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The Relationship between Intelligence, Working Memory, Academic Self-Esteem, and Academic
Achievement

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Abstract

Academic achievement is crucial for life and long-term outcomes. The aim of the present study is to examine the joint role of cognitive (intelligence and working memory) and non-cognitive (academic self-esteem) factors in predicting academic achievement (mathematics and reading literacy) in a sample of Italian sixth and eighth graders. The results showed that within the cognitive factors considered, intelligence was the best predictor of achievement. As regards to non-cognitive factors, academic self-esteem was effective at predicting achievement after controlling for cognitive measures. Academic self-esteem was also found to have an indirect effect, mediated by intelligence, on academic achievement. Both theoretical and practical implications of the present results are discussed.

Keywords: intelligence (*g*); achievement; working memory; academic self-esteem; children

Research Highlights

- Achievement and intelligence are closely related but are two distinct constructs.
- Intelligence was the best predictor of academic achievement, not working memory.
- Academic self-esteem explained a unique portion of the variance in achievement.
- Academic self-esteem had an indirect effect on achievement, mediated by intelligence.

The Relationship between Intelligence, Working Memory, Academic Self-Esteem and Academic Achievement

Academic achievement reflects the capacity to attain learning goals included in the school curricula and is related to important outcomes. There is increasing evidence that the capacity to solve typical scholastic problems (e.g., in mathematics and reading) can predict future outcomes such as educational (Fischbach, Keller, Preckel, & Brunner, 2013) or academic ones (Coyle & Pillow, 2008). The fact that achievement is strongly related to life outcomes is not surprising; in fact, academic achievement tests involve intelligence, extensive reasoning and problem-solving capacity (Hunt, 2011). It should also be noted that other factors, non-cognitive in-nature, are related to academic achievement (e.g., Heckman & Rubinstein, 2001; Valentine, DuBois, & Cooper, 2004; Weber, Lu, Shi, & Spinath, 2013).

Within the cognitive factors, working memory has been shown to predict academic achievement. Working memory (WM) is a limited-capacity system that enables information to be temporarily stored and manipulated (Baddeley, 2000). A large body of research has shown that WM predicts achievement outcomes. Working memory is involved in complex cognitive tasks (Kane, Hambrick, & Conway, 2005) such as reading comprehension (Borella & de Ribaupierre, 2014), arithmetic problem-solving (Passolunghi & Mammarella, 2012; Rasmussen & Bisanz, 2005), mental calculations (Caviola, Mammarella, Cornoldi, & Lucangeli, 2012; Mammarella et al., 2013), magnitude representation (van Dijck & Fias, 2011), geometrical problem solving (Giofrè, Mammarella, & Cornoldi, 2014; Giofrè, Mammarella, Ronconi, & Cornoldi, 2013), and general mathematical achievement (Bull, Espy, & Wiebe, 2008; Passolunghi, Mammarella, & Altoè, 2008).

In addition to WM, intelligence has been found to predict valuable academic and work outcomes (Deary, Strand, Smith, & Fernandes, 2007; Gottfredson, 1997; Schmidt & Hunter, 2004). In fact, intelligence tests were traditionally developed to predict school performance (Binet & Simon, 1905). Intelligence tests, along with achievement tests, also require abilities such as abstract reasoning and problem-solving. Based on these commonalities, it was suggested that achievement

tests do not merely measure achievement, but also general cognitive abilities (i.e., intelligence) (Frey & Detterman, 2004; Lynn & Mikk, 2007). Results of international achievement examinations and values of intelligence, at a national level, were found to be very highly related (Hunt & Wittmann, 2008; Lynn & Mikk, 2007). Based on these premises, it was proposed that academic achievement tests are in fact intelligence tests (Rindermann, 2007). This topic has generated a harsh debate. On the one side, if achievement measures are identical to intelligence then differences in achievement (e.g., in the PISA) can be considered differences in intelligence (Lynn, 2010; Rindermann, 2007). In contrast, other scholars hold the view that the use of achievement as a proxy of intelligence is questionable as these two concepts are distinguishable (Cornoldi, Belacchi, Giofrè, Martini, & Tressoldi, 2010; Kaufman, Reynolds, Liu, Kaufman, & McGrew, 2012).

In addition, intelligence and WM appear to be strongly related and there is a large debate on whether these two constructs are distinguishable or not (Kane et al., 2005). However, despite the strong relationship between these two constructs, there is evidence indicating that they are, at least in part, independent in children (Gignac & Watkins, 2015; Giofrè, Mammarella, & Cornoldi, 2013), in young adults (Engle, Tuholski, Laughlin, & Conway, 1999; Unsworth & Engle, 2007), and in older adults (de Ribaupierre & Lecerf, 2006). Working memory and intelligence also have a different predictive power on academic achievement. In certain domains, for instance, WM predicts performance over and above intelligence, for example, in literacy and numeracy (Alloway & Alloway, 2010) or in mathematics skills (Passolunghi, Vercelloni, & Schadee, 2007).

In addition to cognitive factors, such as WM and intelligence, non-cognitive factors were found to be related to academic achievement. A large body of research has supported, for example, the implicit theory that motivation and other personal skills, along with intelligence, can have an impact on academic performances (Diseth, Meland, & Bredablik, 2014; Dweck, 1999; Hong, Chiu, Dweck, & Sacks, 1997; Huang, 2011; Valentine, Dubois, & Cooper, 2004) and on school-work-related performances (Stajkovic & Luthans, 1998). Among various non-cognitive variables, a positive effect of self-esteem on achievement explaining 4–7% of the variance (Hansford & Hattie,

1982) was found in a meta-analysis across more than two hundred studies. In the present study, we were interested in academic self-esteem, which has been found to be strongly related to academic achievement (e.g., Diseth et al., 2014). In particular, academic self-esteem was shown to be strongly related both to reading (Piran, 2014) and to mathematics literacy (Levpuscek, Zupancic, & Socan, 2012). The effect of academic self-esteem was found to be significant even when controlling for other variables (e.g., Duckworth & Seligman, 2005). Nevertheless, there is also evidence indicating that academic self-esteem is unrelated to achievement (Baumeister, Campbell, Krueger, & Vohs, 2003, 2005).

Very few studies have examined the role of both cognitive and non-cognitive factors on academic achievement. The main aim of the present study was thus to examine the joint role of cognitive (i.e., intelligence and working memory) and non-cognitive (i.e., academic self-esteem) skills on academic achievement in sixth and eighth graders. There is, in fact, a host of research looking at the effects of both cognitive (Kaya, Juntune, & Stough, 2015) and non-cognitive factors (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013) on academic achievement. However, very few studies tested the joint role of all these factors on academic achievement by examining their relationship at the latent level (e.g., using structural equation modeling) (e.g., Lu, Weber, Spinath, & Shi, 2011; Pérez, Costa, & Corbí, 2012).

In order to reach our aim, we first evaluated the relationship between intelligence and academic achievement. In fact, it seems of particular interest to study whether academic achievement can be used as a proxy of intelligence or not, as presented before. Confirmatory factor analyses were also performed to determine the structure for WM, intelligence and achievement. As for WM, we tested different models: a single model (Pascual-Leone, 1970), a domain-specific factors model (Shah & Miyake, 1996), and the tripartite models (Baddeley & Hitch, 1974). As for intelligence, we tested a unique factor model (Spearman, 1904) and a model distinguishing between fluid and crystallized intelligence (Horn & Cattell, 1966). Alternative models were also examined to determine whether intelligence and achievement were distinguishable (Rindermann, 2007). Finally,

the joint role of cognitive factors (i.e., intelligence and working memory) and non-cognitive factors (i.e., academic self-esteem) on academic achievement was examined. As previously mentioned, academic self-esteem was found to be strongly related to achievement (Diseth et al., 2014; Marsh & Craven, 2006). However, few studies were able to prove the incremental effect of non-cognitive variables on academic achievement (e.g., Duckworth & Seligman, 2012). In fact, the effect of non-cognitive variables on academic achievement, after controlling for other cognitive factors, was found to be negligible and not statistically significant in other studies (Lu et al., 2011; Spinath, Spinath, Harlaar, & Plomin, 2006).

Method

Participants

One hundred sixty-nine children in sixth grade and eighth grade participated in the study. We selected these age-groups because intelligence seems to be relatively stable from this age on, as confirmed by the fact that the IQ at 11 years predicts intelligence at 90 years of age (Deary, Pattie, & Starr, 2013). A second reason for choosing participants at these ages was because, starting in the ninth grade, children are introduced to secondary education, which has different curricula (such as scientific, professional or classical schools) in Italy, making the recruitment process more complex. Children with clinical diagnoses and that belonged to disadvantaged sociocultural or linguistic groups were not included in the study. Unfortunately, ten children were absent in at least one session and they were excluded from the analysis. A total of 159 children (87 male and 72 female, $M_{\text{age}} = 11.87$ years, $SD = 1.09$) in sixth grade ($n = 95$, Females = 44%) and eighth grade ($n = 64$, Females = 46%) were included in the final sample. The children—from families of middle socioeconomic status—were attending schools in the urban area of Veneto (a North-East Italian region). The children were tested from January to May in four sessions.

Instruments

Working memory.

Word span (WS-F, -Forward, and WS-B, -Backward). These tasks examined short-term memory abilities involving the passive storage and recall of information (Cornoldi & Vecchi, 2003). Words were presented verbally at a rate of 1 item per second, proceeding from the shortest series to the longest (from 2 to 8 items). There was no time limit for recalling the words in the same forward order or in the backward order (the Cronbach's alphas calculated for the present report were .75 and .64 for the forward and backward versions, respectively). The score was the number of words accurately recalled in the correct order.

Matrices span (MS-F, -Forward, and MS-B, -Backward). These tasks measured visuospatial short-term memory (Cornoldi & Vecchi, 2003). The children had to memorise and recall the positions of black cells that appeared briefly (for 1 second) in different positions on the screen. After a series of black cells had been presented, the children used the mouse to click on the locations where they had seen a black cell appear. The number of cells presented in each series ranged from 2 to 8. The target appeared and disappeared in a visible (4×4) grid in the centre of the screen. There was no time limit for recalling the cells in the same, forward order or in the backward order (the Cronbach's alphas were .79 and .76 for the forward and backward version, respectively). The score was the number of cells accurately reproduced in the right order.

Dual tasks (DT-V, verbal, and DT-VS). These two tasks required a concurrent manipulation of the stimuli presented, and they were more demanding, compared to short-term memory tasks in terms of cognitive control; therefore, they can be considered measures of WM (Engle, 2010). The DT-V material consisted of a number of word lists containing four words of high-medium frequency presented in an auditory manner. The word lists were organised into sets containing word lists of different length (i.e., from 2 to 6 words to recall). The children were asked to press the space bar when there was an animal noun. After completing each set, they had to recall the last word in each list, in the right order of presentation. This task - adapted from the Categorization WM span by

De Beni, Palladino, Pazzaglia, and Cornoldi, (1998) – showed adequate psychometric properties (Cronbach's alpha = .69) and a good predictive power (Giofrè, Mammarella, & Cornoldi, 2013). In the DT-VS, a series of positions in two-dimensional 4×4 matrices, comprising 16 empty cells, were centred on the screen. Seven out of the sixteen cells were always coloured in grey while the others were coloured in white. The task was organised into sets of three cells in which a black dot appeared and disappeared on the grid. In each set, the children had to press the spacebar if the dot was presented on a grey cell and at the same time had to remember the last position of the dot (i.e., the third position for each set). The number of to-be-remembered dots varied from 2 to 6. This task was adapted from Mammarella and Cornoldi (2005) (Cronbach's Alpha = .82). The score was the number of cells/words accurately reproduced in the right order.

Intelligence.

Cattell Culture Fair Intelligence Test (Cattell & Cattell, 1981). The task consisted of four timed subtests (series completion, odd-one-out, matrices and topology) with items of increasing difficulties within each subtest. The test consists of a total of 46 multiple-choice items (Cronbach's alpha = .66). The score was the sum of correct answers.

Primary Mental Abilities – Spatial (PMA-S; Thurstone & Thurstone, 1963). In this task, the subject was required to find out, among six different rotated figures, figures that are exactly alike: figures that were rotated but mirrored. The test consisted of 20 trials with two or more correct alternatives for each (Cronbach's alpha = .89). The difference between correct and incorrect responses was measured.

Primary Mental Abilities – Verbal (PMA-V; Thurstone & Thurstone, 1963). In this paper-pencil test, the children had to choose a synonym for a given word from among four options, e.g. small: (a) slow, (b) cold, (c) simple and (d) tiny (the answer is tiny). There was only one correct answer. The test included 50 items and had to be completed within 4 minutes. The score was the sum of the correct answers (Cronbach's alpha = .85). The score was the sum of the correct answers.

Primary Mental Abilities – Reasoning (PMA-R; Thurstone & Thurstone, 1963). In this paper-pencil test, the child had to complete a sequence of letters, choosing among various alternatives which letter logically completed the series, e.g., abm, cdm, efm and ghm (the answer is “i”). The test included 30 items and had to be completed within 5 minutes (Cronbach’s alpha = .85). The score was the sum of the correct answers.

Achievement.

Mathematics literacy (INVALSI, 2011). For each grade, we used the appropriated version of the INVALSI test. The INVALSI test is divided into four areas of measuring: space and figures (MAT-SF), which involves problems on bi- or tri- dimensional solids or other tasks mainly related to geometrical aspects; numbers (MAT-N), which measures number fractions and other mathematics elements; relations and functions (MAT-RF), which require solving problems including equivalence or algebraic expressions such as $y=ax$, $y=a/x$ or $y=x^2$; and data and previsions (MAT-DP), which require calculating the probability of an event, or means, medians, frequencies and other statistical properties. The task consisted of 31 questions with 49 items for children in the sixth grade and 25 questions with 46 items for children in the eighth grade. The test lasted 75 minutes (Cronbach’s alpha = .84 for the sixth and .85 for the eighth grade).

Reading literacy (INVALSI, 2011). The INVALSI included two types of tasks: reading comprehension or grammar. Concerning reading comprehension (READ-RC), children are presented with two or three written texts, in which they have to answer to various multiple choices or open answers. Concerning the grammar (READ-G), children are requested to answer orthographical, morphological and lexical questions about the Italian language. The task consisted of 45 questions for children in the sixth grade (36 on reading comprehension and 9 on grammar) and 49 questions in the eighth grade (38 on reading comprehension and 11 on grammar).

To make the result comparable, we used the proportion of correct response as suggested by the INVALSI statistical team (4 June 2015, personal communication). The test lasted 75 minutes (Cronbach’s alpha = .87 for the sixth and .88 for the eighth grade).

Academic Self-esteem.

Multidimensional Test of Self-Esteem (Bracken, 2003). A single subscale was employed: academic self-esteem (ACAD-SE). This self-report scale aimed to evaluate children's feelings about themselves within the school context or in relation to achievement. The subscale consisted of 25 likert positive and negative items in which the participants were asked to rate their agreement with a 4-point scale (from absolutely true to absolutely false). Total scores were obtained following the instruction in the original manual (Bracken, 2003) (Cronbach's alpha = .87).

Procedure

The selection of the tasks was based on agreements with the schools participating in the study. In particular, the tasks were administered as part of a broad study on the relationship between cognitive, non-cognitive, and academic achievement factors. The children were tested in different phases: (a) a group session in their classroom that lasted approximately 1 h, in which intelligence and self-esteem measures were assessed, (b) an individual session in a quiet room away from the classroom lasting approximately 60 min, in which WM was assessed, and (c) two group sessions, in which we assessed academic achievement. It is worth noting that we followed the instruction required by the INVALSI protocol, having an external investigator and a teacher always present during the examination minimising cheating or other problems.

During the first group session, the intelligence tests and the academic self-esteem questionnaire were administered in a fixed order (Cattell, PMA-V, PMA-S, PMA-R, and Academic Self-Esteem). During the individual sessions, the WM tasks were also administered in a fixed order as follows: (1) WS-F; (2) DT-VS; (3) WS-B; (4) MS-F; (5) DT-V; (6) MS-B. During the individual sessions, all the tasks were programmed using the E-prime 2 software and presented on a 15-inch touchscreen laptop. Each task began with two training trials followed by the simplest level of the task, and the complexity then gradually increased thereafter, using two trials for each level of complexity. The partial credit score was used for scoring purposes (Giofrè & Mammarella, 2014).

Results

Descriptive Statistics

Table 1 shows zero-order and partial correlations (controlling for age), as well as mean and standard deviations obtained by children. The measure of multivariate kurtosis was under one, which is considered relatively small, so the estimation method that we chose (maximum likelihood) is robust against several types of violation of the multivariate normality assumption (Bollen, 1989). The R programme (version 3.1.3; R Core Team, 2014) with the “lavaan” library (version 0.5-18; Rosseel, 2012) was used. Model fit was assessed using various indexes according to the criteria suggested by Hu and Bentler (1999). We considered the chi-square (χ^2), the comparative fit index (CFI), the non-normed fit index (NNFI), the standardised root mean square residual (SRMR), and the root mean square error of approximation (RMSEA); the chi-square difference ($\Delta\chi^2$), and the Akaike information criterion (AIC) were also used to compare the fit of alternative models (Kline, 2011).

Table 1 about here

Preliminary Analysis

Separated correlation analyses were initially performed for 6th and 8th grade children. However, correlation matrices were very similar in the two groups. This result is consistent with the developmental literature, in which these children are often considered together (Demetriou et al., 2013, 2014). Further, the partial correlation matrix controlling for age, was very similar to the zero-order correlation matrix, confirming that age effects were modest (Table 1). For all these reasons, and to increase the statistical power of our analyses, we decided to consider together 6th and 8th graders.

We used structural equation modelling to examine the relationship between WM, intelligence, academic self-esteem and academic achievement. We tested different theoretical frameworks to account for the role of cognitive and non-cognitive factors on academic achievement. To this end, we used a cascade approach - largely used in the developmental

literature (Demetriou et al., 2013, 2014; Giofrè, Mammarella, & Cornoldi, 2013) - in which intelligence is mediating the relationship between WM and achievement. As for academic self-esteem, measured by only one indicator, we fixed the residual factor using the formula 1 - Reliability (Kline, 2011). We first ran a series of Confirmatory Factor Analyses (CFA) to determine the best-fitting models of WM, intelligence, and achievement. All these analysis are provided in the online appendix (Model 1-6).

The Structure of Intelligence, WM, and Achievement

Having established the factorial structure of WM, intelligence and achievement (see models 1-6 in the Appendix), the next step was to investigate the relationship between these factors, including a measure of academic self-esteem. We used a two-step modeling approach (Kline, 2011). In the first step, we estimated a CFA measurement model testing the relationship between all factors (Model 7). In subsequent models, we first investigated the relationship between WM, *g*, and achievement factors (Models 8a, 8b, and 9) and only later on - having established the best factorial solution - we investigated the effect of academic self-esteem (Model 10 and following).

Model 7 was a baseline CFA model to study the links between all the factors. As shown in Table 3, the relation between the factors ranged from moderate to strong, being higher between WM, intelligence, and achievement measures.

In Model 8a, we only included WM, *g* and achievement factors. In this model both the *g*-factor and WM predicted the performance on mathematics and reading factors (i.e., were exogenous variables) (e.g., Alloway & Alloway, 2010) (Figure 1). Not surprisingly, the correlation between WM and *g* was very high. The model was reorganized assuming that the relationship between WM and achievement factors was mediated by *g* but the direct effects of WM on the achievement factors (Model 8b) were also maintained (Figure 1). The two models had the same fit and differ only on a theoretical level. However, this latter model (8b), in

which a cascade approach was used, was theoretically sound and efficiently used in previous studies (e.g., Demetriou et al., 2013, 2014; Giofrè et al., 2014; Giofrè, Mammarella, & Cornoldi, 2013). For these reasons, model 8b was used in all subsequent analyses. In both models, the parameters from g to the mathematics and reading factors exceeded 1, and the parameters from WM to mathematics and reading literacy were negative and not significant. For this reason, in the next model, we excluded the direct link from the WM to the mathematics and reading factors, assuming that the relation with the achievement factors was fully mediated by the g -factor (e.g., Demetriou et al., 2013, 2014; Giofrè et al., 2014; Giofrè, Mammarella, & Cornoldi, 2013).

In Model 9, we investigated the relationship between g and achievement factors excluding the direct link from WM to achievement (Figure 1). This model implies that WM is not explaining a portion of the academic achievement variance above and beyond intelligence (Rohde & Thompson, 2007). In this model, all the parameters were significant, and intelligence, measured by the g -factor, had significant and large effects on achievement, which were stronger in the case of mathematics ($\beta = .85$) compared to the reading factors ($\beta = .75$).

In Model 10, we included a direct link from academic self-esteem to the mathematics and the reading factors. This model is coherent with the observation that academic self-esteem is explaining a portion of the academic achievement variance but not independently from intelligence (e.g., Lu et al., 2011; Spinath et al., 2006). In this model, academic self-esteem and WM were considered as exogenous factors (Figure 1). All links were significant. The fit indices were higher compared to previous models. This model was also significantly better compared to the previous one (i.e., Model 9; see Table 2).

In Model 11, we tested whether the link from academic self-esteem and the other factors was also mediated by the g -factor, by including a link from academic self-esteem to g . This model included direct and indirect effects of academic self-esteem on academic

achievement through intelligence (Figure 2). This model implies that academic self-esteem is explaining academic achievement over and above intelligence (e.g., Duckworth & Seligman, 2005). The model was statically better compared to the previous one (Table 2). We also calculated both indirect and total effects of self-esteem on mathematic (indirect effect $\beta = .155, p = .033$; and overall effect $\beta = .317, p < .001$), and on reading (indirect effect $\beta = .118, p = .033$; and overall effect $\beta = .588, p < .001$). In this model, the portion of variance explained in achievement was high overall, explaining 70% and 69% of the variance in mathematics and in reading, respectively.

Figure 1 and 2 about here

Discussion

On the one hand, the effect of intelligence on academic achievement has been well documented; alternatively, the role of WM on academic achievement has been noted as well; further, the role of self-esteem, between the non-cognitive factors, was also considered in different studies. Nevertheless, few studies have simultaneously evaluated the role all of these cognitive and non-cognitive factors on academic achievement in children.

Before discussing the contribution of intelligence, WM and self-esteem on academic achievement, we firstly analyzed the structure of the different factors considered. As for WM, the classical tripartite model with an STM-V, an STM-VS and a WM (Baddeley & Hitch, 1974) was superior compared to both the unitary (or single WM) (Pascual-Leone, 1970) and modality-dependent (Shah & Miyake, 1996) models. This result is important because we confirmed the superiority of the classical three-factor model in children using a different set of tasks compared to previous studies (Gathercole et al., 2004; Giofrè, Mammarella, & Cornoldi, 2013). Moreover, in line with the developmental literature, we found that intelligence and WM were very highly related but distinguishable and that they only shared about 60% of the variance (Gignac & Watkins, 2015; Giofrè, Mammarella, & Cornoldi, 2013). We operationalized intelligence as a single factor. In fact, the correlation between the

fluid and crystallized intelligence factors was very high, making impossible to distinguish between these two factors. This is in line with evidence indicating that *gF* and *gC* are hardly distinguishable in young children (e.g., Giofrè, Mammarella, & Cornoldi, 2013).

Subsequently, we investigated the relationship intelligence has with mathematics and reading literacy. As for the relationship between intelligence and achievement, we found that, as expected, achievement and intelligence were very closely related but distinguishable. Overall, these findings, in line with the literature (Deary et al., 2007), indicated that, although highly related, academic achievement and intelligence are not identical, meaning that other factors can be related to one of them, but not necessarily to the other.

We found that only intelligence was significantly related to achievement and mediated the relationship between achievement and WM. The fact that the effect of WM on achievement was indirect and mediated by intelligence is not surprising. While WM, over and above intelligence, is linked to important outcomes in the early stages of development (Alloway & Alloway, 2010; Giofrè et al., 2014), in older children, such as the ones considered in the present research, intelligence takes over in explaining these aspects (Demetriou et al., 2013, 2014). We can speculate that in older children WM alone is not powerful enough to explain achievement; this is also because academic curricula require additional skills such as knowledge, reasoning and problem-solving. Our results are consistent with previous studies of young adults, indicating that intelligence can predict achievement (both mathematics and reading literacy) above and beyond the effect of WM (Rohde & Thompson, 2007).

We find out that achievement does not uniquely rely on cognitive factors but also depends on other non-cognitive factors. First, we confirmed that cognitive factors are important in academic achievement, and this is in line with a large body of literature (e.g., Deary et al., 2007; Hunt & Wittmann, 2008). Second, we investigated both WM and intelligence at the latent level, which allowed us to increase their predictive power on both

reading and mathematical achievement. Finally, we found that cognitive variables alone do not fully explain academic achievement and that other non-cognitive variables are involved; in fact, we found that academic self-esteem is related to reading and mathematical literacy.

These findings have important theoretical implications. Concerning the theories of intelligence, we found that achievement and intelligence are not the same and should not be considered as identical (e.g., Kaufman et al., 2012). Our results are in line with the idea that intelligence is fundamental in achievement and is also in line with other findings indicating that intelligence can predict achievement, but the opposite is not necessarily true (Watkins, Lei, & Canivez, 2007). Of course, it cannot be denied that some aspects of achievement are closely related to intelligence. Our findings are in keeping with a large body of research indicating that mathematics literacy is strongly related to intelligence and that intelligence also is a significant predictor of reading literacy variance (Rajchert, Żułtak, & Smulczyk, 2014). In agreement with previous evidence (Deary et al., 2007), we found that mathematics is more strongly related to intelligence, compared to other achievement measures such as reading literacy. However, although a conspicuous portion of the variance in academic achievement can be attributed to intelligence, there is a large contingent of unexplained variance, which may, in part, indicate errors in measurement, but also reflect real differences between these constructs (Deary et al., 2007; Jensen, 1998). This finding is further confirmed by the fact that achievement tests are sometimes even more important than intelligence, for example in explaining academic success (Coyle & Pillow, 2008). Notably, academic success does not only depend on cognitive capacities but also on other non-cognitive skills, such as academic self-esteem (Diseth et al., 2014; Marsh & Craven, 2006).

The fact that achievement and intelligence are not identical is also confirmed by the relationship between achievement measures and non-cognitive skills. One of these skills is academic self-esteem, which has been tested in the present study, confirming previous findings indicating that academic self-esteem uniquely explains achievement beyond the

effect of other variables (e.g., Duckworth & Seligman, 2012). In line with previous evidence, we found that the relationship between academic self-esteem is stronger in reading literacy compared to mathematics literacy, while the opposite is true for intelligence (Weber et al., 2013). This is particularly interesting because we also confirmed the result of Weber and co-authors (2013) using a different set of tasks, objective measures for assessing academic achievement, and a completely different sample. A possible explanation for this finding might be that mathematical literacy depends on the *g*-factor to a greater extent (Deary et al., 2007). We can speculate that reading literacy – being less dependent on the *g*-factor - can be influenced by other factors, particularly by contextual factors (e.g., academic self-esteem), as our results seem to indicate. However, further research is needed in order to clarify this finding.

In the present paper, we found that academic self-esteem was directly and indirectly related to academic achievement. Many previous studies focused on the incremental validity of academic self-esteem and on the direct effect on academic achievement. However, we believe that indirect effects are also noteworthy. We found a positive association between intelligence and academic self-esteem. In fact, we found that academic self-esteem also had an indirect effect on academic achievement mediated by intelligence. It can be hypothesized that individuals with higher cognitive abilities also tend to have higher levels of academic self-esteem, which in turn lead to higher achievements. As for reading literacy, the effects of academic self-esteem are stronger and quite stable at different levels of the *g*-factor. In fact, students with high levels of academic self-esteem outperform children with much higher levels of the *g*-factor in reading literacy. The effects of academic self-esteem are smaller, but statistically significant, on mathematical literacy and in fact at equal levels of the *g*-factor, children with higher academic self-esteem outperform children with lower levels of academic self-esteem.

The fact that academic self-esteem is predicting a portion of academic achievement above intelligence is in line with other evidence (e.g., Duckworth & Seligman, 2005). However, in the present paper, we also tried to overcome the limitations of previous studies. Firstly, we investigated the joint role of these constructs on achievement at the latent level. In fact, the percentage of explained variance in achievement was quite high in our research. In addition, unlike previous studies (e.g., Duckworth & Seligman, 2005), we used objective measures - and not an evaluation provided by the teachers (e.g., GPA, or grade point average), which may be influenced by personality and other non-cognitive factors – to gauge academic achievement. Finally, we differentiated between reading and mathematical literacy, which allowed us to investigate the different contributions of intelligence and academic self-esteem within these two constructs.

Though it contains some insightful findings, the present study also has some limitations that should be addressed by future studies. Further research is needed to understand the reciprocal influence during cognitive development of WM, intelligence, academic self-esteem, and academic achievement. For example, we found that academic self-esteem may have more of an impact on children's achievement than cognitive factors. Since there is evidence indicating a reciprocal effect between academic self-esteem and achievement (Marsh & O'Mara, 2008), it will be of a particular interest to study the longitudinal interaction between these factors. For example, it has been suggested that the magnitude of the correlation between intelligence and academic achievement is highest in primary school and lower thereafter (Jensen, 1980). In fact, we believe that non-cognitive factors can progressively impact children's performance in achievement independently from his/her basic cognitive capacities, and this can explain—at least in part—the decrement in the prediction of intelligence test on achievement. In addition, we only measured academic self-esteem, while other factors (both protective and risk factors) can have an impact on achievement. Concerning protective factors, resilience (Hanson, Austin, & Lee-Bayha, 2003)

and emotional intelligence (Parker, Summerfeldt, Hogan, & Majeski, 2004) seem to be significantly related to achievement. For example, a measure of resilience was able to predict achievement over the course of three years while also controlling for other aspects (Scales, Benson, Roehlkepartain, Sesma, & van Dulmen, 2006), while academic success was strongly associated with several dimensions of emotional intelligence (Parker, Creque, et al., 2004). As for risk factors, there is abundant evidence that anxiety can impair performance during achievement tasks both in reading (Carroll & Iles, 2006; Carroll, Maughan, Goodman, & Meltzer, 2005) and in mathematics literacy (Devine, Fawcett, Szűcs, & Dowker, 2012; Hill et al., 2016). Importantly, there is also evidence that academic self-esteem can mediate the relationship between anxiety and achievement (Ahmed, Minnaert, Kuyper, & van der Werf, 2012). For these reasons, future research should address this point, for example including all of these measures in the same model and testing direct and indirect relationships among resilience, anxiety and academic achievement. In fact, we believe that the results of our study, which are based only on a limited number of participants and measures, should be validated by other studies on a larger sample that includes more measures. Despite these limitations, the results of the present study have important implications.

In conclusion, the present study, which tests the joint role of cognitive (i.e., intelligence and working memory) and non-cognitive (i.e., academic self-esteem) factors on academic achievement, offers several important theoretical insights; it shows that i) academic achievement is explained in large part by intelligence, and in fact WM is only indirectly related to academic achievement, and ii) self-esteem can influence achievement above the effects of WM and Intelligence. Practical implications can also be drawn from our findings by suggesting that, although intelligence (measured by the *g*-factor) can predict achievement, the use of achievement tests as proxies of intelligence have some important limitations. Although our findings cannot support a causal relationship between the construct of interest, it can be speculated that improving academic self-esteem could lead to positive benefit on both

mathematical and reading in all children, but more evidence is needed to support and confirm this conclusion.

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INTELLIGENCE, WM, SELF-ESTEEM & ACADEMIC ACHIEVEMENT

Table 1

Correlations, means (M), and standard deviations (SD), for all children

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
01. WS-F	–	.377	.227	.199	.418	.258	.135	.174	.275	.240	.241	.138	.168	.289	.163	.250	.151
02. WS-B	.380	–	.221	.252	.282	.195	.184	.134	.144	.226	.120	.230	.253	.270	.315	.224	.225
03. MS-F	.232	.237	–	.568	.345	.385	.454	.183	.210	.215	.234	.346	.311	.363	.242	.186	.211
04. MS-B	.205	.267	.583	–	.355	.378	.433	.192	.308	.203	.227	.355	.314	.334	.305	.220	.145
05. DT-V	.419	.297	.370	.379	–	.363	.376	.252	.342	.251	.379	.311	.329	.353	.325	.281	.154
06. DT-VS	.262	.206	.400	.393	.379	–	.329	.167	.219	.141	.177	.280	.174	.268	.160	.123	.228
07. Cattell	.135	.182	.445	.425	.367	.325	–	.271	.396	.359	.420	.452	.460	.413	.421	.272	.165
08. PMA-S	.181	.162	.231	.239	.299	.199	.255	–	.297	.332	.202	.171	.138	.084	.092	.168	.069
09. PMA-R	.277	.149	.217	.313	.346	.224	.395	.300	–	.301	.405	.459	.439	.382	.364	.362	.232
10. PMA-V	.244	.241	.242	.230	.280	.161	.352	.368	.306	–	.312	.406	.295	.368	.465	.464	.306
11. MAT-SF	.224	.092	.183	.177	.317	.143	.411	.117	.382	.259	–	.569	.480	.512	.354	.315	.253
12. MAT-N	.131	.216	.318	.327	.281	.262	.450	.128	.449	.377	.575	–	.601	.602	.410	.377	.296
13. MAT-RF	.174	.275	.354	.357	.375	.209	.425	.242	.428	.338	.352	.515	–	.539	.490	.392	.254
14. MAT-DP	.280	.251	.327	.300	.315	.246	.410	.035	.370	.333	.525	.608	.444	–	.406	.379	.286
15. LIT-RC	.157	.299	.217	.279	.296	.145	.419	.054	.356	.435	.366	.417	.413	.414	–	.534	.446
16. LIT-G	.223	.179	.118	.150	.200	.077	.261	.055	.327	.379	.359	.389	.233	.399	.538	–	.391
17. ACAD-SE	.137	.196	.164	.101	.105	.194	.162	-.002	.214	.256	.286	.310	.153	.306	.456	.426	–
M	31.27	36.35	47.03	42.63	21.63	18.62	35.11	22.01	14.32	14.87	42.4	38.76	39.22	43.2	57.84	63.14	68.48
SD	8.26	5.96	10.08	10.88	6.13	9.08	4.81	11.38	5.83	5.91	18.43	20.02	19.86	22.6	16.25	20.3	9.57

Note. All coefficients $\geq .16$ are significant at .05 level. Zero order below and partial correlations (partialling out for age) above the diagonal. WS-F = Word Span Forward, WS-B = Word Span Backward, MS-F = Matrix Span Forward, MS-B = Matrix Span Backward, DT-V = Dual Task Verbal, DT-VS = Dual Task VisuoSpatial, PMA -S = - Spatial, PMA-R = Primary Mental Abilities – Reasoning, PMA-V = Primary Mental Abilities, Verbal, -SF = Space and Figures, -N = Numbers, -RF =relations and functions, DP = data and previsions, RC = reading comprehension, G = Grammar; ACAD-SE = Academic self-esteem

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Table 2

Fit indices for different CFA and SEM overall models

	$\chi^2(df)$	$\Delta\chi^2(\Delta df)^{(mc)}$	<i>p</i>	<i>RMSEA</i>	<i>SRMR</i>	<i>CFI</i>	<i>NNFI</i>	<i>AIC</i>
<u>Overall Models</u>								
(7) Baseline model (CFA)	143.12(99)	--	--	.053	.058	.945	.925	19753
(8) WM & g on math & read	199.2(113)	--	--	.069	.098	.893	.872	19782
(9) Only g on math & read	203.9(115)	4.62(2) ⁽⁸⁾	.099	.070	.099	.890	.870	19782
(10) Self-est. on math & read	165.0(113)	38.89(2) ⁽⁹⁾	.000	.054	.080	.936	.923	19747
(11) Self-est. on g	160.3(112)	4.68(1) ⁽¹⁰⁾	.031	.052	.072	.940	.927	19744

Note. χ^2 = chi-square, *RMSEA*=root mean square error of approximation, *SMSR*=standardized root mean square residuals, *CFI*=comparative fit index, *NNFI*=non-normed fit index, *AIC*=Akaike information criterion.

.000 means that the value is zero when approximated to the third decimal.

^{mc} = model comparison

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Table 3

Factor loadings and inter-factor correlation for the measurement model

Factor loading matrix							
	STM-V	STM-VS	WM	g-Factor	Math	Read.	Self-est.
01. WS-F	.66*						
02. WS-B	.58*						
03. MS-F		.76*					
04. MS-B		.77*					
05. DT-V			.68*				
06. DT-VS			.56*				
07. Catt				.70*			
08. PMA-S				.35*			
09. PMA-R				.56*			
10. PMA-V				.61*			
11. MAT-SF					.68*		
12. MAT-N					.81*		
13. MAT-RF					.63*		
14. MAT-DP					.74*		
15. READ-C						.78*	
16. READ-G						.69*	
17. Self-Est.							1 ^F
Inter-factor correlation matrix							
STM-V	1						
STM-VS	.490*	1					
WM	.803*	.795*	1				
g-Factor	.523*	.699*	.790*	1			
Math	.439*	.528*	.598*	.830*	1		
Reading	.459*	.357*	.431*	.743*	.706*	1	
Self-esteem	.281*	.186	.240*	.322*	.404*	.642*	1

Note. WS-F = Word Span Forward, WS-B = Word Span Backward, MS-F = Matrix Span Forward, MS-B = Matrix Span Backward, DT-V = Dual Task Verbal, DT-VS = Dual Task VisuoSpatial, PMA -S = - Spatial, PMA-R = Primary Mental Abilities – Reasoning, PMA-V = Primary Mental Abilities, Verbal, -SF = Space and Figures, -N = Numbers, -RF =relations and functions, DP = data and previsions, RC = reading comprehension, G = Grammar, Math = Mathematics literacy, Reading = Reading literacy.

* $p < .05$,

^F=Fixed.

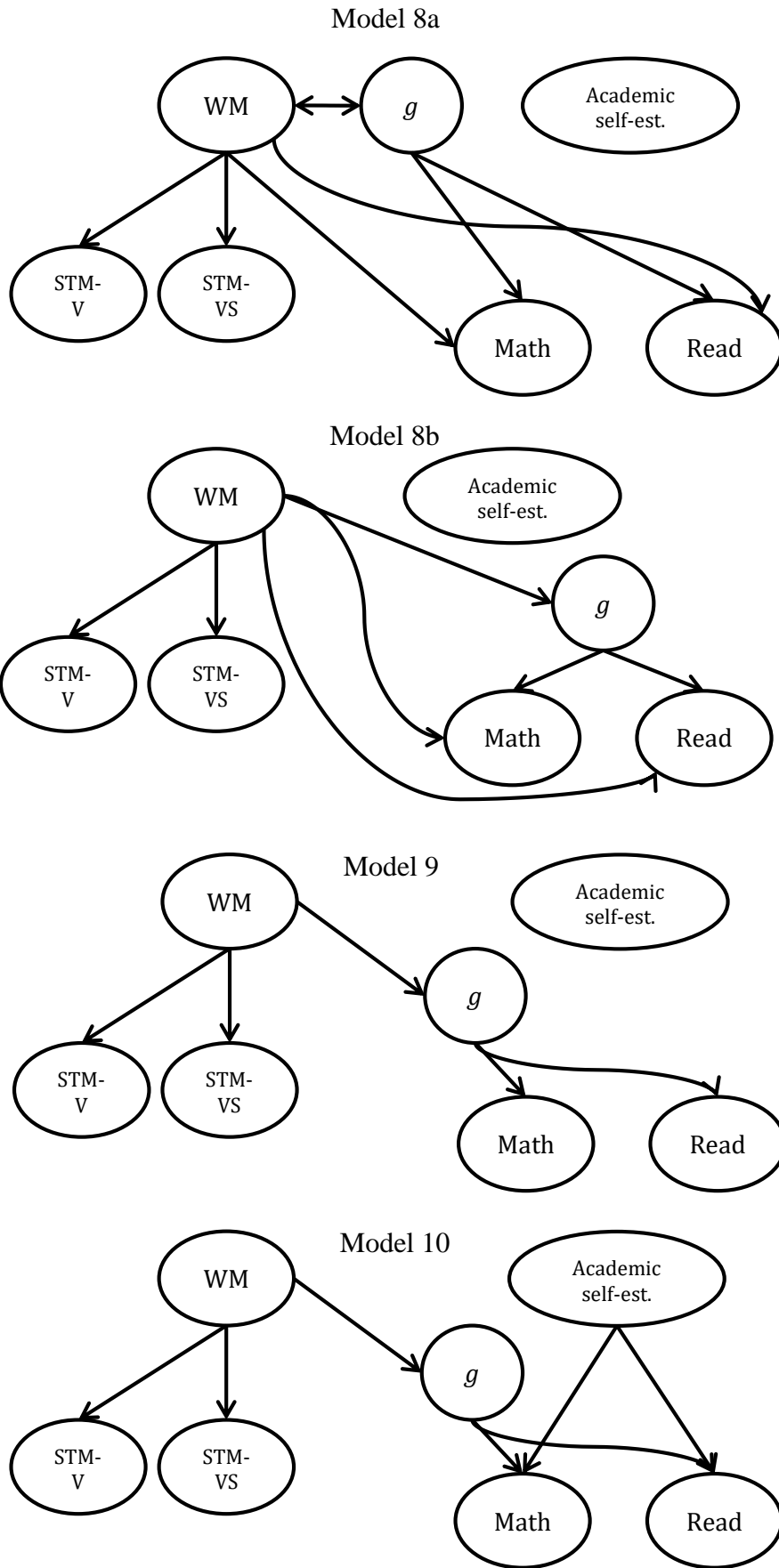


Figure 1. Conceptual diagrams Models 8-10

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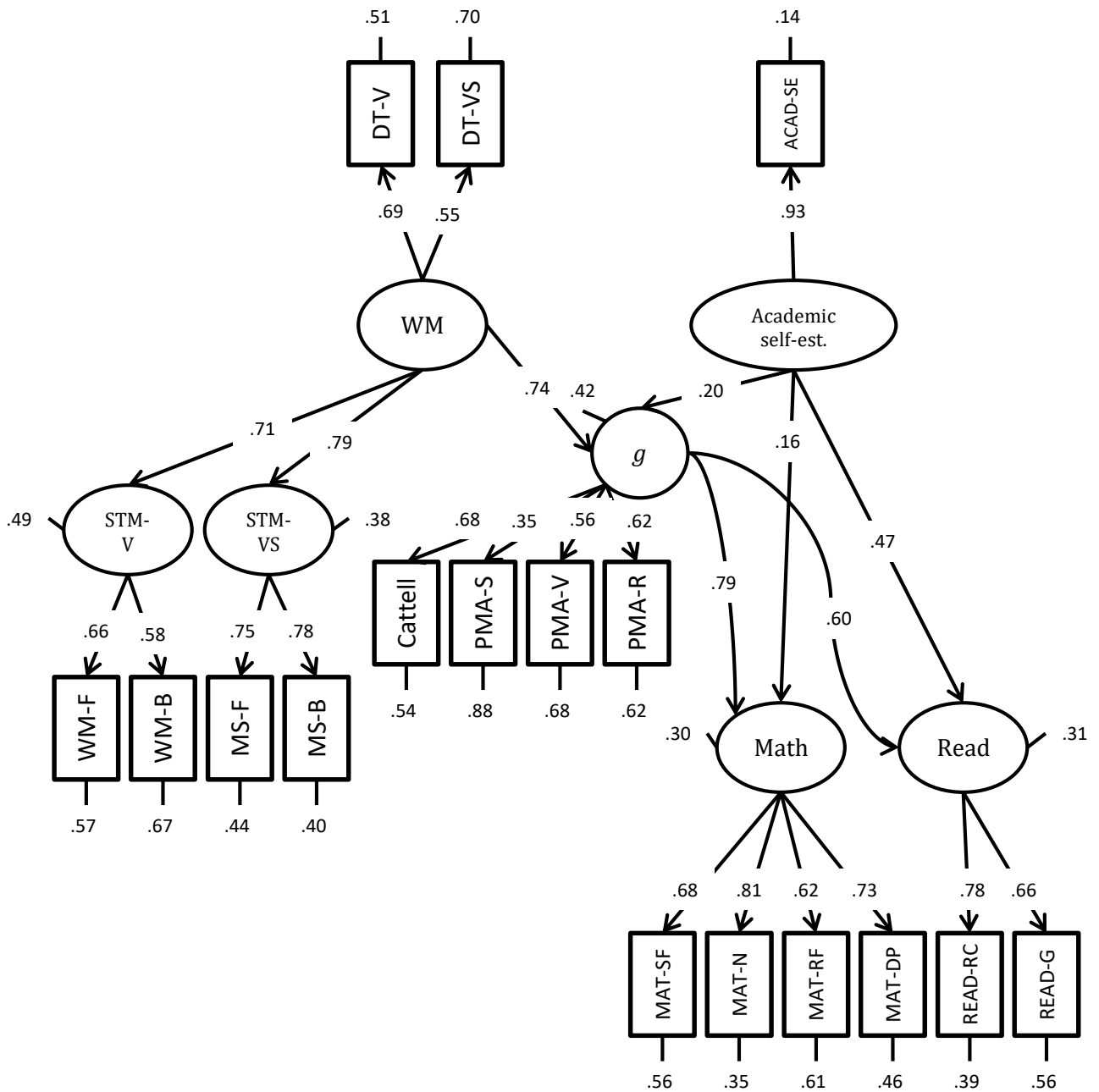


Figure 2. Model 11. All paths are statistically significant with $p < .05$. WS-F = Word Span Forward, WS-B = Word Span Backward, MS-F = Matrix Span Forward, MS-B = Matrix Span Backward, DT-V = Dual Task Verbal, DT-VS = Dual Task VisuoSpatial, PMA -S = - Spatial, PMA-R = Primary Mental Abilities – Reasoning, PMA-V = Primary Mental Abilities, Verbal, -SF = Space and Figures, -N = Numbers, -RF =relations and functions, DP = data and previsions, RC = reading comprehension, G = Grammar, Math = Mathematics literacy, Reading = Reading literacy.

Appendix.

In this section a series of Confirmatory Factor Analyses (CFA) are reported, aiming to determine the best-fitting models of WM, intelligence, and achievement. We first ran a series of Confirmatory Factor Analyses (CFA) to determine the best-fitting intelligence, WM, and achievement models. In the tripartite model (or three-factor model) of WM initially proposed by Baddeley and Hitch (1974), the central executive is the component responsible for controlling resources and monitoring information processing across informational domains, while the storage of information is mediated by two domain-specific slave systems, e.g., the phonological loop, which handles the temporary storage of verbal information, and the visuospatial sketchpad, which specialises in retaining and manipulating visual and spatial representations (Baddeley, 1996). Notably, the three-factor model was met with strong support when applied to young adults and children (Gathercole et al., 2004; Giofrè, Mammarella, & Cornoldi, 2013). However, an alternative approach (i.e., the modality-dependent model) assumes that WM is supported by two separate sets of domain-specific resources for handling verbal and visuospatial information (Shah & Miyake, 1996). Further, other authors have argued that short-term memory (STM) and WM are hardly distinguishable suggesting a unitary model of WM (Pascual-Leone, 1970).

Model 1 investigated a single WM factor (Pascual-Leone, 1970), and it proved a poor fit for the data (Table A1; Figure 1).

Model 2 investigated two distinct verbal (measured by word span forward and backward and dual-task verbal) and visuospatial factors (measured by matrix span forward and backward and dual-task spatial) (Shah & Miyake, 1996). This model proved a better fit for the data (Table A1; Figure A1).

Model 3 investigated the classical tripartite model (Baddeley, & Hitch, 1974) with an STM-V component (measured by word-span forward and backward), an STM-VS component

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(measured by matrix-span forward and backward) and a WM component (measured by dual-task verbal and spatial) (Figure A1). Model 3 presented a better fit for the data (Table A1; Figure A1) and was retained because having a lower AIC compared to previous models (Kline, 2011).

Having found the best-fitting model for WM, we decided to go further and test various models for intelligence. In the intelligence literature fluid intelligence (gF), which is supposed to be independent from culture, and crystallized intelligence (gC), which is supposed to highly rely on the culture and instruction, factors are often contrasted (Horn & Cattell, 1966). We tested two models: i) Model 4a, which was a unique model with four indicators (Figure A1)(Spearman, 1904); and ii) Model 4b, in which we distinguished between gF (measured by PMA Spatial and Cattell) and gC (measured by PMA reasoning and verbal) (Figure A1). We found a good fit for Model 4a, while the other model (4b) did not converge because the correlation between the two factors exceeded one. In fact, fixing the latent correlation between gF and gC to 1 the model converged to an admissible solution, but the model was statistically equivalent to Model 4a and was therefore rejected.

Since intelligence and achievement are in many cases treated as identical, in one model we did not differentiate between intelligence and achievement (Rindermann, 2007) (Model 5; Figure A1), and in a different model we distinguished intelligence from the reading and mathematics factors (Weber et al., 2013) (Model 6; Figure A1). We also preliminary tested two different models to assess achievement—one in which the achievement was considered as a single factor without a distinction between reading and mathematics factors, and a model distinguishing between reading and mathematics. The model distinguishing between the two topics provided a good fit, $\chi^2(8) = 9.90$, $p = .272$, $RMSEA = .039$, $SRMR = .029$, $CFI = 994$, $NNFI = .988$, and statistically better when compared to the single-factor model, $\Delta\chi^2(1) = 20.56$, $p < .001$.

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In Model 5, the single-factor model of *g*-factor including intelligence measures (i.e., Cattell, PMA-S, PMA-V, PMA-R), and achievement measures (i.e., the four mathematics literacy and the two reading literacy measures) tested was not very good, and we decided to test other models (Table A1; Figure A1).

In Model 6, a distinction was introduced between the *g*-factor (measured by Cattell, PMA-S, PMA-V, PMA-R), a mathematics factor (measured by the four mathematics literacy measures), and a reading factor (measured by the two reading literacy measures) (Figure A1). The fit of the model was significantly better compared to the previous one (i.e., Model 5; Table A1).

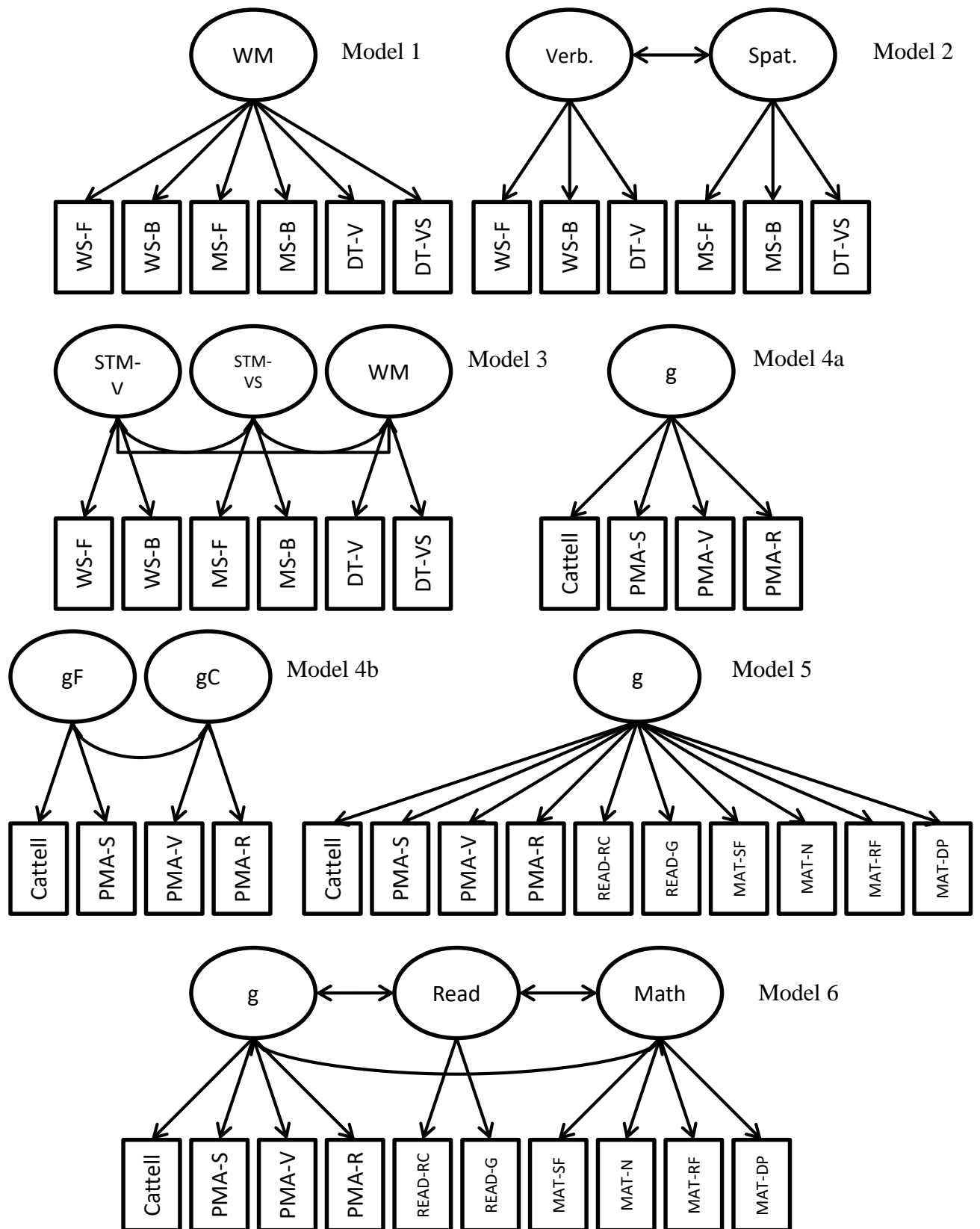


Figure A1. Conceptual diagrams Models 1-6. WS-F = Word Span Forward, WS-B = Word Span Backward, MS-F = Matrix Span Forward, MS-B = Matrix Span Backward, DT-V = Dual Task Verbal, DT-VS = Dual Task VisuoSpatial, PMA -S = - Spatial, PMA-R = Primary Mental Abilities – Reasoning, PMA-V = Primary Mental Abilities, Verbal, -SF = Space and Figures, -N = Numbers, -RF =relations and functions, DP = data and previsions, RC = reading comprehension, G = Grammar, Math = Mathematics literacy, Reading = Reading literacy.

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Table A1

Fit indices for different CFA models for WM, g, and achievement

	$\chi^2(df)$	$\Delta\chi^2(\Delta df)^{(mc)}$	<i>p</i>	<i>RMSEA</i>	<i>SRMR</i>	<i>CFI</i>	<i>NNFI</i>	<i>AIC</i>
<u>CFA on WM</u>								
(1) Single WM factor	30.09(9)	--	--	.121	.069	.891	.819	6557
(2) Modality dependent	11.65(8)	--	--	.054	.044	.981	.965	6541
(3) Three-factor model	6.29(6)	--	--	.017	.033	.998	.996	6539
<u>CFA on g and achievement</u>								
(4a) g-factor	3.65(2)	--	--	.072	.032	.979	.938	4133
(5) g-factor incl. math & read.	90.17(35)	--	--	.100	.069	.889	.857	12156
(6) g-factor, math and read.	61.53(32)	28.64(3) ⁽⁵⁾	.000	.076	.059	.940	.916	12134

Note. χ^2 = chi-square, *RMSEA*=root mean square error of approximation, *SMSR*=standardized root mean square residuals, *CFI*=comparative fit index, *NNFI*=non-normed fit index, *AIC*=Akaike information criterion.

.000 means that the value is zero when approximated to the third decimal.

^{mc} = model comparison