulated Learning	Subjective Competence	Online Motivation Questionnaire
	Personal relevance of the task/Learning Intention	
	Task Attraction	
	Emotion-Task	
Learning Strategies	Learning Strategies	Learning Strategies Questionnaire
Math Performance	Math Score: sum of correct responses	Equated Math test (50 items from local test +15 items from TIMSS)
Math Performance by item characteristics: Complexity: cognitive domains in TIMSS Difficulty: b parameter (Item Response Theory)	High Complexity & High Difficulty items score: 24 items (ω = 0.73)	Equated Math Test
	Low Complexity & High Difficulty items score: 5 items (ω = 0.73)	
	High Complexity & Low Difficulty items score: 17 items (ω = 0.74)	
	Low Complexity & Low Difficulty items score: 16 items (ω = 0.81)	

the true effect of the interference task.

Mathematics Test. This test consisted of 65 multiple choice items with four or five options and only one correct answer (50 items were taken from a national mathematics test developed for last-year (end-of year assessment) high-school students (Cortada de Kohan & Macbeth, 2007) and 15 items were selected from disclosed items of the TIMSS test (TIMSS, 1995). The local calibration for the test was done applying a 1-parameter IRT model (difficulty parameter) centered on ability. This analysis was done in order to classify the items according to their difficulty levels, but the mathematics score was calculated based on the sum of correct responses. The items measure simple algorithms for arithmetic problems: some items required the use of percentages or proportions, decimal numbers, and a few others are algebra and geometry questions. There was no time limit to take the test, but its duration for all students was under two hours. In order to guarantee that it was not a speeded test (which would violate the IRT assumptions), it was required that > 95% of students had to be able to attempt to respond to all of the items; this number was actually much higher in the study, close to 99%.

On-line Motivation Questionnaire: The latest version of the original On-line Motivation Questionnaire, namely the OMQ91 (Boekaerts, 2002a) is a self-report questionnaire to measure student's appraisals and emotions before and after a specific task. This study only analyzed the relationships between the pre-task variables and MP. The section administered before the task (the mathematics test) included 18 items that measure three factors according to an exploratory and confirmatory factor analysis of the Spanish version (Musso, Boekaerts, & Cascallar, 2015): 1) subjective competence (seven items: $\alpha = 0.876$); 2) personal relevance/learning intention (six items; $\alpha = 0.814$); 3) task attraction (three items; $\alpha = 0.824$). In addition, one subscale regarding "task-related emotion" (four items; $\alpha = 0.666$) was included. The four-factor model showed an acceptable fit ($\chi 2 = 766.095$; $df = 164$; $p < .001$; CFI = 0.91; RMSEA = 0.06). The students complete the OMQ just before the math task and immediately afterwards. For Part 1 they were asked to respond to the questions focusing on the upcoming math test. The researcher showed examples of the kind of item types to be presented to the test-takers.

Learning Strategies Questionnaire (LASSI,Weinstein & Palmer, 2002). A validated Spanish-version of the LASSI was administered (Meza & Lazarte, 1998). It is a 77-item questionnaire grouped in 10 subscales that assesses "the students' awareness about, and use of, learning and study strategies related to skill, will, and self-regulation components of strategic learning" (Weinstein & Palmer, 2002, p. 4). This study considered the total score of the learning strategies measure, which was included in the SEM on total math performance ($\alpha = 0.827$).

Item complexity: The level of complexity classification of the items in the mathematics test involved the participation of three judges, experts in mathematics teaching and in cognitive psychology, who carried out the classification according to the pre-established categories of complexity as per the definitions of complexity by cognitive domains in TIMSS 2008 (Garden et al., 2006). Three cognitive domains were defined: Knowing, Applying and Reasoning, each one involving different behaviors. At the end of the classification process, an additional group of three expert consultants, experienced researchers in cognitive psychology and with ample mathematical background, received the complete final item set and were asked to validate the complexity categorization of each item. The inter-judge agreement was satisfactory: Spearman correlation was 0.803 and Cohen's Kappa was 0.735.

Item difficulty: refers to the probability of correct response. It was defined by the "difficulty parameter" of the IRT analysis of the math test. Table 1 shows the four types of items based on the resulting 2×2 matrix of item-characteristics (low/high levels of complexity by low/high levels of difficulty), and reliability coefficients of each math score obtained from our sample). Low and high levels were defined based on median split. All the math scores achieved an acceptable reliability considering the recommended cut-off of 0.70 (Campo-Arias & Oviedo, 2008). Reliability analyses were carried out for the math scores using the Omega-coefficient because of their dichotomic scales and the small number of items for the low complexity/high difficulty set (Elosua Oliden & Zumbo, 2008; McNeish, 2017).

Background variables: gender and socio-economic status were measured in order to control their direct and mediation effects given the evidence from previous studies (Eccles, 2009; Simpkins, Davis-Kean, & Eccles, 2006). Gender was registered and coded 1 for females and 2 for males, so that positive coefficients designate higher scores for males. Graffar's modified scale was applied to control socioeconomic variables (Méndez-Castellano & de Méndez, 1994). This method ranks 1 to 5 each of four indicators: profession of family head, maternal education level, income of main source of family, and housing conditions. Higher total scores correspond to a lower level of SES.

4.3. Procedure

Before conducting this study, institutional permission for carrying out research with human subjects was obtained after the study was reviewed by the Ethics Committee of the university. Before the administration of the instruments, informed consent was obtained from each participant following the current APA Code of Conduct guidelines (APA, 2002). Students were informed of the purpose of the research, expected duration of the session, their right to decline to participate, and to withdraw from the research once participation had begun.

All stimuli of the cognitive tasks were presented via *E*-Prime software, on an IBM-compatible personal computer running Windows 7, and presented on a 17-inch monitor, with a resolution of 1024×768. The distance between the subjects' eyes and the screen remained constant at 60 cm, for both cognitive tasks, maintaining the visual angle. All the instruments were individually administered in the same order during the first 2 h of the session, in a computer-based classroom, with a short break (15 min) between the computerized cognitive tasks and the rest of the tasks. The order was as follows: 1) ANT; 2) AOSPAN;3) a brief socio-demographic questionnaire; 4) Learning Strategies Questionnaire; 5) OMQ pre-task; 6) Math Test; and 7) OMQ post-task. Before the OMQ pre-task, the researcher explained to the students the type of questions and exercises of the mathematics task: a set of 65 multiple choice items about arithmetic problems and basic concepts of mathematics corresponding to the content at the end of the high school curriculum. All instruments were presented using individual personal computers linked to the same network but presenting the instruments at the individual pace of each student, and with individual timing of events.

4.4. Data analysis

Standard model fit indices such as the confirmatory fit index (CFI) and the root mean square error of approximation (RMSEA) were used for a series of structural equation models (SEM) to evaluate the model fit. CFI values > 0.90 and 0.95 indicate acceptable and excellent fit to the data respectively. RMSEA values between 0.06 and 0.08 are considered indicators of a good/acceptable fit, respectively (Hu & Bentler, 1999).

First, we identified the measurement model for math performance as a construct, including the four types of items, as continuous score data with a confirmatory factor analyses, using maximum likelihood (ML) estimation, with AMOS 22.0.

Second, a structural equation model was created including all the

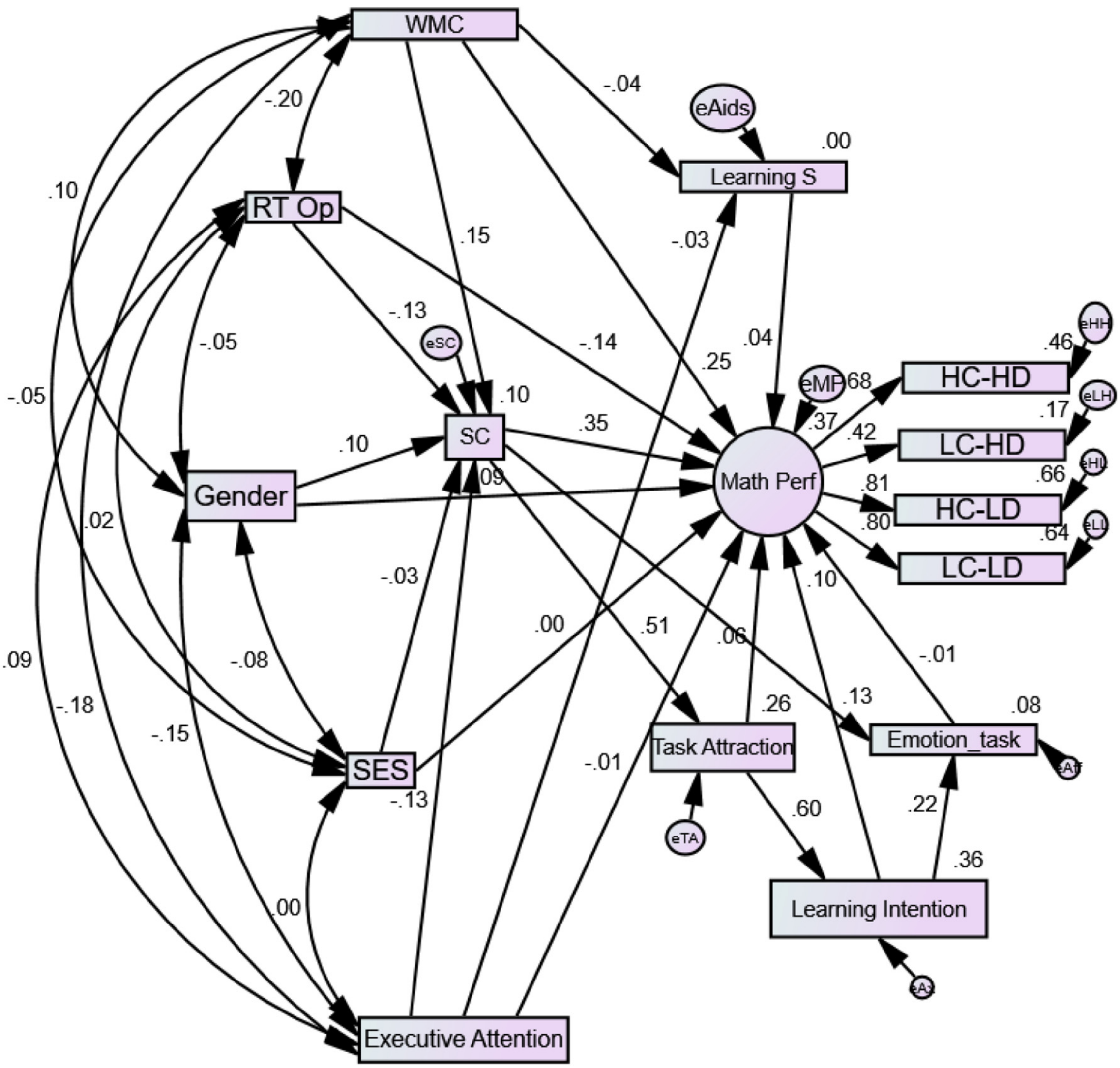

Fig. 1. Inclusive model 1 for Math Performance [indicated by High Complexity-High Difficulty (HC-HD), Low Complexity-High Difficulty (LC-HD), High Complexity-Low Difficulty (HC-LD), and Low Complexity-Low Difficulty (LC_LD)]: WMC (Working Memory Capacity), Reaction Times solving math operations (RT Op), SES (Socio-Economic Status), Executive Attention, Subjective Competence (SC), Task Attraction, Learning Strategies (Learning S), Emotion Task, Learning intention. Path coefficients are standardized.

variables to test hypotheses 1 and 2 (see Fig. 1). In addition, to test hypothesis 3 we run a nested more parsimonious model with non-significant parameters fixed to zero, and a chi-square difference test statistic was used to test if this parsimonious model fitted the data equally well.

Finally, to test hypotheses 4–6 about the differential contribution of cognitive processes and SRL on performance given complexity vs difficulty, we created another structural model with the scores of two type of items as dependent measures, based on the more parsimonious model (Fig. 2). Three items of "low complexity/high difficulty measure" were dropped out of this math measure because of their very low factor loading (<0.30), in order to run this SEM (Bacon, Sayer, & Young, 1995). The default models were compared with more restricted models in which the regression paths from subjective competence and learning intention to each type of items were set equal to each other.

The regression assumptions for linearity, homoscedasticity of residuals, and lack of outliers were met analyzing skewness and kurtosis values. The plot of the standardized predicted values of math performance with the residuals revealing a relatively random pattern of scatter, given evidence that the data do not appear to violate assumptions of linearity, normality, and homoscedasticity.

5. Results

5.1. Descriptive statistics and inter-correlations

Means, standard deviations, skewness and kurtosis for all the variables are shown in Table 2. Multivariate normality for all the models was tested and all results were satisfactory (Mardia's coefficients within critical values -1.96 to 1.96). Correlations between all variables are provided in Table 3.

5.2. Math performance measurement model

We used four scores corresponding to the four types of items to analyze the underlying math performance construct. The model showed an excellent fit ($\chi 2 = 1.501$; $df = 2$; $p > .05$; CFI = 1.00; NFI = 0.998; RMSEA = 0.000) and acceptable reliability ($\alpha = .753$).

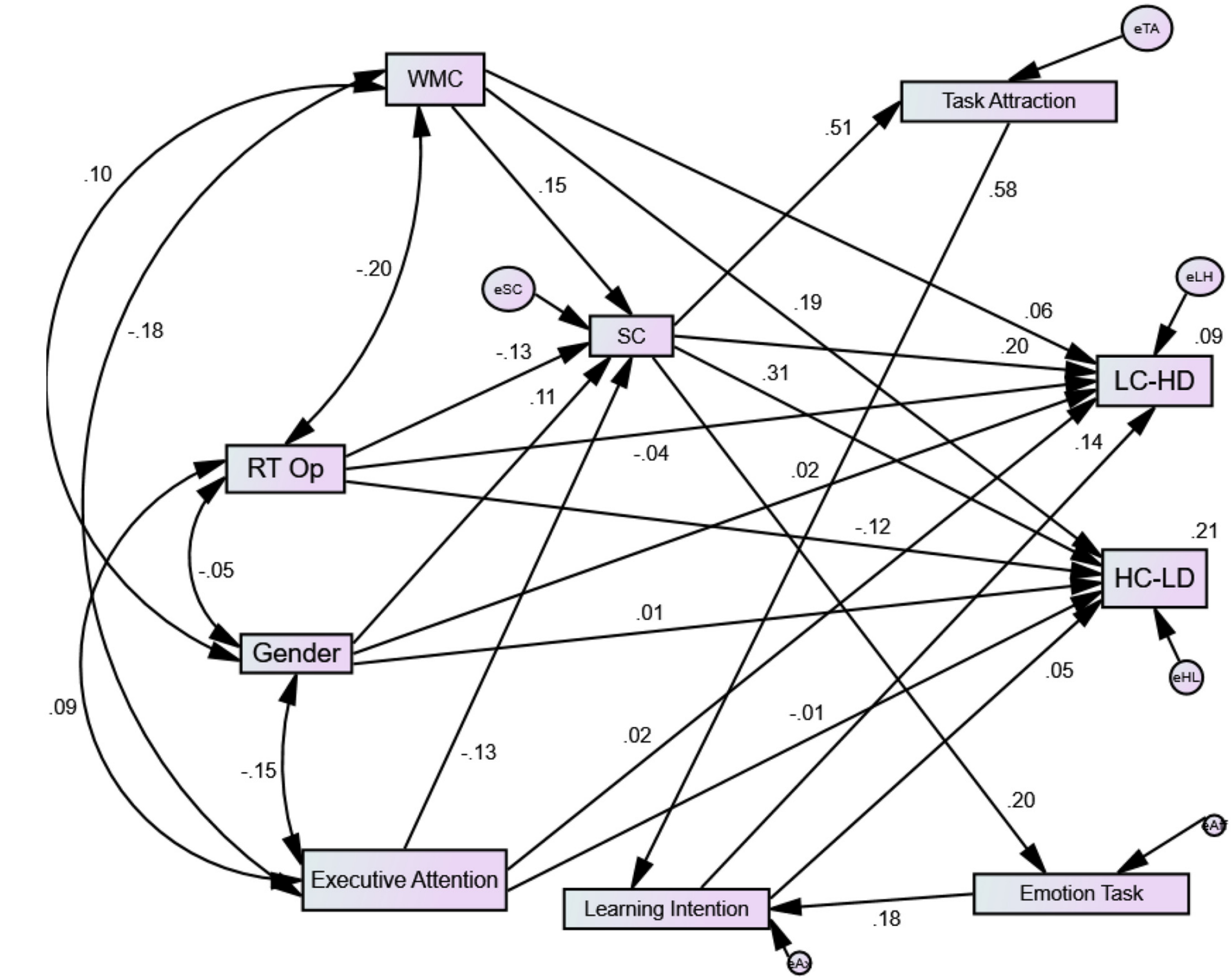

Fig. 2. Model 2: mediated model for High Complexity-Low Difficulty (HC-LD) and for Low Complexity-High Difficulty items performance (LC-HD): WMC (Working Memory Capacity), Executive Attention, Subjective Competence (SC), Learning Intention, Reaction Times (RT Op). Path coefficients are standardized.

Table 2
Means (M), standard deviations (SD), scale, skewness, and kurtosis.

Variable	M	SD	Scale	Skewness	Kurtosis
Executive Attention	97.05	27.56	RT in ms	0.50	0.25
Working Memory Capacity (WMC)	28.46	13.18	1–75	0.30	−0.47
Ln Reaction Time Operation	7.01	0.18	RT in ms	0.21	−0.15
Subjective Competence (SC)	12.35	2.75	7–28	−0.19	−0.10
Personal relevance of the task/ learning intention	16.46	3.66	6–24	−0.39	−0.24
Emotion Task	9.53	1.53	4–16	−0.82	−0.04
Task Attraction	4.44	1.48	3–12	0.21	−0.64
Learning Strategies	243.74	23.27	77–385	0.22	2.74
Math Performance	30.50	8.41	1–65	0.40	−0.27
High Complexity- Low Difficulty items	10.06	3.04	1–17	−0.01	−0.65
Low Complexity- High Difficulty items	2.44	1.38	1–8	0.45	−0.19
High Complexity- High Difficulty items	7.36	3.31	1–24	0.75	0.22
Low Complexity- Low Difficulty items	10.64	2.85	1–16	−0.34	−0.35

5.3. Structural equation model (SEM)

5.3.1. Cognitive processes & self-regulated learning on total math performance

The general model, in which no restrictions were applied, provided a good fit to the data ($\chi2 = 113.18$; $df = 56$; $p < .001$; CFI = 0.961; NFI = 0.928; RMSEA = 0.042) explaining a total of 37% of variance of math performance (see Table 4: model 1; Fig. 1). Given that SES, learning strategies, task attraction, emotion, and executive attention had no significant impact on math performance (p-values $> .05$), we compared this unconstrained model to a nested model with all these non-significant paths fixed to zero ($\chi2 = 121.823$; $df = 65$; $p < .001$; CFI = 0.961; NFI = 0.924; RMSEA = 0.039). This more parsimonious model did not fit the data worse than the general model, providing a more elegant and practical way to explain the relationships within the model ($\chi^2_{\text{diff}} = 8.64$, $df_{\text{diff}} = 9$, $p = .47$). This model shows that WMC has a significant direct effect on math performance ($\beta = 0.042$, $b = 0.25$, $SE = 0.007$, $p < .001$), but also shows that subjective competence mediates significantly this effect on math performance (indirect effect: $\beta = 0.010$, $b = 0.061$). WMC also has a significant direct effect on subjective competence ($\beta = 0.032$, $b = 0.15$, $SE = 0.009$, $p < .001$). In addition, subjective competence has a direct positive effect on math performance ($\beta = 0.283$, $b = 0.35$, $SE = 0.041$, $p < .001$).

Reaction times has a significant direct effect on total math score ($\beta = -1.735$, $b = -0.14$, $SE = 0.499$, $p < .001$) and a direct effect on

Table 3
Correlations between all variables included in the models.

Variable	1	2	3	4	5	6	7	8
1-Executive Attention	–							
2-Working Memory Capacity	−0.18***							
3- Ln RT Operation	0.047	−0.205**						
4- Subjective Competence	−0.19***	0.21***	−0.148**					
5- Task Attraction	−0.09*	0.10*	−0.041	0.51***				
6- Emotion Task	−0.002	−0.019	−0.095*	0.21***	0.14***			
7- Personal Relevance Task/Learning Intention	−0.09*	0.04	−0.006	0.35***	0.61***	0.26***		
8- Learning Strategies	−0.02	−0.04	−0.020	0.03	0.18***	0.10*	0.22***	
9- Math Performance	−0.14***	0.33***	−0.225**	0.45***	0.30***	0.10*	0.24***	0.06

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

subjective competence ($\beta = -2.024$, $b = -0.13$, $SE = 0.622$, $p < .001$). In other words, faster reaction times, better math performance. Executive attention has a direct effect on subjective competence ($\beta = -2.070$, $b = -0.13$, $SE = 0.626$, $p < .001$), and an indirect effect on math performance through SC ($\beta = -0.004$, $b = -0.055$). Thus, high executive attention students outperformed low executive attention students in math performance if they also had high subjective competence.

Gender had a direct effect on math performance ($\beta = 0.388$, $b = 0.09$, $SE = 0.177$, $p < .05$) and on subjective competence ($\beta = 0.574$, $b = 0.10$, $SE = 0.224$, $p < .01$), suggesting that males students not only achieved higher scores in math performance, but that they also self-perceive more competent in math, which leads to a higher math score.

Subjective competence has a significant direct effect on task attraction ($\beta = 0.277$, $b = 0.51$, $SE = 0.020$, $p < .001$) and task related emotion ($\beta = 0.073$, $b = 0.13$, $SE = 0.024$, $p < .01$). Task attraction has a significant direct effect on learning intention ($\beta = 0.930$, $b = 0.60$, $SE = 0.052$, $p < .001$) and in turn, learning intention on emotion ($\beta = 0.145$, $b = 0.22$, $SE = 0.028$, $p < .001$). Learning intention shows a significant positive path to math performance ($\beta = 0.099$, $b = 0.10$, $SE = 0.048$, $p < .05$).

5.3.2. Mediation model on specific item types

In order to test hypotheses about the differential contribution of cognitive processes and the mediation of SRL factors on specific type of items (high complexity/low difficulty, and low complexity/high difficulty), we run another model considering only the most significant variables (see Fig. 2). This model achieved an acceptable fit to the data ($\chi 2 = 86.687$; $df = 19$; $p < .001$; CFI = 0.917; NFI = 0.901; RMSEA = 0.079; see Table 4: Model 2). The predictors explained more variance of high complexity-low difficulty items performance ($R^2 = 0.23$) than for the performance in low complexity-high difficulty items ($R^2 = 0.08$). WMC has a significant positive direct effect on high complexity/low difficulty items, but not on low complexity/high difficulty items. Subjective competence (SC) mediates this effect contributing significantly to the explanation of the variance of high complexity/low difficulty items ($\beta = 0.310$, b = 0.28, $SE = 0.046$, $p < .001$), and SC also contributes significantly to low complexity/high difficulty items performance ($\beta = 0.089$, b = 0.21, $SE = 0.019$, $p < .001$). Learning intention has a positive significant path on both types of items (for high complexity/low difficulty items: $\beta = 0.193$, b = 0.15, $SE = 0.052$, $p < .001$; for low complexity/high difficulty items: $\beta = 0.049$, b = 0.10, $SE = 0.021$, $p < .05$). In addition, reaction times only have a significant effect on high complexity/low difficulty items performance, indicating that faster RT is important for complexity, and not for difficulty ($\beta = -2.108$, b = −0.12, $SE = 0.639$, $p < .001$). EA only has an indirect effect on both types of items through subjective competence (for high complexity/low difficulty items: $\beta = -0.005$, b = −0.043; for low complexity/high difficulty items: $\beta = -0.001$, b = −0.03). Gender impacts both scores only through the mediation of subjective competence (direct effect of gender on subjective competence: $\beta = 0.587$, b = 0.11, $SE = 0.223$, $p < .01$): males have higher subjective competence which leads to a higher math score in both item types (indirect effect for high complexity/low difficulty items: $\beta = 0.213$, b = 0.035; for low complexity/high difficulty items: $\beta = 0.060$, b = 0.02).

To test the differential contribution of SRL components on both types of items, the default model 2 was compared with more restricted models in which the regression paths from subjective competence and learning intention to both scores were set equal to each other, separately (see Table 4: constrained model 2 SC & constrained model LI). Chi-square (χ^2) differences test showed significantly worse model fit for both restricted models. In line with hypothesis 6, SRL components

Table 4
Model fit indices and results of nested model comparisons.

	Fit indices				Model comparison		
	χ 2	*df*	RMSEA [CI]	CFI	*df*	ΔCMIN	*p*
Model 1: Total Math	113.18**	56	0.042 [0.031, 0.053]	0.961			
Parsimonious model	116.81**	61	0.040 [0.029, 0.051]	0.962	5	3.631	0.60
Model 2: Complexity- Difficulty	86.687***	19	0.079 [0.062, 0.096]	0.917			
Constrained SC	106.533***	20	0.087 [0.071, 0.103]	0.894	1	19.846	0.001
Constrained LI	93.155***	20	0.080 [0.064, 0.097]	0.910	1	6.468	0.01

Note. $N = 575$. RMSEA = root mean square error of approximation with 90% confidence interval (CI) in brackets; CFI = comparative fit index. RMSEA ≤0.06 and CFI ≥ 0.95 represent a good model fit (Hu & Bentler, 1999), whereas RMSEA ≤0.08, SRMR ≤0.10, and CFI ≥ 0.90 still indicate an acceptable fit (Browne & Cudeck, 1993; Hu & Bentler, 1999).
Constrained SC: Regression paths from Subjective Competence (SC) to High Complexity- Low Difficulty Items and to Low Complexity-High Difficulty Items were set equal to each other; Constrained LI: Regression paths from Learning Intention (LI) to High Complexity- Low Difficulty Items and to Low Complexity-High Difficulty Items were set equal to each other.
*** $p < .001$.

contributed significantly more in the prediction of performance in high complexity-low difficulty items, than in low complexity-high difficulty items.

6. Discussion

6.1. Cognitive processes on math performance

The general objective of this research was to understand the relationships between basic cognitive processes and self-regulated learning factors in their impact on mathematics performance, and to examine these effects more specifically given certain characteristics of the items (complexity and difficulty). In line with our hypothesis 1 and previous studies, WMC contributed more substantially to the prediction of math performance, supporting the crucial role of WMC in math performance (e.g. Engle & Kane, 2004; Passolunghi & Pazzaglia, 2004, in Pickering, 2006; Peng et al., 2016). One recent meta-analysis of 110 studies has also found a significant moderate correlation between WM and mathematics performance ($r = 0.35$) (Peng et al., 2016). However, in addition to the replication of those findings, our results show that WMC impacts directly and independently of executive attention and subjective competence, and that it shows a greater contribution than EA to the prediction of math performance. This differential contribution can be explained if we consider that WMC has a central role in maintaining relevant information, goals and standards, and in the retrieval of previous information from inactive memory (Shipstead, Harrison, & Engle, 2016) while executive attention network is responsible for interference control (Fan et al., 2002). According to recent findings focusing on the mental processes that account for the correlation among different tests (Shipstead et al., 2016), an operational definition of WMC emphasizes more its role in the maintenance of active information, rather than in the disengagement process from irrelevant information (Engle, 2018). Executive attention, on the other hand, measured through a flanker task, would have a greater role in the mechanism of disengagement from irrelevant information than that of the maintenance of activation. From the ACT-R theory perspective, and avoiding the central control problem, the interference control provided by executive attention could be understood as a mechanism that collaborates in the maintenance of active relevant information for the goal (taking place in WM), arising from a network which is constantly updated by input modules (and constantly disengaging irrelevant information through executive attention processes), without the need to assume a central executive (Logie, 2016; Nijboer, Borst, van Rijn, & Taatgen, 2014; Parra, Della Sala, Logie, & Morcom, 2014).

Processing time (reaction times) as a main component of WMC also provides a unique contribution to the prediction of math performance, over and above what was accounted for by the storage component. This finding is consistent with previous studies (Blair & Li, 2011; Unsworth et al., 2009). In line with these previous studies and with several theories of WMC (e.g. Friedman & Miyake, 2004, Daneman & Carpenter, 1980), results of the present study regarding the negative correlation between processing time and recall, suggest that students who process math operations faster tend to remember more words than students who are slower in processing math operations. These theories have pointed out that storage and processing components compete for a limited resource (Daneman & Carpenter, 1980). Other hypothesis suggests that if less time is consumed by the processing activity, the items will have less opportunity to be forgotten and more time for rehearsal processes (Towse, Hitch, & Hutton, 1998). At the same time, these students have better math performance, but the processing time component doesn't fully mediate the relationship between storage/recall and math performance, in line with previous studies (Unsworth et al., 2009).

6.2. SRL as mediators on MP

Regarding the second hypothesis, a mediated model involving cognitive processes, gender, affective and cognitive SRL components before the task (subjective competence, relevance of the task, task attraction, emotional factors, and learning strategies), explained 37% of the variance in math performance. In line with our hypothesis 2, the main contribution of SRL factors is provided by subjective competence: higher SC contributes to the achievement of better results in math performance. This result is consistent with the self-efficacy literature and the social cognitive theory which considers SC as a central cognitive mechanism that explains motivation and self-directedness (Bandura, 1991; Locke & Latham, 1990). Efficacy beliefs shape the basis on which students decide how much effort to invest in a task, how long to persevere when facing difficulties, and what challenges to undertake (Bandura, 1991; Locke & Latham, 1990). "Those who have a strong belief in their capabilities redouble their efforts and try to figure out better ways to master the challenges." (Bandura, 1999; p. 49). Previous research supports the strong influence of self-efficacy beliefs on mathematics performance (Fast et al., 2010; Marcou & Philippou, 2005; Pajares & Graham, 1999). Fast et al. (2010) have found a pattern of effects where students with higher levels of math self-efficacy achieve higher scores in math performance. Moreover, Kingston and Lyddy (2013) obtained similar results for proportional reasoning in a numeracy task, suggesting that "self-efficacy explained a significant proportion of the variance in performance above and beyond the effects of short-term memory" (Kingston & Lyddy, 2013, p. 185).

WMC and processing time had a very basic role impacting directly on math performance, independently of subjective competence. In addition, both WMC and processing time were mediated by subjective competence. On the other hand, EA was almost fully mediated by this motivational belief. Bell and Kozlowski (2002) have also found significant interactions between goal orientation and abilities, suggesting that learning orientation would be of help only to high ability individuals. Results from PISA 2012 regarding the positive impact of perseverance only on high performance students in complex problem-solving tasks (OECD, 2013), are also in line with our results.

Although other affective components related to the appraisal of the task (a task perceived as interesting, and self-confidence/at ease emotions) do not contribute significantly to the prediction of math performance, the general model shows that they participate in a positive (or negative) representation of the learning situation. This is in line with some studies which have found that being attracted by the content of a domain predicts the enrollment and the attendance in courses in that domain better than success in the course (Harackiewicz, Barron, Tauer, Carter, & Elliot, 2000; Wigfield et al., 2002). Students are more willing to work hard on more interesting and affectively rewarding learning tasks (Frenzel, Pekrun, & Goetz, 2007). According to our results, a student with high cognitive resources and high subjective competence is more likely to feel attraction to the task and would feel able to cope with it. This attraction, in turn, promotes a positive attitude towards the task and then, a learning intention which contributes to a better math performance. In line with the Model of Adaptable Learning (Boekaerts & Niemivirta, 2000), the students' appraisals of a learning situation impact on their goal setting (learning intention) and their goal striving (learning vs coping strategies), through a fast processing. The goals are based on fast interpretations which can be focused on the task or on themselves. If students self-perceive with less competence, they will focus on negative self-related and motivational beliefs. Therefore, this primary appraisal maps onto goal striving, which is oriented towards restoring well-being, impacting negatively on performance. Given the limited nature of cognitive resources, it is expected that those students with low WMC will deplete their source activation decreasing math performance.

In addition, this result lends support to the hypothesis that emotions are interpreted as a signal that the students either had or did not have enough resources to do the task (Boekaerts, 2007, 2011; Fredrickson & Losada, 2005). Positive or negative feelings may combine with cognitive information to regulate the management and allocation of effort (Boekaerts, 2011). If students who feel anxious when trying to cope with a math task would re-focus on different and more efficient strategies to control this negative emotion they would bring into play their own cognitive abilities, thus reinforcing a growth pathway instead of a well-being pathway. Our findings emphasize the importance of individual differences in cognitive processing capacity for the explanation of differences in the efficiency of emotional regulation on math performance.

Gender differences found in the present results suggest that male students outperform female students in math performance and that this effect is not fully mediated by motivational beliefs, as previous studies have shown (e.g. Guo, Marsh, Parker, Morin, & Yeung, 2015). This relative independence could be explained if we consider the significant -but weak- correlation between gender and WMC, on the one hand, and gender-executive attention on the other hand: male students tend to recall more items and have higher executive attention (faster reaction times). If we consider both direct and mediated effects of gender on math performance, findings also indicate that male students not only achieved higher scores in math performance, but that they also self-perceive more competent in math, which leads to a higher math score. However, the evidence in the literature is controversial regarding gender differences in the relationships between self-efficacy, SES, and educational outcomes across different cultures (Guo et al., 2015; Schoon & Polek, 2011; Watt et al., 2012).

No evidence has been found regarding the mediating role of learning strategies, unlike what was reported by previous research (Dupeyrat & Marine, 2005; Fenollar et al., 2007; Simons et al., 2004). This could be a measurement problem: the self-report learning strategies scale used asks for the reporting of decontextualized behaviors applied on academic studies in general, while the other self-regulated learning components refer to the specific math task used in the study.

6.3. Mediation model by item characteristics

Regarding the effects of cognitive and non-cognitive factors on math performance given certain item characteristics, we found that WMC is a key resource required in high complexity/low difficulty items. These items have high probability of being answered correctly, but they demand greater level of reasoning operations, such as: analyzing, generalizing, integrating, justifying information, and solving non-routine problems. A large body of literature provides supporting evidence for WMC playing a crucial role in these complex cognitive behaviors (e.g. Engle, 2002; Hofmann et al., 2012). According to a WMC model within the ACT-R cognitive architecture, complex items would add interference impairing the retrieval of goal-relevant information by a limited attentional resource which is spread more thinly (Lovett et al., 1999). However, EA has no effect either on high complexity/low difficulty or on high difficulty/low complexity items. Difficult items demand recall, recognition, computation and/or retrieval but they have a lower probability of being answered correctly (independently of their level of complexity). The performance in these items would be explained by other factors which we have not controlled in this study, such as prior knowledge or a long-term memory factor, rather than WMC and executive attention (EA).

Differential effects of WMC and EA on complexity vs difficulty, as item characteristics, have important implications for the measurement of performance in the context of Item Response Theory (IRT) models. If the complexity of items is not carefully controlled during test construction according to the cognitive processes involved, a new hidden dimension could be introduced, not completely explained by difficulty (or discrimination), which would violate the unidimensionality assumption of commonly used Item Response Theory (IRT) models.

The present study also finds a significant additional relationship between cognitive processes and subjective competence, not just on the overall performance in the math task, but also when taking into account certain item characteristics. Subjective competence mediates the effects between both storage and processing time components of WMC and high complexity/low difficulty items performance. Hoffman and Schraw (2009) have found that self-efficacy was beneficial when demands on working memory increase. Self-efficacy seems to increase the problem-solving efficiency of the cognitive system through strategic performance. These authors explained the results following the motivational efficiency hypothesis which predicts that self-efficacy would facilitate focused effort and strategy use, thus increasing the efficiency of problem-solving (Hoffman & Scharaw, 2009). However, self-regulation mechanisms and executive attention share the same available cognitive resource pool for processing, requiring flexibility to modify our thoughts and behaviors (Ilkowska & Engle, 2010; Schmeichel, 2007). This assumption leads to the expectation that there will be a depletion of the cognitive resources when the student performs a task under a high cognitive load condition and in demanding social situations (Ilkowska & Engle, 2010). Therefore, when the resources are limited and below a certain threshold, the positive effect of self-efficacy would not be able to manifest itself. These results can also be explained in terms of the greater efficiency of WMC as a result of better strategy use (McNamara & Scott, 2001). Another hypothesis related to "strategy-as-effect" suggests that a high WMC enables students to produce and apply effortful strategies when performing a complex task (Dunlosky & Kane, 2007; Dunlosky & Thiede, 2004; Dunning & Holmes, 2014). Further research is needed to evaluate this last hypothesis.

6.4. Educational implications

The focus of this study has been the interrelationships between constructs derived from two relatively independent research areas (e.g., Metcalfe & Shimamura, 1994; Fernandez-Duque, Baird, & Posner, 2000). On the one hand, metacognition, learning strategies, and motivation, from the educational psychology literature, based on more naturalistic tasks and self-report data. On the other hand, WMC and executive attention which originate from cognitive and neuroscience research, experimental in nature, and more interested in the cognitive processes and their links to certain brain areas, using an information processing approach (Fernandez-Duque et al., 2000). The findings regarding the relative independency of WMC and EA could have important implications for more targeted interventions training specific strategies on math performance.

For educational practice, as many previous studies have found, it is important to notice that subjective competence has proven to be the most important variable to explain achievement in math. Task attraction and positive emotion related to the task increase when students trust in their own abilities in a specific domain. Therefore, teachers should be aware of students' cognitive processing capacity (WMC and EA in a domain) and give feedback according to these cognitive differences in order to increase the students' sense of self-efficacy for specific tasks. The intervention should include a reinforcement of positive motivational beliefs and the awareness of own goals, taking into consideration individual differences in cognitive resources (especially differences in WMC). In particular, task complexity which is influenced by individual differences in cognitive resources, should be taken into account in the design of targeted intervention programs.

6.5. Limitations

It is important to consider some limitations regarding the self-report measures used for SRL. Specifically, cognitive components related to learning strategies involved the recall of learning episodes in various undefined school-subject areas and not for a specific domain. Future research should select instruments that measure metacognitive regulation related to the demands of math problem solving, preferably on-line. In addition, additional studies should also consider the students' use of metacognitive strategies.

7. Conclusion

The results of this study confirm the crucial role of individual differences in WMC for both metacognitive regulation and metacognitive knowledge applied to math performance at a functional processing level. WMC impacts directly on math performance, mediated by positive appraisals, specifically a positive subjective competence assessment. Moreover, the effect of motivational/affective variables depends on the availability of WMC and executive attention resources. The interaction effects between motivational or cognitive components of SRL at a strategic level, emerge from the processing capacity of the cognitive system. Furthermore, results also partially confirmed our hypotheses about the differential contribution of WMC and executive attention in the prediction of complexity vs difficulty effects in item performance.

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