Intelligence 39 (2011) 357–369

Contents lists available at ScienceDirect

Intelligence

Mental abilities and school achievement: A test of a mediation hypothesis

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ARTICLE INFO

Article history:
Received 8 June 2010
Received in revised form 9 June 2011
Accepted 9 June 2011
Available online 2 July 2011

Keywords:
Academic achievement
Mental speed
Short-term memory
Reasoning
Divergent thinking
Grades
Prediction

ABSTRACT

This study analyzes the interplay of four cognitive abilities – reasoning, divergent thinking, mental speed, and short-term memory – and their impact on academic achievement in school in a sample of adolescents in grades seven to 10 ($N = 1135$). Based on information processing approaches to intelligence, we tested a mediation hypothesis, which states that the complex cognitive abilities of reasoning and divergent thinking mediate the influence of the basic cognitive abilities of mental speed and short-term memory on achievement. We administered a comprehensive test battery and analyzed the data through structural equation modeling while controlling for the cluster structure of the data. Our findings support the notion that mental speed and short-term memory, as ability factors reflecting basic cognitive processes, exert an indirect influence on academic achievement by affecting reasoning and divergent thinking (total indirect effects: $\beta = .22$ and .24, respectively). Short-term memory also directly affects achievement ($\beta = .22$).

Measures of general and specific cognitive abilities have been used successfully to predict students' academic achievement. Strong positive correlations between intelligence and academic performance are a frequently replicated finding in numerous studies and in several meta-analyses. Intelligence has been shown to be one of the best predictors of academic success (Neisser et al., 1996; Ones, Viswesvaran, & Dilchert, 2005). Particularly strong correlations have been identified in analyses combining values from different intelligence scales (e.g., Deary, Strand, Smith, & Fernandes, 2007; Krumm, Ziegler, & Bühner, 2008; Süß, 2001). The nature of the relationship between intelligence and academic achievement, however, is still a matter of debate among educational researchers and in the literature on intelligence. Current models and taxonomies of intelligence describe a large number of different specific cognitive abilities, which – to varying degrees – comprise general intelligence (e.g., Carroll, 1993; McGrew, 2009). These specific cognitive abilities differ, among other things, in the *complexity* of the cognitive processes they require. Fluid reasoning, for instance, requires far more complex cognitive processes than, for example, mental speed. While fluid intelligence often involves diverse mental operations (e.g., classifying, testing hypotheses, or solving problems), mental speed involves the routine, rather automatic performance of relatively easy, over-learned cognitive activities.

The question of how different *specific* intelligence factors relate to academic performance, and, in particular, how they interact in the prediction of performance, still remains largely unanswered (Floyd, 2005; Luo, Thompson, & Detterman, 2003). In this paper, we analyze the interplay between complex and basic cognitive abilities in their impact on academic performance in school.

1. Cognitive abilities and academic achievement

Traditionally, general cognitive ability (*g*) has been considered to be the best single predictor of academic achievement (e.g., Glutting, Watkins, & Youngstrom, 2003; Jensen, 1998; Rohde & Thompson, 2007). The attempts to identify *specific* intelligence factors that could improve the prediction of

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0160-2896/$ – see front matter
doi:10.1016/j.intell.2011.06.006

academic achievement beyond the impact of a g-factor typically failed since g appeared to account for virtually all sources of predictable variance in academic achievement (Jensen, 1984). Advances in both intelligence models and statistical modeling have created new possibilities for determining the possible explanatory power of specific intelligence factors. Recent publications on this topic stress the important role of more specific cognitive abilities in the prediction of achievement (e.g., Lohman, 2005; Luo, Thompson, & Detterman, 2006; McGrew, 2005; Taub, Floyd, Keith, & McGrew, 2008; Vock & Holling, 2008).

In the following, we discuss the relationship between basic and more complex cognitive processes from a theoretical perspective. We then present empirical findings on their relationships with each other and with academic achievement.

1.1. Theoretical approaches to the relationship between basic and complex cognitive processes

Recent models dealing with the structure of intelligence, such as the Cattell–Horn–Carroll model of intelligence (CHC; Alfonso, Flanagan, & Radwan, 2005; McGrew, 2009) and the Berlin model of intelligence structure (BIS; Jäger, 1984; Jäger et al., 2006; for English descriptions, see Bucik & Neubauer, 1996, or Carroll, 1993) posit a hierarchical structure of intelligence and incorporate complex as well as basic cognitive abilities. These models typically do not specify functional or causal relationships between their components, e.g., by defining some of the operations as the basis for the development or exertion of certain other operations. The BIS model, for instance, describes four cognitive operations, two of which might in fact be classified as reflecting rather elementary, basic processes (namely, the operations of mental speed and short-term memory) and two reflecting higher-order, more complex cognitive processes (i.e., the operations of reasoning and divergent thinking). These differences in complexity are also reflected in the simple vs. complex demands of the tasks used to assess these abilities in tests.

Psychometric mental speed tasks and short-term memory tasks have in common that they require the fairly "automatic" – that is, routine and unconscious – cognitive handling of simple, usually trivial information. Mental speed tasks are easy in the sense that virtually all test-takers would be able to solve them correctly if they had enough time to work on them; it is the tight time limits that make them difficult and that enable the researcher to differentiate among test-takers. Short-term memory tasks only require the storage of information for a short period of time and the mere reproduction or retrieval of that information. Test-takers do not need to use higher-order cognitive processes to solve these kinds of tasks.

Reasoning tasks, however, demand far more complex, multi-step manipulations of given information, and also require the linkage of new information to information stored in long-term memory as well as the storage of intermediary results in working memory (Carpenter, Just, & Shell, 1990; Verguts & de Boeck, 2002). Divergent thinking (also denoted as divergent production or fluency; Carroll, 1993) can generally be described as the ability to generate numerous diverse ideas (Runco, 1991). Divergent thinking tasks require that participants access stored knowledge quickly, make associations, and combine given pieces of information in new and different ways (Batey & Furnham, 2006). Despite the different levels of complexity between processing speed or short-term memory tasks on the one hand and reasoning or divergent thinking tasks on the other, recent models of the structure of intelligence generally place these different aspects of intelligence on the same level within the hierarchy of abilities, based on the results of factor analysis.

Danthiir, Roberts, Schulze, and Wilhelm (2005) distinguish two approaches to analyze the relationship between basic cognitive abilities and more complex cognitive abilities: the *descriptive* approach and the *explanatory* approach. These approaches have emerged from the research on individual differences and have given rise to rather different research traditions, but have only rarely been combined. Researchers using the descriptive approach apply factor-analytic methods to describe the structure of human abilities based on correlations between a range of different cognitive tasks (mostly paper-and-pencil test items), and on this basis, they develop models of the structure of intelligence. In this research approach, basic cognitive abilities like mental speed and short-term memory are considered at the same hierarchical level as other, more complex cognitive abilities.

In the explanatory approach, on the other hand, the focus is on identifying basic cognitive processes that are the source of higher-order cognitive processes and that can help explain the individual differences found in intelligence tests. The typical research methods used here employ a few basic cognitive tasks, often stemming from the experimental paradigm of cognitive psychology, as predictor variables, as well as measures of one or more complex cognitive ability factors as dependent variables (often equated with intelligence). Within this explanatory framework, researchers develop information-processing models of intelligence. In an early information-processing model of intelligence, Campione and Brown (1978) conceived of the speed of information processing as well as memory as basic building blocks of the cognitive system. They described processing speed as a determinant of intelligent behavior, meaning that more intelligent people are faster in processing information. This parallels the modern mental speed theory (e.g., Deary, 2000; Neubauer, 1997), which states that the speed of information processing is important in determining higher mental abilities and that it acts as a limiting factor, meaning that faster processing over the years results in cumulatively higher intelligence and knowledge, whereas slower processing constantly hampers learning and the development of higher-order cognitive abilities (Deary, 1995).

More recently, Woodcock (1998), Dean, Decker, Woodcock, and Schrank (2003) and Mather and Woodcock (2001) proposed a model that combines features of both information processing models and structure of intelligence models (for a critical review, see Floyd, 2005). Woodcock's model describes interactions among cognitive abilities, as specified in the CHC model, that take place during information processing, as well as the different influences facilitating and inhibiting cognitive performance. The model conceives of short-term memory and mental speed as relatively low-level, automatic processes determining cognitive efficiency during information processing. Information that is registered by the senses enters the system and, if attended to, is encoded into immediate awareness, which is represented in the model by the CHC ability short-term memory. Mental speed has the function of a valve, which helps to control the speed of

information flow within the system. After the encoding of information, information is then processed in a processing loop involving several CHC thinking abilities (i.e., reasoning, long-term storage retrieval, auditory thinking, visual-spatial thinking), which are integrated into the model at different levels of complexity of information processing, with reasoning being at the highest level. These thinking abilities interact with stores of declarative and procedural knowledge. Executive control processes manage these thinking abilities and can activate a "meta-knowledge filter." With the help of this filter, the system can search the knowledge stores for specific contents needed to work on an actual cognitive problem. Although this model has been criticized for several reasons (e.g., lack of a visual short-term store and more specific, narrow abilities), it offers a plausible depiction of the interactions among broad cognitive abilities during information processing (Floyd, 2005).

1.2. Empirical findings on the relationship between basic and complex cognitive processes and school achievement

There is some empirical evidence that different first-order abilities in hierarchical models of intelligence vary in their relation to general school achievement and specific subject domains, but the results are inconsistent. For example, several studies have found that reasoning predicts academic achievement better than mental speed, and that mental speed is a better predictor than divergent thinking, while others have found divergent thinking to be a better predictor than speed (e.g., Freund & Holling, 2008; Rindermann & Neubauer, 2000, 2004). In the following, we address the empirical findings on the relationships between different aspects of intelligence in greater detail. First, we document the construct and criterion validity of mental speed and short-term memory for the prediction and explanation of academic achievement. Second, we briefly address the question of how basic and complex cognitive processes interact in affecting academic achievement. In the first section dealing with this interaction, we compare findings on the criterion validity of mental speed and short-term memory with those found for higher-order cognitive processes. In the second, we present findings for models in which the influence of a particular cognitive ability on academic achievement is mediated by another (more basic or more complex) cognitive ability.

1.2.1. Mental speed

A considerable body of research testifies to the strong relationship between mental speed – mostly assessed via basic cognitive tasks – and general intelligence (for recent reviews, see: Jensen, 2006; Sheppard & Vernon, 2008). In the many studies on this topic, which have employed a vast array of mental speed tasks, the correlations between mental speed and reasoning range somewhere between $r = .30–.40$ (Sheppard & Vernon, 2008). Grudnik and Kranzler (2001) conducted various meta-analyses of the relationship between speed (visual and auditory inspection time measures) and intelligence, and found that the mean correlation between mental speed and intelligence does not differ significantly between adults ($r = -.51$) and children ($r = -.44$, after correction for artifactual effects).

Although a number of studies may slightly overestimate the strength of the relationship between mental speed and reasoning due to the common practice of speeded assessment of reasoning (i.e., testing under time constraints), as shown by Wilhelm and Schulze (2002), the correlation between mental speed and reasoning nevertheless remains substantial even after eliminating measurement artifacts resulting from speeded testing. Wilhelm and Schulze, studying a population of students aged 13 to 22, reported a zero-order correlation of $r = .34$ between a reasoning scale administered without time constraints and a mental speed scale, and a correlation of $r = .47$ between latent factors for both constructs in a confirmatory factor analytic model. The relationship between mental speed and creativity, however, has not been studied extensively to date. Rindermann and Neubauer (2000) reported a correlation of $r = .31$, which remained almost the same when reasoning was statistically controlled for ($r = .30$). Preckel, Wermer, and Spinath (in press) assessed divergent thinking under power conditions in ninth and tenth grade students. Using structural equation modeling, they found a strong latent correlation of $r = .61$ between divergent thinking assessed under power conditions and mental speed.

Several studies have investigated the validity of mental speed, assessed using either basic cognitive tasks or psychometric tasks, to predict academic achievement (e.g., Carlson & Jensen, 1982; Keith, 1999; Luo & Petrill, 1999; Luo et al., 2006; Taub et al., 2008). Strong relationships between mental speed and academic achievement have been found (e.g., Evans, Floyd, McGrew, & Leforgee, 2002), suggesting that basic cognitive processes play a role in academic achievement in school.

1.2.2. Short-term memory

As with mental speed, the finding of a strong relationship with general intelligence has also been replicated frequently for short-term memory, and short-term memory measures are part of many intelligence test batteries. Grubb and McDaniel (2000) reported a correlation of $r = .38$ between short-term memory and intelligence in a meta-analysis ($k = 22$ studies with $N = 692$). Common sense suggests that a good short-term memory should be decisive for successful learning, and hence for academic achievement since remembering new facts and concepts seems to be an important part of classroom learning. Therefore, the use of short-term memory measures for the prediction of academic achievement seems plausible. Evans et al. (2002), for example, report a moderate to strong relationship between short-term memory and reading achievement. Yet it remains to be clarified whether short-term memory affects academic achievement directly or whether it does so indirectly, by supporting students' higher-order cognitive processes, i.e., their reasoning and divergent thinking abilities.

Jensen (1993) suggests improving the prediction of academic achievement by g by incorporating measures of short-term memory, especially for low-intelligence students. His findings provide evidence that achievement levels of participants with low-intelligence can be predicted using a short-term memory test. Other researchers have not been able to corroborate the incremental validity of short-term memory beyond g. In a study of Dutch and immigrant children in the Netherlands, teNienhuis, Resing, Tolboom, and Bleichrodt (2004) were unable to find evidence supporting the assumption that measures of short-term memory add information beyond g in predicting school achievement. This is in line with findings based on the working memory paradigm, in which short-term memory (as a form of "passive storage") has little predictive power for cognitive

abilities, general intelligence, or school achievement (Daneman & Carpenter, 1980), but working memory as a form of "active storage" (meaning that the information that is to be stored is simultaneously actively manipulated or transformed) does serve as a good predictor of these abilities (e.g., Vock & Holling, 2008).

To sum up, mental speed and short-term memory correlate substantially with general intelligence and academic achievement in school. When looking at investigations in which short-term memory operates as the only predictor of complex cognitive abilities and school achievement, there is evidence of predictive validity; however, in studies with multiple predictors, the incremental validity of short-term memory seems to be limited, and the proportions of direct and indirect predictive effects are largely unknown.

1.2.3. General versus specific cognitive abilities as predictors of academic achievement

Some recent studies have aimed at simultaneously analyzing the impact of different cognitive abilities on academic achievement using structural equation modeling. These models specify second-order intelligence factors as well as one general factor for data from an intelligence battery, and use both simultaneously (i.e., second-order factors and *g*-factor) to predict achievement. In the first such study, Gustafsson and Balke (1993) used a nested factor model to analyze the predictive power of various intelligence factors for school achievement. Although they demonstrated rather strong relationships between both general and crystallized intelligence and a general school achievement factor, their lower-order intelligence factor "memory span" (consisting of a letter span task and a number span task) was, rather unexpectedly, weakly *negatively* associated with general school achievement.

In a series of subsequent studies, researchers used data from the standardization sample of the Woodcock–Johnson III test (Woodcock, McGrew, & Mather, 2001) to analyze the effects of several abilities depicted in the CHC structure of intelligence model on school achievement. Floyd, Keith, Taub, and McGrew (2007) and Taub et al. (2008) analyzed, in higher-order models, the impact of seven CHC broad abilities and a CHC *g*-factor on specific components of academic achievement, namely reading decoding skills and mathematics achievement. In these hierarchical models, cognitive ability tasks load on broad CHC ability factors, which in turn load on a *g*-factor. The direct path between *g* and achievement was statistically non-significant. Direct age-specific effects of several CHC abilities on achievement were found, but only indirect effects of general intelligence. Mental speed had direct effects on achievement only in children: for reading decoding skills, Floyd et al. (2007) reported strong effects from mental speed for younger children (aged five to eight) but not for older children or adults. For achievement in mathematics, Taub et al. (2008) found a strong direct effect of mental speed in children aged five to six and a weak direct effect in older children (aged nine to 13), but no direct effect for adolescents or adults. Short-term memory, however, affected reading decoding skills directly in children and adolescents from ages seven to 19 (but not in adults), while it produced no significant direct effect on mathematics achievement in any of the age groups under examination. Similar findings have been reported by Benson (2008), who also analyzed the impact of several CHC broad abilities as well as a CHC *g*-factor on reading comprehension and reading fluency in students K-12. In his initial model, he hypothesized that mental speed and short-term memory, in addition to *g*, directly influence reading fluency, and that memory also directly influences reading comprehension. The expected influence of speed on reading fluency fitted the data well, but the causal paths from memory to the two reading abilities were not confirmed. Instead, only an indirect effect of short-term memory on reading fluency, mediated by some basic reading skills (which, in turn, were influenced by *g*), could be corroborated. *g*, however, had only a direct effect on basic reading skills in younger children, but no direct effect on reading comprehension or reading fluency.

To summarize, when *g* and specific intelligence factors were jointly specified in a single higher-order model estimating their impact on academic achievement, mental speed had direct effects on achievement in young children, whereas short-term memory failed to impact achievement directly in most subsamples. Also, *g* had no direct effect on achievement in most of the studies.

1.2.4. Mediator models

Some recent studies have investigated possible mediator effects when jointly analyzing the impact of different cognitive abilities on academic achievement. Rindermann and Neubauer (2004), studying a sample of high school students, analyzed the structural relations between mental speed, reasoning, divergent thinking, and school achievement. There are very few studies, however, investigating the impact of divergent thinking on academic achievement. Correlation coefficients between measures of divergent thinking and academic achievement typically range between about $r = .20$ and $r = .30$ (cf. Freund & Holling, 2008). Rindermann and Neubauer (2000) reported rather low correlations between a combined score from two divergent thinking tests and school achievement (e.g., GPA: $r = -.25$; mathematics/physics: $r = -.08$); only achievement in the social sciences has shown slightly stronger correlations with divergent thinking ($r = -.37$). In their mediator study, Rindermann and Neubauer (2004) found the influence of mental speed to be mediated by reasoning and divergent thinking (with the effect on school achievement being rather strong for reasoning and weaker for divergent thinking). Based on results from structural equation modeling, they proposed a speed-factor model in which mental speed influences school achievement only indirectly. Specifically, they argued that the more fundamental intellectual ability of mental speed had only an indirect impact on school achievement, since the relationship between mental speed and achievement was fully mediated by the higher cognitive abilities of reasoning and divergent thinking.

Luo et al. (2003) studied primary school students and found the correlation between psychometric *g* and scholastic achievement to be mediated mainly by achievement in basic cognitive tasks measuring elementary processes such as mental speed or memory processing. These findings, based on data on younger school children, are in line with the findings of Floyd et al. (2007) and Taub et al. (2008) (reported above), who demonstrated age-specific effects on achievement for different intelligence factors: in their analyses, mental speed directly influenced complex cognitive abilities in children, but not in adults. In the model proposed by Luo et al. (2003), the specific impact of mental speed and memory processes on achievement could not be separated.

There are, however, findings reported in the literature, as documented above, indicating that the relationships between each of these constructs and school achievement differ widely in strength. Substantial positive correlations between mental speed and academic achievement seem to be a more or less consistent finding in the research literature of recent years. Yet the empirical evidence on the impact of short-term memory processes on academic achievement is less conclusive.

1.3. Research aims of the present study

In the present study, we build on the mediator studies documented above. The primary objective of this study is to describe more specifically the relationships between school achievement on the one hand and reasoning, divergent thinking, short-term memory, and mental speed on the other, and to test a mediation hypothesis for these relationships.

Drawing on theoretical constructs that underlie information processing approaches to intelligence (Deary, 2000; Neubauer, 1997; Woodcock, 1998), we conceive of mental speed and short-term memory as lower-order, basic cognitive abilities, and reasoning as well as divergent thinking as higher-order, more complex abilities. We assume that the basic cognitive abilities are the basic building blocks for the more complex cognitive processes. Based on the findings reported by Rindermann and Neubauer (2004) and Luo et al. (2003), we hypothesize that achievements in school are influenced directly by the higher-order, more complex cognitive abilities of reasoning and divergent thinking and only indirectly by the lower-order, basic cognitive abilities of mental speed and short-term memory. That is, we expect to find the impact of mental speed and short-term memory on academic achievement to be mediated by reasoning and divergent thinking.

2. Methods

2.1. Participants and procedure

We gathered the data used here during the standardization of the Berlin Structure of Intelligence Test for Youth (BIS-HB; Jäger et al., 2006; see below). Between 2001 and 2003, approximately 1500 German students from grades seven to 10 were given the full BIS-HB test. As the original aim of the assessment was to standardize the BIS-HB test, we aimed to draw a sample that was as representative as possible of the general student population in Germany. Assessments took place in five German states, and special attention was paid to a representative distribution (compared to census data) of gender, parents' SES, and school track. Most of these students were tested at their regular school together with their classmates. A subsample, however, consisted of special groups of students, mainly gifted students from different schools who did not share a common classroom. As measures of academic achievement, we used teacher-assigned school grades (see below). Teachers use a classroom-related social frame of reference when assigning grades ("grading on a curve"; Ingenkamp, 1971) with the consequence that it is difficult to compare the grades assigned in different classrooms. In order to be able to statistically control for this cluster structure of the data (students in classrooms), we only included those students in the sample who participated at their regular school and for whom data from classmates were available.

We were able to retain a total of 1135 students (524 females) from 60 different classrooms in our sample. The German three-track education system separates students at the end of grade four into three achievement tracks (lower, middle, and upper) according to their level of achievement (about 30–50% of an age group enroll in the upper track while about 20–30% enroll in the lower and middle tracks, respectively). In our sample, 189 students were enrolled in the lower track (11 classrooms), 185 in the middle track (eight classrooms), and 423 in the upper track (20 classrooms). In addition, 338 sample members attended special classes for the gifted at an upper-track secondary school (21 classrooms). Mean age of the sample was 14.48 years (SD = 1.07 years).

A student questionnaire assessed demographic data. Two trained researchers conducted the testing in regular classrooms, adhering to appropriate ethical standards. The combination of test and questionnaire took about 200 min to complete. Students completed the test anonymously and received no rewards, but did receive feedback in the form of a simple intraindividual ranking, stating the student's best cognitive ability first, then his second-best ability, and so on.

2.2. Study measures

2.2.1. Intelligence

For the assessment of students' intelligence, we used the Berlin Structure of Intelligence Test for Youth: Assessment of Talent and Giftedness (BIS-HB) (Jäger et al., 2006), which is the most recent paper-and-pencil test based on the BIS model by Jäger (1984); for recent studies using the BIS model see Beauducel and Kersting (2002), Kuhn and Holling (2009a, 2009b), Preckel et al. (in press), and Wilhelm and Schulze (2002). The BIS-HB assesses four operational abilities (reasoning, divergent thinking, mental speed, and short-term memory), three content abilities (verbal, numerical, and figural), and general intelligence with 45 types of tasks. As a consequence, all cognitive abilities under study were assessed over central content areas of intelligence, i.e., the verbal, numerical, and figural content area (Marshalek, Lohman, & Snow, 1983). For the purpose of this paper, the following four operations are important:

Reasoning (*R*). Reasoning is the ability to process complex information in types of tasks that cannot be solved immediately or easily. This requires the test-taker to establish diverse relations, use exact formal-logical thinking, and appropriately evaluate relevant information. The BIS-HB test assesses reasoning via five different tasks for each content domain, i.e., figural, numerical, and verbal (15 reasoning tasks).

Divergent Thinking (*DT*). The divergent thinking scale evaluates the ability to flexibly develop new ideas; this requires access to diverse information, a wealth of imagination, and the ability to see many different sides, variations, reasons, and possibilities in problem-oriented – not purely imaginative – solutions (Freund & Holling, 2008; Kuhn & Holling, 2009b). The BIS-HB test assesses divergent thinking via four tasks for each content domain, resulting in a total of twelve divergent thinking tasks. Nine of these tasks are scored for fluency (i.e., total number of solutions), and five of

these tasks are scored for flexibility (i.e., variability of solutions).

Mental Speed (*S*). Mental speed is the ability to work quickly, to perceive information easily, and to focus on the task. This ability is decisive in solving simply structured, low-difficulty tasks. Conceptually, mental speed in the BIS model matches most closely with the concept of "processing speed" within Gf-Gc theory (Horn & Noll, 1994) or with that of "broad cognitive speediness" (Gs) in Carroll's (1993) three-stratum theory. Mental speed in the BIS-HB test is expressed as number of correct answers obtained during a brief, specified period of time and is assessed via three tasks for each content domain, resulting in a total of nine mental speed tasks. The tasks can be classified as clerical–perceptual speed tasks, in which a large amount of information has to be scanned quickly (cf. Danthiir et al., 2005). Neubauer and Bucik (1996) found a correlation between factor scores of a general mental speed factor (consisting of 24 different mental speed tasks) and BIS mental speed of $r = .75$. Based on these findings, Süß (2001), and Wilhelm and Schulze (2002) equated speed as assessed with the BIS test with mental speed.

Short-Term Memory (*M*). The short-term memory scale evaluates the ability to memorize different kinds of stimuli and to recognize or reproduce verbal, numerical, or figural material after a short time interval. In these tasks, the stimulus material (e.g., a list of numbers or words, marked buildings on a city map) is depicted on separate pages of the test booklet, and test-takers have to memorize the information presented. After a certain period of time (between 30 s and 2 min), test-takers are prompted to turn the page and on a new page of the booklet to write down either all the information they still remember or to retrieve the memorized information from among many distracting stimuli (e.g., a large number of buildings on a city map), depending on the type of task. The BIS-HB test assesses short-term memory via three tasks for each content domain, resulting in a total of nine short-term memory tasks.

2.2.1.1. Psychometric properties. Objectivity of scoring, as indexed by the unadjusted intraclass correlation coefficient between the ratings of two independent raters, was satisfactory for all divergent thinking tasks (ICC: $M = .94$, $SD = .04$, range = .82–.99). There were no ceiling effects. Internal consistency was satisfactory for all scales (reasoning: $\alpha = .93$; divergent thinking: $\alpha = .81$; mental speed: $\alpha = .90$; short-term memory: $\alpha = .90$; verbal intelligence: $\alpha = .95$; figural intelligence: $\alpha = .93$; numerical intelligence: $\alpha = .90$). Confirmatory factor analyses demonstrated construct validity of the BIS-HB as the structure of the BIS could successfully be replicated with the data (CFI = .98; AGFI = .93; RMSEA = .04, lo90 = .03, up90 = .05). Criterion validity was documented by correlations with various reference tests (e.g., BIS scale "reasoning" and Culture Fair Test $r = .74$; BIS scale "mental speed" and the speed scale of the German Wechsler test for children $r = .66$) and school grades (BIS-HB IQ with grade point average: $r = .50$; BIS-HB reasoning with grade point average in Math and sciences: $r = .47$), and – for the divergent thinking scale – by correlations with self-estimated creativity ($r = .28$, $N = 192$).

2.2.2. Academic achievement

Students self-reported their end-of-year grades in all school subjects. Thus, self-reported grades do not reflect grades on individual tests but represent cumulative achievement across an entire school term. Recent research supports that self-reported grades are approximately as valid as teacher-reported grades. Although students tend to slightly exaggerate their grades in self-reports, correlations between self-reported and actual grades typically range between $r = .90$ and $r = .95$ (Dickhäuser & Plenter, 2005; Frucot & Cook, 1994). We formed three composite scores of school grades: the first score (in the following abbreviated as "math-science") includes grades in mathematics and the natural sciences of biology, chemistry, and physics; the second one ("languages") consists of grades in German and English as a foreign language; and the last score ("social") is a composite of grades in the social science subjects of geography, history, and political science. The three composites correlate positively with each other ($r = .65$–$.68$, $p < .01$). To facilitate interpretation of results, we reversed the usual grading scale used in German schools (1 to 6, with 1 being the best grade a student can attain) so that in our study, 6 is the highest and 1 the lowest possible grade.

2.3. Data analysis

First, we calculated zero-order correlations between academic achievement and the four cognitive abilities. Because each task in the BIS-HB (the test battery from which our tasks were obtained) assesses one cognitive ability (reasoning, divergent thinking, mental speed, or short-term memory) within a certain content area (verbal, numerical, or figural) we had to aggregate the assessments for each cognitive ability over content areas before estimating structural equation models. Based on Jäger's (1984) proposition from his work on model development and the practice of modeling BIS data that has been standard since then (Beauducel & Kersting, 2002; Bucik & Neubauer, 1996; Jäger et al., 2006; Preckel et al., in press), we created three parcels (i.e., sets of three to six tasks each), as indicators for each cognitive ability. The parcels were heterogeneous aggregates of BIS-HB tasks with respect to the content area but homogenous with respect to the respective cognitive ability (e.g., mean of six z-standardized reasoning tasks, two of which are verbal, two are numerical, and two are figural). This theory-driven aggregation results in more reliable measures, a suppression of unintended content variance, and a focus on intended variance in the respective cognitive ability.

For the test of the mediation hypothesis, we used latent variables within a structural equation modeling (SEM) approach, which has the benefit of controlling for measurement error and conducting the analysis at the construct level (rather than at the level of test scales), and which also allows confirmatory tests of model fit. We specified a series of models following the common testing procedure used in the SEM approach to detect mediation (Holmbeck, 1997; MacKinnon, 2008).

In a first step, we assessed the fit of two models, specifying only direct effects of mental speed or short-term memory on

achievement (Models 1 and 2). We then tested a series of more complex models, starting with a model in which mental speed was allowed to have both direct and indirect effects (mediated by reasoning and divergent thinking) on academic achievement (Model 3), followed by a similar model with short-term memory instead of mental speed as predictor (Model 4). Finally, in Model 5, we specified the whole mediation model with short-term memory and mental speed as predictors, and with reasoning and divergent thinking as mediators. In Model 5a we removed the direct paths from processing speed and short-term memory and compared the fit of this model with Model 5 to investigate whether the direct paths were dispensable.

Structural equation models were specified using Mplus Version 6.1 (Muthén & Muthén, 1998–2010). Since the students were nested within classes, we used the "complex" option in Mplus to obtain correct standard errors for the model parameters, and corrected fit statistics given a nested data structure. We estimated the model parameters using maximum likelihood estimation with robust standard errors (MLR), as implemented in the Mplus 6.1 software. Adequate model fit was demonstrated by using standard fit indices (Kline, 2005): the scaled model chi-square statistic, the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), the Tucker Lewis Index (TLI), and the Standardized Root Mean Square Residual (SRMR). According to Hu and Bentler (1999), a RMSEA below .05, a CFI and TLI above .95, and a SRMR below .08 can be considered indicative of a good model fit. Nested models were compared using the Satorra–Bentler scaled chi-square difference test (Satorra, 2000). The significance of indirect effects was assessed with the Sobel test statistic (Sobel, 1982).

3. Results

In Table 1, we report zero-order correlations between the different cognitive abilities (age-based standardized IQ norms) and academic achievement in different subject areas. The four cognitive abilities were positively correlated (range: $r = .49$ to .68), but the findings did not indicate multicollinearity (tolerance values range from .41 to .57). The magnitude of the correlations between cognitive abilities on the one hand and academic achievement in different subject areas on the other was similar to findings reported in other studies (e.g., Rindermann & Neubauer, 2004).

In the following, we present the results of our structural equation analyses. The direct effects of mental speed and short-term memory on academic achievement in school were tested separately in Models 1 and 2 (see Figs. 1 and 2). Both abilities were significant predictors of academic achievement (mental speed: $\beta = .43$; short-term memory: $\beta = .52$). The model fit was good for Model 1 and adequate for Model 2 (see Table 2).

Model 3 tested direct and indirect effects of mental speed, including both mediators (see Fig. 3). The direct path from mental speed to academic achievement in school was negative but not significant ($\beta = -.07$, $p > .05$). All paths representing indirect effects, however, were positive and significant (via reasoning: $\beta = .30$, via divergent thinking: $\beta = .20$; total indirect effect: $\beta = .50$, all $ps < .01$). These findings indicated a full mediation of the effect of mental speed on school achievement. Model 4 paralleled Model 3, but tested the effect of short-term memory instead of the effect of mental speed (see Fig. 4). The direct effect of short-term memory just missed significance at the 5% level ($\beta = .18$, $p = .059$). All paths representing indirect effects were positive and significant (via reasoning: $\beta = .23$, via divergent thinking: $\beta = .13$; total indirect effect: $\beta = .36$, all $ps < .01$), indicating a mediation of the effect of short-term memory on school achievement. Models 3 and 4 showed good model fit (see Table 2).

Finally, Model 5 specified the complete mediation model with two predictors and two mediators (see Fig. 5, Table 3). Both predictors were highly correlated ($r = .75$, $p < .01$). The direct path from mental speed to academic achievement in school had a negative regression weight and just failed to reach significance ($\beta = -.13$, $p = .062$). Instead, mental speed had an indirect positive association with academic achievement (via reasoning: $\beta = .08$, via divergent thinking: $\beta = .14$; total indirect effect: $\beta = .22$, all $ps < .01$). Short-term memory in this model affected academic achievement both directly ($\beta = .22$, $p < .01$) and indirectly (via reasoning: $\beta = .19$, via divergent thinking: $\beta = .06$; total indirect effect: $\beta = .24$, all $ps < .01$). The total effect of short-term memory on academic achievement was $\beta = .46$ ($p < .01$), and was hence much larger than the total effect of mental speed on academic achievement. When both basic operations were considered in one model, short-term memory had significant direct and indirect effects (partial mediation), while the impact of mental speed on academic achievement was fully mediated by reasoning and divergent thinking. In sum, short-term

Table 1
Descriptives and zero-order correlations between the BIS operations and school achievement in different subject areas ($N = 1135$).

	Mean (SD)	Mental speed	Short-term memory	Divergent thinking	Reasoning
Cognitive ability					
Mental speed	104.19 (14.93)	*.90*			
Short-term memory	103.90 (15.46)	.63	*.90*		
Divergent thinking	102.93 (15.03)	.63	.49	*.81*	
Reasoning	105.39 (16.27)	.68	.64	.55	*.93*
Subject area					
Languages	4.06 (.85)	.43	.43	.38	.46
Math–Science	4.23 (.76)	.40	.38	.36	.49
Social	4.33 (.79)	.35	.34	.39	.37

Notes: Age-based standardized IQ norms (separately for years 12–16) were used for the operations. School grades range from 1 ("insufficient") to 6 ("very good"). All correlations were significant with $p < .001$. Italicized numbers at the diagonal in the upper part of the table: Cronbach's Alpha of the BIS scales.

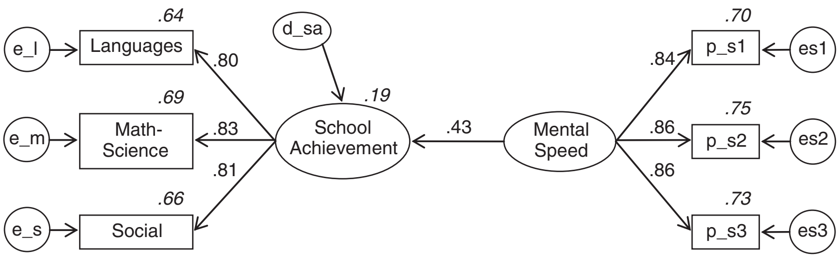

Fig. 1. SEM Model #1 with mental speed as predictor for school achievement (standardized solution). Note. Proportions of explained variance are depicted in italics.

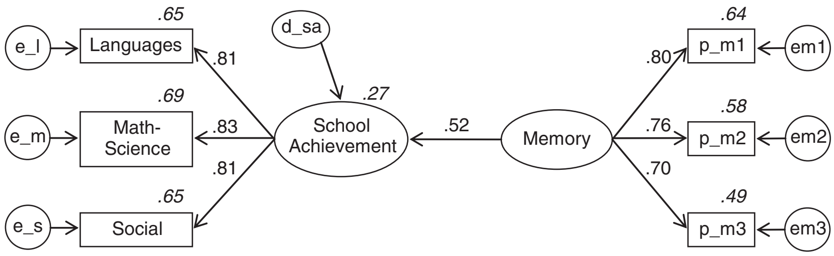

Fig. 2. SEM Model #2 with short-term memory as predictor for school achievement (standardized solution). Note. Proportions of explained variance are depicted in italics.

memory had a stronger impact on academic achievement in school than mental speed.

The two basic cognitive abilities also differed in the impact they exerted on each of the complex cognitive abilities (Model 5): while mental speed had a strong influence on divergent thinking and a weaker influence on reasoning ($\beta = .56$ and $\beta = .25$, respectively), short-term memory had a fairly strong impact on reasoning and a weaker influence on divergent thinking ($\beta = .60$ and $\beta = .23$, respectively). Therefore, although both basic abilities were interrelated and both affected complex abilities, mental speed was more closely related to divergent thinking, and short-term memory was more closely related to reasoning. The variables in Model 5 explained 34% of the variance in academic achievement in school. The model fit was good (see Table 2).

In a final step, with a restricted version of Model 5, we tested whether the two direct paths from the predictors to the criterion are statistically necessary, i.e., whether their regression weights differed significantly from zero (cf. Holmbeck, 1997; Schermelleh-Engel, Moosbrugger, & Müller, 2003). To do so, we removed the direct paths from mental speed and short-term memory to academic achievement (Model 5a). The fit of Model 5a was significantly worse than that of the unrestricted Model 5 (Table 2; Satorra–Bentler scaled χ^2 difference test: TRd = 10.62, $p < .01$). Hence, the direct paths should not be eliminated, as the direct effect of short-term memory on school achievement was found to be substantial.

Table 2
Model fit of structural equation Models 1 to 5a.

Model	$\chi2$	*df*	*p*	RMSEA (90% CI)	CFI	TLI	SRMR
1	22.55	8	<.01	.040 (.021–.060)	.998	.997	.021
2	33.54	8	<.001	.053 (.035–.072)	.995	.990	.024
3	223.31	49	<.001	.056 (.049–.064)	.989	.985	.024
4	211.18	49	<.001	.054 (.047–.062)	.989	.985	.033
5	285.68	81	<.001	.047 (.041–.053)	.988	.985	.029
5a	294.79	83	<.001	.047 (.042–.053)	.988	.985	.030

4. Discussion

The present study investigated the relationships between academic achievement in school and reasoning, divergent thinking, short-term memory, and mental speed. Based on information-processing approaches to intelligence, we expected the influence of mental speed and short-term memory on academic achievement in school to be mediated by the more complex cognitive abilities of reasoning and divergent thinking. Our results confirmed these expectations.

Our series of SEM analyses (Models 1 to 5) delivered empirical evidence in favor of the mediation hypothesis for a representative sample of 1135 German seventh to tenth grade students. Mental speed influenced academic achievement in school indirectly via reasoning and divergent thinking; the impact of mental speed was therefore fully mediated by reasoning and divergent thinking. In Model 4, we found a similar pattern of results for short-term memory: the direct path from memory to academic achievement in school just failed to reach significance and hence indicated a full mediation. The final model (Model 5), however, which integrated both basic cognitive abilities as predictors, also showed a significant direct effect of short-term memory. The coefficient of the direct path was only marginally larger than in the preceding model (Model 4: $\beta = .18$, Model 5: $\beta = .22$), and the results are hence fairly consistent. Further, Model 5a confirmed that the direct path between short-term memory and school achievement should not be dismissed since the

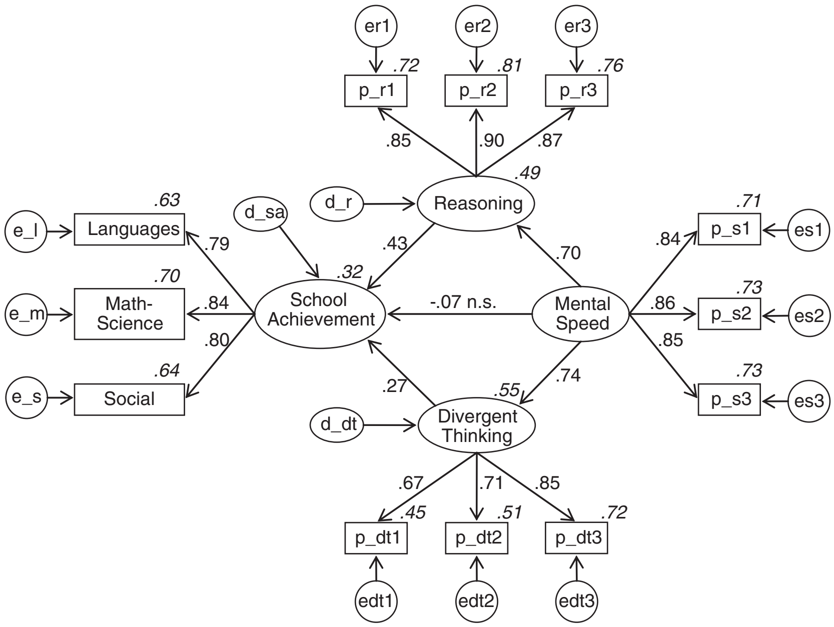

Fig. 3. SEM Model #3 with mental speed as predictor for school achievement and reasoning and divergent thinking as latent mediating variables (standardized solution). Note. Proportions of explained variance are depicted in italics.

model fit worsened significantly when the direct path was eliminated. We therefore conclude that short-term memory affects school achievement both directly and indirectly, i.e., the effect of short-term memory is partially mediated by both complex cognitive abilities.

Note that the study design is not longitudinal and lacks repeated measurements, which would be a prerequisite for testing truly causal relationships. The analyses in this paper are based on mediator models, we did not study hierarchical models in which a *g*-factor is assumed to influence several further intelligence factors. Further, we built our mediator models in order to test a specific mediation hypothesis which we had derived from information processing theory. There is no psychological theory assuming the reverse mediation effect, i.e., that reasoning or divergent thinking might influence academic achievement via memory and

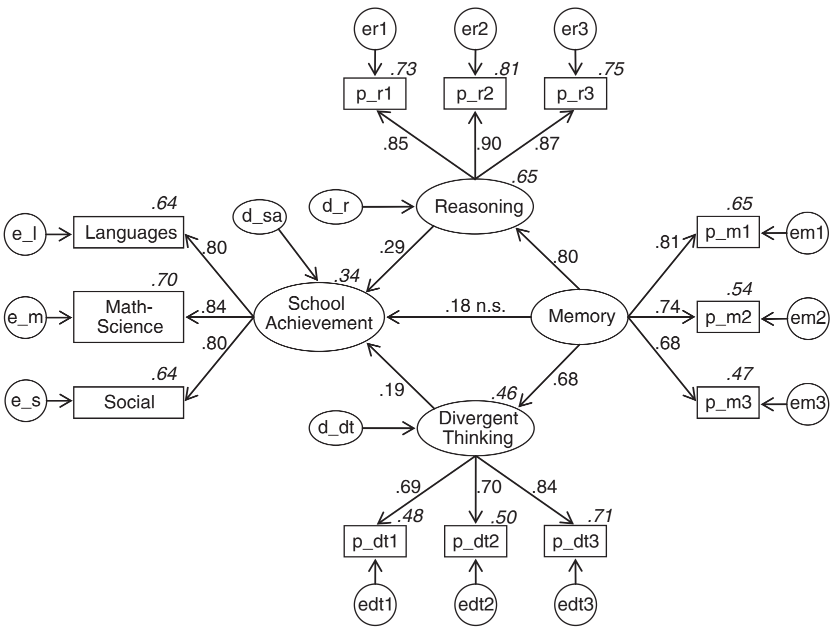

Fig. 4. SEM Model #4 with short-term memory as predictor for school achievement, and with reasoning and divergent thinking as latent mediating variables (standardized solution). Note. Proportions of explained variance are depicted in italics.

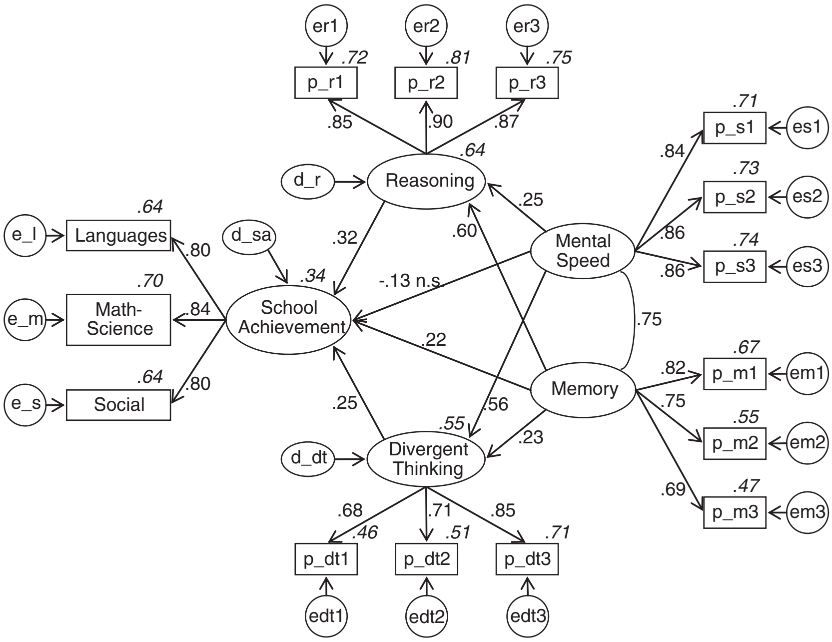

Fig. 5. SEM Model #5 with mental speed and short-term memory as predictors for school achievement, and with reasoning and divergent thinking as latent mediating variables (standardized solution). Model #5a: without direct paths between predictors and school achievement. Note. Proportions of explained variance are depicted in italics.

speed (cf. Rindermann & Neubauer, 2004). Hence, we refrained from statistically testing this assumption because of its lack of a theoretical framework. The findings are discussed in more detail in the following sections.

4.1. Mental speed and short-term memory: relationships with complex cognitive abilities and impacts on academic achievement

The total indirect effects of mental speed and short-term memory on achievement were substantial (βs = .22 and .24, respectively). Yet, in the final model, short-term memory also affected school achievement in a direct way, resulting in a substantial total effect of β = .46. This reveals that the ability to store information in short-term memory has a beneficial effect that goes beyond the effect of remembering information while reasoning or engaging in divergent thinking. In all school subjects, learning generally requires the memorization of facts, dates, and concepts, and students who can remember information easily will, over the years, amass more knowledge than students who have difficulties remembering information, even when the reasoning and divergent thinking abilities of these two student groups are comparable. These individual differences in memory abilities seem to be reflected in school achievement in our data.

Table 3
Standardized direct, indirect, and total effects of the final Model 5.

Effects	Beta	*S.E.*	*p*
From speed to school achievement			
Total effect	.08	1.49	>.05
Total indirect effect	.22	4.31	<.01
Specific indirect effect			
Via reasoning	.08	3.18	<.01
Via creativity	.14	3.58	<.01
Direct effect	−.13	−.87	>.05
From memory to school achievement			
Total effect	.46	7.38	<.01
Total indirect effect	.24	5.12	<.01
Specific indirect effect			
Via reasoning	.19	4.04	<.01
Via creativity	.06	3.23	<.01
Direct effect	.22	2.94	<.01

Mental speed was a good direct predictor of academic achievement in school in Model 1, in which it was the sole predictor (β = .43), but it failed to directly impact school achievement when reasoning and divergent thinking were entered into the model as mediators (Model 3 and Model 5).

That is, we found a full mediation for the effect of mental speed on academic achievement, with a rather strong indirect effect (β = .50, Model 3). However, the indirect effect decreased when mental speed *and* short-term memory were included in the model (β = .22, Model 5), as both predictors share common variance (r = .75). The degrees of variance in mental speed that contribute to reasoning and divergent thinking were hence relevant for academic achievement in school. In other words, the quick production of convergent and divergent solutions and ideas promotes achievement in school. But beyond these aspects of mental speed captured by reasoning and divergent thinking, mental speed does not have an incremental positive impact on school achievement. A speculative interpretation of this finding might be that some of the students with higher abilities to work quickly through routine tasks (who therefore score high on mental speed tasks) might have disadvantages when faced with cognitively more demanding tasks (although the negative regression weight on the direct path did not reach significance). This might be due to a tendency to work quickly but less carefully, that is, to trade off accuracy for speed.

It has to be taken into account that the BIS-HB test assessed all of the cognitive abilities under time constraints. Students' abilities to process information more quickly or more slowly therefore influence their achievement on most of the test tasks, regardless of the operation the task was intended to measure. Consequently, mental speed ability is not only expressed in achievement in mental speed tasks but is also responsible for part of the achievement variance in other tasks. In our analyses, this might have resulted in a slight underestimation of the impact of mental speed on academic achievement because variance due to mental speed is incorporated into the factors representing the other three operations. This effect is probably not very large, however, as Wilhelm and Schulze (2002) and Preckel et al. (in press) demonstrated in their comparison of BIS reasoning and divergent thinking task administration with and without time restrictions. Note that cognitive operations are almost impossible to measure in a completely pure form, since cognitive operations do not act independently of one another. Mental speed is a psychological construct that is still under debate, and researchers in the field use many different tasks to assess it (Danthiir et al., 2005). Our operationalization of mental speed covers a large part of the construct, as indicated by the findings of rather high latent correlation between mental speed as assessed by the BIS-tasks and a general mental speed factor (consisting of 24 different mental speed tasks) ($r = .75$; Neubauer & Bucik, 1996). A replication study with a different test battery incorporating tasks that reflect other operationalizations of the mental speed domain could nevertheless help to clarify this issue. To sum up, individual differences in reasoning and divergent thinking can partly be traced back to basic cognitive processes. Our analyses show that both short-term memory and mental speed are basic factors in reasoning and divergent thinking, which in turn directly influence one's abilities to perform academically at school.

4.2. Reasoning and divergent thinking as predictors of academic achievement: their relationship to lower-order cognitive abilities

Reasoning, according to the existing literature, is the operation that most strongly affects academic achievement in school. A vast body of research has documented the impact of mental speed and short-term memory on reasoning. Many studies have indeed shown mental speed to be a powerful predictor of reasoning. Yet, in our analyses, short-term memory turned out to be more important for reasoning than for mental speed. As noted above, the influence of mental speed might be underestimated due to the speeded testing of all four cognitive abilities assessed by the BIS-HB test. Students make use of their short-term memory when working on reasoning problems in which they have to keep in mind hypotheses about solutions and intermediary results (e.g., which of the distractors can definitely be eliminated; Carpenter et al., 1990). Further, they have to use their short-term memory to store rules and procedures that they have identified and that may prove helpful in solving future tasks of the same type (e.g., series completion, analogies) (cf. Verguts & de Boeck, 2002).

Divergent thinking also predicted school achievement quite well. The strong impact of mental speed on divergent thinking in Model 5 was striking. This strongly positive relationship might, in part, be explained by the nature of the typical divergent thinking tasks employed in the BIS-HB test: the divergent thinking tasks demand the generation of either many general ideas (fluency scoring) or many diverse ideas (flexibility scoring), which in either case may be simple, since there is no scoring for quality or sophistication of ideas. Tested students hence have to quickly draw from their knowledge stores to make associations, and, in some of the tasks, to combine given pieces of information in new and different ways. The speed of information processing seems to be a central prerequisite for the generation of numerous innovative and divergent ideas in the face of these kinds of creativity problems entailing a strict time limit of just a few minutes. Faster information processing should help a person to produce many different ideas under severe time constraints. Our analyses do not allow conclusions concerning the extent of the influence of these timed testing conditions on the reported relationship between divergent thinking and mental speed. Only a comparison of test scores stemming from timed vs. untimed testing conditions could deliver this kind of information. Preckel et al. (in press) found a zero-order correlation of $r = .58$ between untimed divergent thinking and mental speed and of $r = .50$ between timed divergent thinking and mental speed, which indicates that the relationship between both constructs is only weakly influenced by timed testing.[1]

Short-term memory also affected divergent thinking, albeit to a smaller degree than mental speed. This positive relationship might be the result of a larger short-term memory capacity enabling the test-taker to remember which answers he had already given or which categories of ideas he had already produced while working on the divergent thinking task (Batey, Chamorro-Premuzic, & Furnham, 2009).

4.3. School achievement as the criterion variable

In this study, we assessed school achievement on a very general level, that is, on the level of grades in various subjects that have been assigned during a whole school term. Teacher assigned grades not only reflect academic achievements but also a bundle of further characteristics of students and teachers, e.g., teacher–student relationship, individual grading styles of teachers etc. However, in our data analyses we controlled for possible reference group effects that influence teachers when assigning school grades ("grading-on-a-curve"). The relations between cognitive abilities and achievements in standardized assessments might differ slightly from the results presented in this article. Results probably also differ when very specific aspects of school achievement are investigated (e.g., mathematical problem solving, reading fluency).

[1] Early analyses by Mednick (1962) and more recent replications by Howard-Jones (1999) suggest that tight time limits in divergent thinking tasks might in fact favor less creative people: These studies found that individuals with a flat "associative hierarchy" (i.e., those who are able to access remote associations for a given stimulus and who can hence be classified as very creative) generate more diverse and uncommon ideas than individuals with a steep hierarchy of associations, but that they do so steadily at a rather slow pace. Yet individuals with steep hierarchies, who deliver predominantly ordinary ideas and can hence be termed less creative, produce their responses quickly but have soon depleted their limited reservoir of ideas. When test subjects are allowed to work on a divergent thinking task for only a few minutes, those with steep hierarchies might in total produce more ideas than those with flatter hierarchies. The administration of divergent thinking tasks with more relaxed time limits might therefore improve the operationalization of the construct.

4.4. Future directions and implications

The results presented in this paper support the existing evidence that multimodal assessments are beneficial when the prediction of academic achievement is of interest. We considered four cognitive abilities that, to our understanding, represent a central subset of the universe of cognitive abilities. However, a more extensive sampling of cognitive abilities would provide more insight into mediation effects within the hierarchy of cognitive abilities when predicting academic achievement. Future research should include further basic abilities as well as more complex abilities, which have been shown to be relevant for predicting academic achievement. For example, a unique contribution to the explanation of variance in school achievement has been reported for measures of working memory (Luo et al., 2006; Vock & Holling, 2008) and for crystallized intelligence (Luo et al., 2006).

We assume that the ability of cognitive abilities to directly affect academic achievement differs across age groups, since to our understanding, more complex cognitive abilities develop on the basis of fundamental abilities. Different structural relations among intelligence factors and academic achievement have been reported in the literature for different age groups. Mental speed, for instance, has been shown to be more important for reading abilities in younger children than in older children or adults (e.g., Floyd et al., 2007). While the assessment of more complex cognitive abilities may have been sufficient to assess the individual potential for academic achievement in the sample of adolescents under examination here, the assessment of more fundamental abilities might be more useful in a sample of children at an earlier stage of development. For younger students, the assessment of fundamental cognitive abilities may therefore yield relevant additional information, as had been demonstrated for mental speed and working memory (Luo et al., 2006; Vock & Holling, 2008). Since the results presented here are confined to students between the ages of approximately 12 and 16, it would be illuminating to replicate similar analyses for younger age groups in future studies.

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