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Relational integration as a predictor of academic achievement

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ABSTRACT

The current study aimed at applying a broad model of cognitive functions to predict performance in science and language courses at school as well as performance in a science course at university. We hypothesized that performance in science courses was predominantly related to the cognitive function known as relational integration, whereas performance in language courses should be best explained by individuals' short-term memory capacity. The sample consisted of 161 German undergraduate students who were asked to complete 33 cognitive tasks. School grades were also obtained. The analyses revealed that relational integration incrementally explained variance in science grades. Short-term memory acted as a predictor of language grades. However, mental speed was also substantially related to language grades. Predicting university exam scores revealed that short-term memory yielded an incremental predictive power. We conclude that academic performance requires different cognitive functions depending on a domain of study.

Being successful in secondary and tertiary education is fundamental for students' future career (e.g., Kuncel, Hezlett, & Ones, 2001; Roth & Clarke, 1998; Schuler, Funke, & Baron-Boldt, 1990), particularly when admission to colleges and professional programs (e.g., trainee programs) depends on grades and degrees obtained. In general, predictors of academic performance are typically dichotomized into cognitive and non-cognitive characteristics (Rindermann & Neubauer, 2001; Robbins et al., 2004; Rothstein, Paunonen, Rush, & King, 1994). Typically, cognitive variables — in particular general mental ability and fluid intelligence — have been shown to explain more variance in individuals' achievement than non-cognitive abilities (e.g., Kuncel et al., 2001; Rohde & Thompson, 2007) although non-cognitive predictors such as Big-5 personality dimensions add significantly to this predication (e.g., Laidra, Pullmann, & Allik, 2007; Poropat, 2009).

In a number of studies, various measures of intelligence, or more specifically fluid intelligence, accounted for up to 58% of explained variance in measures of academic achievement (cf. Deary, Strand, Smith, & Fernandes, 2007). However, the applied measures of fluid intelligence do not denote a specific cognitive function or process, and have been criticized for being too broad (Oberauer, Schulze, Wilhelm, & Süß, 2005). Hence, by relating broad components of intelligence (such as fluid intelligence) to academic achievement, the cognitive processes involved cannot be identified. As a consequence, scientists who examine effective predictors of academic achievement directed their attention to distinct cognitive processes that are assumed to be limiting factors of fluid intelligence (e.g., Krumm, Ziegler, & Bühner, 2008; St. Clair-Thompson & Gathercole, 2006). The most prominent and frequently examined limiting factors of fluid intelligence are represented by the concepts of mental speed and working memory (Schweizer, 2005). In the current study we aim to identify cognitive processes particularly relevant to various aspects of academic achievement. To this end, we apply basic cognitive processes that are subsumed under a broad model (Krumm et al., 2009) as predictors of several indicators of academic achievement (including school grades and university exam grades).

1. Mental speed and working memory as limiting factors of intelligence

Research on individual differences in intelligence discusses approaches that aim at describing intelligence (e.g., Carroll, 1993). These approaches comprise several cognitive abilities (e.g., mental speed) in a general model of intelligence. Other approaches aim at explaining (fluid) intelligence by a set of limiting factors that may be considered the cognitive basis of intelligence (e.g., the mental speed approach, cf. Vernon, 1987). In the current research, we consider mental speed and working memory as limiting factors and *not* as sub-facets of fluid intelligence.

The mental speed approach to identifying the cognitive basis of general mental ability presumes that the speed of information processing determines the quality of higher cognitive functioning. This is due to the fact that information can only be held mentally present for a short period of time and needs to be processed within this limited amount of time. Individuals higher in mental speed are less likely

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to experience information decay before it has been properly encoded or processed (cf. Vernon, 1987). Danthiir, Wilhelm, Schulze, and Roberts (2005) summarized existing literature on the relationship between mental speed and fluid intelligence. The researchers found that typical zero-order correlations ranged from .30 to .50. These correlations indicate that mental speed might be the cognitive basis of fluid intelligence. Hence, in the current study we consider mental speed a relevant cognitive function which predicts academic achievement.

The working memory approach to identifying the cognitive basis of fluid intelligence posits that information may be unavailable for higher mental processing because of the limited capacity of the working memory system to temporarily store and retrieve information — and not just because of the low processing speed (cf. Oberauer, Süß, Wilhelm, & Wittman, 2003). The reported correlations between working memory and measures of fluid intelligence vary considerably (from .50 to .90) (e.g., Bühner, Krumm, & Pick, 2005; Colom, Abad, Rebollo, & Chun Shih, 2005; Engle, Tuholski, Laughlin, & Conway, 1999) but usually exceed those reported for the relationship between mental speed and fluid intelligence (e.g., Ackerman, Beier, & Boyle, 2005; Krumm et al., 2009; Kyllonen & Christal, 1990).

The variation in these studies may be attributed to differences in the authors' conceptualization of working memory. Some authors posit that working memory can simply be conceptualized as the capacity of short-term memory (cf. Colom, Abad, Quiroga, Shih, & Flores-Mendoza, 2008), whereas others claim that working memory is best described by a set of distinct cognitive functions that limit higher mental processing (Oberauer et al., 2003). Several potential candidates for such limiting functions were associated with the concept of working memory (e.g., executive functions, see Friedman et al., 2006; or relational integration, see Bühner et al., 2005). Hence, we posit that examining determinants of academic achievement beyond fluid intelligence requires careful consideration of working memory facets. Given the current debate in working memory research, we decided to apply a broad model of cognitive functions that includes most of the current working memory conceptions.

2. A model of mental speed, working memory and reasoning

Krumm et al. (2009) attempted to identify common factors in a broad set of cognitive tasks that ranged from very simple elementary choice tasks to complex reasoning tasks. This was not a new approach; broad factors reflecting cognitive abilities were reported by many authors, including Horn and Noll (1994) and Carroll (1993). However, previous studies did not explicitly focus on those cognitive functions that are assumed to be the cognitive basis of fluid intelligence, namely, mental speed and working memory-related functions. In their investigation, Krumm et al. (2009) also considered recent models of working memory that yielded very high predictive power in explaining fluid intelligence. The cognitive functions that the researchers examined included several mental speed task classes, sustained attention, executive functions, short-term storage, and facets of working memory (see Schweizer, 2005 for the functions' relevance as a cognitive basis of g). Based on a sequence of exploratory and confirmatory factor analyses, Krumm et al. (2009) proposed a model with three orthogonal factors to best explain their empirical data. These factors were: relational integration, short-term storage, and mental speed (see Fig. 1).

According to Oberauer et al. (2003) relational integration reflects individuals' ability to build a mental representation of several elements that are related to each other and to integrate new elements into it. According to Oberauer et al. (2003, p. 169) interpreting a table containing a three-way interaction is an example of a tasks that requires relational integration: One needs to compare pairs of numerical values, differences between pairs, and differences of differences. Several researchers repeatedly showed that relational integration was highly related to reasoning (e.g., Bühner et al., 2005; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002). The second factor (Krumm et al., 2009), short-term storage, is predominantly defined by short-term storage tasks (with and without additional processing requirements), which require participants to temporarily store and retrieve information. The third factor — mental speed — showed loadings on all the tasks. This was not surprising because all the tasks were more or less speeded. The highest loadings on this factor were observed for simple cognitive tasks (e.g., the sustained attention and perceptual speed tasks) in which performances are largely determined by the participants' speed (see Fig. 1).

In sum, the model proposed by Krumm et al. (2009) brought together cognitive functions (mental speed, short-term storage, executive functions and components of working memory) that were frequently and successfully applied as predictors of intelligence (e.g., Ackerman et al., 2005; Conway, Cowan, Bunting, Therriault, & Minkoff, 2002). Hence, this model is a good basis for simultaneously examining the predictive power of several cognitive functions in explaining academic achievement, thereby helping us to gain better understanding of the cognitive processes that are relevant to academic achievement. In the current research, we intend to examine whether the three factors proposed by

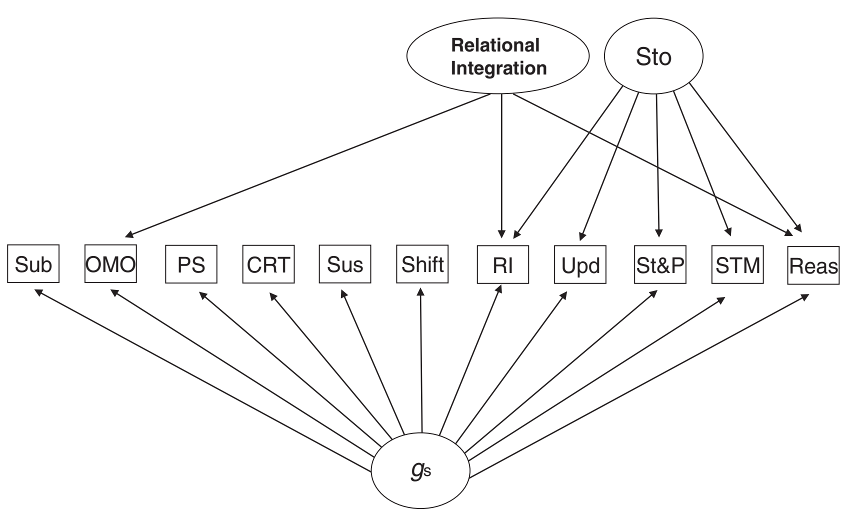

Fig. 1. *Three orthogonal factors explaining cognitive task performances* (Krumm et al., 2009). *Notes*. Abbreviations: Sub = substitution, OMO = odd-man-out, PS = perceptual speed, CRT = choice reaction time, Sus = sustained attention, Shift = shifting, RI = relational integration, Upd = updating, St&P = storage in the context of processing, STM = short-term memory, Reas = reasoning, gs = general (mental speed) factor, Sto = storage.

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Krumm et al. (2009) are effective in predicting academic achievement. This approach differs from what has been examined before in that we simultaneously examine a unique set of cognitive functions (including relational integration) that emerged from an even broader set of cognitive tasks as limiting factors of fluid intelligence.

3. Working memory and mental speed as predictors of academic achievement

A number of studies have examined the relevance of working memory in predicting academic achievement. However, results are not easy to compare as these studies differ considerably with respect to their operationalizations of working memory. D'Amico and Guarnera (2005), for example, followed the prominent concept of working memory proposed by Baddeley and Hitch (1974) and revealed that students with poor arithmetic skills showed lower scores on most of the applied tasks (visuo-spatial sketchpad tasks, central executive tasks, and phonological loop tasks). The verbal phonological loop tasks formed the exception. Verbal storage and processing abilities, on the other hand, proved to be particularly important for performances in language courses. Daneman and Carpenter (1980) found a correlation of $r = .59$ between reading span tests and verbal SAT results. Similarly, Krumm, Ziegler, and Bühner (2008) used the facet model of working memory (Oberauer et al., 2003) and found an incremental contribution of the verbal short-term storage and processing task beyond reasoning in predicting language grades. Relational integration, another facet of this working memory model, yielded an incremental contribution in predicting science grades.

These and other studies contribute to our general understanding of why working memory might be related to academic achievement. Some authors assume that the working memory capacity acts as a "bottleneck for learning in many of the individual learning episodes required to increment the acquisition of knowledge" (Gathercole, Alloway, Willis, & Adams, 2006a, p. 277). However, specific assumptions about the two aspects of working memory (short-term storage and relational integration) can also be made. Daneman and Carpenter (1980) administered a series of verbal working memory tasks with high short-term storage demands and revealed a correlation of .50 to .60 between these tasks and measures of reading comprehension. This correlation may be attributed to the fact that individuals low in working memory span are worse in coping with sentences containing misleading context and find it more difficult to draw inferences from text (Baddeley, Logie, Nimmo-Smith, & Brereton, 1985; cf. Baddeley, 1992). It has been presumed that the capacity of the phonological loop, i.e., the working memory system responsible for short-term storage of information, might help children to acquire new words (Gathercole, Pickering, Knight, & Stegmann, 2004). It seems also plausible that the phonological loop might also be relevant for adults when learning foreign languages. This assumption was strongly supported by a case study with a patient suffering from a pure phonological loop deficit. This patient was able to learn native language pairs, but she was unable to learn any of eight Russian words (Baddeley, Papagno, & Vallar, 1988). Hence, we hypothesize that

Hypothesis 1. Short-term storage significantly and incrementally predicts achievement in language courses.

The central executive as a working memory component has been frequently employed to predict performance in mathematics and problem solving tasks (e.g., Bull & Scerif, 2001; Geary, Hoard, Nugent, & Bailey, 2012; Iuculano, Moro, & Butterworth, 2011; Passolunghi & Siegel, 2001; cf. Pickering, 2001). However, Krumm et al.'s (2009) analyses of a broad range of executive function tasks and other working memory tasks did not yield a separate factor for executive function tasks. Rather, these and other authors (Bühner et al., 2005; Oberauer, Süß, Wilhelm, & Wittmann, 2008; Oberauer et al., 2003) identified a factor labeled relational integration.

Less evidence is available regarding the relevance of relational integration for academic performance. Krumm, Ziegler, and Bühner (2008) examined the predictive power of the relational integration component of working memory. The researchers revealed that relational integration explained 24% of variance in science grades. In line with arguments provided by Swanson and Saez (2003) we posit that student achievement in courses that require integration of information from long-term memory with new information as well as those that require integration of several new interdependent pieces of information largely depends on the working memory component relational integration. Such demands are particularly evident in complex tasks with a hierarchical structure (Gathercole, Alloway, Willis, & Adams, 2006a; Gathercole, Lamont, & Alloway, 2006b) that frequently occur in science courses. Our presumption is further supported by an observational study by Gathercole, Lamont, and Alloway (2006b). These authors reported a higher amount of failures in low working memory individuals when working on tasks with complex hierarchical structure. Hence, we hypothesize that

Hypothesis 2. Relational integration significantly and incrementally predicts achievements in science courses.

Mental speed has been successfully applied as a direct or indirect predictor of academic performance in many studies (Carlson & Jensen, 1982; Luo, Thompson, & Detterman, 2003; Rindermann & Neubauer, 2004; Rohde & Thompson, 2007). The basic assumption as to why mental speed should be related to academic performance is derived from the mental speed theory that posits that higher cognitive processing is limited by the speed of information processing (for an overview see Deary, 2000). Higher cognitive processing (as involved in general mental ability tasks) in turn predicts academic performance. Following these assumptions, the contribution of mental speed to academic performance should be mediated through *g*. This idea is supported by initial empirical findings. For example, Rindermann and Neubauer (2004) reported a mediation model in which mental speed predicted *g*, *g* in turn predicted school grades. No direct path was found between mental speed and school grades. Hence, we hypothesize that

Hypothesis 3. Mental speed does not significantly predict achievements in science or language courses when applied simultaneously with relational integration and short-term-storage.

To our knowledge, no studies have examined the relevance of mental speed and working memory related functions for academic performance at a university level. However, we posit that Hypotheses 1–3 also apply to performance in science courses at university.

In sum, the current study aims at simultaneously investigating the relevance of two important cognitive constructs, working memory and mental speed, in predicting performance at school and university.

5. Method

5.1. Participants

The sample included 161 German undergraduate students (67% female) from the department of Psychology (59%) and other departments of the University of Marburg[1]. Their mean age was 21.02 years ($SD = 2.3$; range = 18 to 28). The vast majority of participants were first year students (73%). Students completed a number of tests and submitted a copy of their previous year's grade report. Participation in the study was voluntary. After the last test session, all participants received performance feedback. A smaller subsample of $n = 73$ students of Psychology (mean age = 20.3, $SD = 1.91$; range = 18 to 28) provided their statistic

[1] This was a sub-sample that was already analyzed by Krumm et al. (2009). However, Krumm et al. did include (several school or university) grades in their analyses.

exam grades, which they obtained about two years after they took the cognitive tests included in the current research.

5.2. Measures

Task selection was guided by the aim to broadly cover the concepts of working memory and mental speed. In order to account for the heterogeneity of working memory models, the current study applied a broad range of cognitive functions that were frequently associated with working memory — including components of the facet model of working memory (i.e., storage in the context of processing, relational integration, and shifting, see Oberauer et al., 2003) as well as simple short-term memory and additional executive functions that were not considered by Oberauer et al. The mental speed tasks were selected following the model proposed by Danthiir et al. (2005). Due to space limitations, the measures applied in the current study (33 tasks altogether) are only briefly described. Readers are referred to Krumm et al. (2009) for a more detailed task description.

5.3. Components of a facet model of working memory (Oberauer et al., 2003)

Verbal, numerical, and figural storage in the context of processing tasks (see *St&P* in Fig. 1) consisted of a stimulus presentation phase, a processing phase, and a recall phase. Nouns, digits, or patterns served as the material to be remembered. The presentation of stimuli to be remembered was followed by a series of processing tasks with a fixed duration of 5 s. Afterwards, participants were asked to recall the material from phase 1. The number of elements remembered in the correct sequence was assessed.

In verbal, numerical, and figural relational integration tasks (see *RI* in Fig. 1) participants had to monitor matrices completely or partially filled with words, numbers or dots. Elements of the matrix were continuously replaced in short time interval. Participants were asked to press a button whenever the current configuration of elements contained critical relations. Critical relations were: (a) three words that rhymed located in either the horizontal, vertical, or diagonal line (verbal task), (b) three numbers with identical last digits located in either the horizontal, vertical, or diagonal line (numerical task), (c) four dots that formed a square (figural task). Scores were obtained by subtracting false alarms from hits.

Verbal, numerical, and figural shifting tasks (see *Shift* in Fig. 1) combined two choice reaction time tasks (according to Rogers & Monsell, 1995) with alternating decision rules. Stimuli appeared in clockwise fashion in one of four cells of a 2×2 matrix. Participants had to make simple decisions and press the appropriate button as fast as possible. However, the required decisions alternated while the stimulus material remained the same. For example, during the verbal switching task participants had to make a decision “plant or animal?” in the upper two cells of the matrix; then they had to switch to the second decision rule “one syllable or two syllables?” in the lower two cells. Switching costs were calculated by subtracting log-transformed no-switching reaction times from log-transformed switching reaction times.

5.4. Short-term memory

Short-term memory tasks (see *STM* in Fig. 1) consisted of sequences of verbal, numerical, or figural elements that had to be recalled correctly. The verbal version consisted of pseudo-random sequences of four to eight nouns with a 1 s inter-stimulus interval. The nouns had to be recalled in the correct order directly afterwards. Sequences of five to nine digits formed the numerical version, sequences of two to five patterns the figural version. The number of correctly recalled stimuli was assessed.

5.5. Executive functions not included in the facet model of working memory

Updating (see *Upd* in Fig. 1) was assessed following Miyake et al. (2000) with a figural N-back task, a verbal Keep Track tasks, and a Tone Monitoring task.[2] [3] In the current study we used an N-back task that presented figural stimuli one after another. In the 2-back condition participants had to press a target button whenever the symbol that appeared on the screen was equivalent to the second to last symbol. The 3-back condition required subjects to respond by pressing a certain button whenever the third to last symbol was equivalent to the symbol at hand. Scores were built by calculating the proportion of actual correct target responses in relation to all the possible correct responses.

The Keep Track task employed six target categories (animals, plants, clothes, furniture, professions, and sports), which were constantly shown at the bottom of the computer screen. Sequences of target words, which could be classified into one of the six categories, were presented to the participants. The participants had to remember the last word presented in each of the relevant target categories and write the word down on an answer sheet. E.g., the words *tiger*, *hockey*, *tennis*, *lecturer*, *accountant*, and *golf* appeared on the screen one after another. Imagine the categories were animals, sports, and professions. In this case the correct answer would be tiger, golf, and accountant (last item from each category). The proportion of correctly recalled words relative to all the words to be recalled was used for further analyses.

In the Tone Monitoring task, a random sequence of three different tones (high, medium, and low pitch) was presented via headphones. Participants had to count the different tones constantly and to respond whenever the fourth tone of the same pitch was presented. If the tone sequence was high, high, low, medium, low, high, low, medium, *high*, medium, *low*, participants had to press a target button when the italicized tones were presented. After incorrect responses subjects were instructed to forget the previously counted tones and start over again. The proportion of correct responses was used for further analyses.

5.6. Mental speed

All the mental speed components proposed by Danthiir et al. (2005) were included in the current study in a paper–pencil format: perceptual speed, odd-man-out, and substitution (see *PS*, *OMO*, and *Sub* in Fig. 1). These tests were supplemented by paper–pencil sustained attention tests (see *Sus* in Fig. 1) and computerized test of processing speed (choice reaction time tasks, see CRT in Fig. 1). Although paper–pencil sustained attention tests as well as computerized processing speed tests were found to be empirically indistinguishable from mental speed tests (Krumm, Schmidt-Atzert, Michalczyk, & Danthiir, 2008), we nevertheless included them to also cover tests that were originally developed in different research traditions.

A task called finding *a*'s as well as a numerical and a figural comparison task were applied to measure perceptual speed (see *PS* in Fig. 1). The test finding *a*'s consisted of single words that were presented on a piece of paper. Words containing the letter *a* served as targets. Participants were asked to mark as many targets as possible within 60 s. Both the numerical and the figural comparison tests consisted of two columns with either numbers or symbols. These columns were either identical or differed by one digit/symbol. Participants were instructed to indicate whether the columns were identical or not. The number of correctly indicated columns within the given time limit was assessed.

[2] Updating formed a task parcel that did not include a numerical task. Instead, we decided to follow the operationalization proposed by Miyake et al. (2000).

[3] Krumm et al. (2009) found that another executive function proposed by Miyake et al. (2000), inhibition, did not form a homogeneous factor. Hence, we did not consider this executive function in the current research.

The verbal, numerical, and figural odd-man-out tasks (see *OMO* in Fig. 1) consisted of sequences of eight letters, digits, or arrows representing one item. These sequences always included three critical characters of the same kind (either "a", "3", or "↑"). The participants' task was to place a circle over the "odd-man-out" (e.g., in the sequence *g a b a t r z a* the underlined "*a*" is separated from the next "*a*" by three other letters, whereas the other two "*a*'s" are separated by only one letter). The number of correctly marked targets within the given time limit was used for further analyses.

Verbal, numerical, and figural substitution tasks (see *Sub* in Fig. 1) consisted of a coding scheme with either 4 different letters, digits, or compass points (north, south, east, west). The coding scheme was presented at the top of the page with 4 arrows pointing into different directions. Rows with 180 spaces in total had to be filled in with the corresponding letter, digit, or compass point, respectively. Scores were built by counting the number of correctly marked targets within the given time limit.

Sustained attention tests (see *Sus* in Fig. 1) were selected following recommendations of Schmidt-Atzert, Bühner, and Enders (2006).[4] The d2 Test (Brickenkamp & Zillmer, 1998) consisted of 14 lines with 47 letters each. The letters were *d*'s and *p*'s with no, one, or two vertical strokes below and/or above each letter. The participants had to mark each *d* that had two strokes. The number of correctly marked items within the given time limit was assessed. The revision test (Marschner, 1980) consisted of 15 lines with 22 items each. Items were represented by three digits positioned in a column. The participants' task was to quickly assess whether the upper two digits add up to the third one. Correct equations had to be marked, incorrect ones struck out. Scores were built by counting the number of correctly marked items within the given time limit. The trail-making test (Oswald & Roth, 1997) required subjects to draw a line connecting numbers from 1 to 90, in ascending order. The numbers were printed in a grid shape on a sheet of paper; the next number was always in either an adjacent line or a column. The mean number of correctly connected numbers across three trials of this test was used for further analyses.

The computerized verbal, numerical, and figural choice reaction time (see CRT in Fig. 1) consisted of stimuli presented sequentially and required a quick categorization into one of two categories: Does a given word consist of one syllable or two syllables? Is a given number above 500 or below 500? Does a given geometrical figure consist of one part or two parts? Participants were asked to respond as quickly and correctly as possible by pressing the keys labelled "right" or "left" on the keyboard. The reaction time of correct decisions was used for further analyses.

5.7. Reasoning

Subtests of the intelligence structure test I-S-T 2000 R (Amthauer, Brocke, Liepmann, & Beauducel, 2001) were administered to measure reasoning (as one of the best indicators of intelligence). Participants had to perform a verbal (verbal analogies), a numerical (number series), and a figural (matrices) subtest. In the verbal analogies test, tasks consisted of three words and a missing fourth word. The semantic relation between the first and the second word had to be identified in order to add the fourth word to the third ("Human Being:Brain = City:?"). The number of correct words was assessed. The number series test required participants to add the next number to a sequence of numbers according to a rule they needed to discern. The number of correctly added numbers was used for further analyses. The matrices test employed tasks that consisted of a 2 × 2 matrix with three different figures. The configuration of the three figures followed a certain rule which had to be identified and the correct missing figure had to be chosen according to that rule.

[4] Sustained attention formed a task parcel that did not include a figural task. Instead, we decided to follow the operationalization proposed by Schmidt-Atzert et al. (2006).

5.8. Academic achievement

Academic achievement was assessed with school grades and psychology students' statistic exam scores obtained at university.

School grades of the final two years of the German high school (obtained from the final school report) were aggregated. Following our hypotheses, course grades were grouped into two areas and mean grades were calculated for two parcels: *language* (German, English, and French) and *science* (math, physics, biology, and chemistry).[5] The German grade-scale ranges from 0 to 15 reflecting the following performance categories: *very good* (15–13), *good* (12–10), *satisfactory* (9–7), *adequate* (6–4), *inadequate* (3–1), and *fail* (0).

Statistics exam scores. Courses at a university cannot be easily classified into *science* and *language*. In the current study, the university course grades of psychology students were available, from which we only used the statistics exams grades. The rationale behind this selection was to obtain the best indicator available for achievement in science. The last two statistics exam grades (obtained in semesters 2 and 3) were averaged to build a parcel. Scores reflected grades ranging from 1 to 5, with 1 being the best grade. No other exams of psychology students were considered, as these exams could not be clearly assigned to either achievements in science or language courses. Statistics exam scores were obtained at least one year after the cognitive test battery was conducted. No grades from university courses were available that could be clearly classified as language courses.

5.9. Procedure

Participants were tested in groups of 2 to 5 in a laboratory. Each participant took part in three sessions lasting approximately 3 h each, separated by 1–4 weeks. Tasks were scheduled in a way that minimized problems with understanding the instructions: similar tasks were administered immediately after each other.

5.10. Statistical analyses

The analyses were conducted on the level of parcels. Each parcel was built by averaging the verbal, numerical, and figural task of the same task class (e.g., a verbal, numerical, and figural reasoning task comprised the reasoning parcel) (for exceptions see footnotes 2 and 4).

5.10.1. Confirmatory factor analysis

The predictive power of the components identified in the Krumm et al. (2009) model (i.e., relational integration, short-term storage, and mental speed; see Fig. 1) was tested with confirmatory factor analyses. The three factors were used as predictors of the school grade parcels (science and language) that were added individually to the confirmatory factor analyses. The statistics exam scores parcel was not added to this model, as the available subsample was too small. To account for the fact that participants attended German high schools located in different federal states (clustered data) that could have differed in quality of education (cf. PISA 2004 ranking; Prenzel et al., 2004), we additionally conducted the confirmatory factor analyses with school grade residuals. These residuals were obtained by regressing the PISA 2004 ranking of the federal states (in either math or reading comprehension, respectively) on language and science course grades. This approach was chosen as an alternative to a multi-level analysis which calls for a much larger sample than was available to us.

Confirmatory factor analyses (maximum likelihood) were conducted with AMOS 18.0 (Arbuckle, 2009). All the test scores were re-coded in a way that high scores expressed high performances.

[5] Some authors considered math (and physics) to fall in a separate cluster (e.g., Rindermann & Neubauer, 2004). The current results, however, remained similar regardless whether math was considered separately or aggregated in a mutual science cluster.

The evaluation of model fit was based on the following guidelines: (a) acceptable fit: RMSEA ≤ .08, SRMR ≤ .09, and CFI ≈ .90; (b) good fit: RMSEA ≤ .05 (or 90% C.I. of the RMSEA including .05), SRMR ≤ .09, and CFI ≥ .95 (e.g., Beauducel & Wittmann, 2005; Browne & Cudeck, 1992; Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004).

5.10.2. Hierarchical regression analysis

Several three-step hierarchical regression analyses were conducted to individually predict the measures of academic achievement (the school grade parcels for science and language, as well as the statistics course scores parcel). The hierarchical regression analyses (method: enter) enabled us to assess the individual contributions of some cognitive abilities while controlling for the contribution of others. Thus, these analyses supplemented the confirmatory factor analyses. The selection of cognitive abilities followed the model proposed by Krumm et al. (2009); task parcels with high loadings on the respective ability factors formed the independent variables. Choice reaction time tasks, perceptual speed tasks, sustained attention tasks, as well as substitution tasks represented the mental speed task class. The short-term storage task class included storage in the context of processing tasks and short-term memory tasks. Finally, the relational integration category comprised relational integration tasks and reasoning tasks. Each task type was entered as a parcel covering verbal, numerical, and figural tasks.

In the first regression analysis, mental speed was controlled for in step 1 and relational integration in step 2, before we predicted academic achievement with short-term storage (Hypothesis 1). Second, we controlled for mental speed in step 1 and for short-term storage in step 2, before we predicted academic achievement with relational integration (Hypothesis 2). Finally, we assessed the predictive power of mental speed after controlling for relational integration and short-term storage (Hypothesis 3).

6. Results

6.1. Descriptive statistics

Descriptive statistics of the measures of academic achievement as well as the applied tasks parcels are presented in Table 1. Multivariate normality was not confirmed (multivariate kurtosis = 8.86, c.r. = 3.07). Thus, we conducted a Bollen–Stine bootstrap procedure (400 samples) to obtain a corrected p-value for the χ^2-test in the confirmatory factor analyses. Statistics exam grades were only moderately related to science grades suggesting that these two performance measures index non-overlapping skills.

6.2. Confirmatory factor analysis

The model applied to predict the science grades parcel is depicted in Fig. 2. This model yielded an acceptable to good overall model fit (χ^2 [44] = 76.26, $p<.05$, RMSEA = .068 [.041–.093], SRMR = .045, CFI = .96). The three latent variables relational integration, short-term storage, and mental speed were simultaneously used as predictors of school grades. Altogether, 19% of variance in the science grades parcel was explained. As expected, only the latent variable relational integration significantly predicted the science grades parcel ($\lambda = .41$, $p<.01$). Neither the latent mental speed variable nor the latent short-term storage variable showed significant paths to the science grades parcel ($\lambda = .12$, $p = .157$ and $\lambda = .06$, $p = .461$, respectively). A post hoc modification of the model revealed that an additional direct path from the reasoning task parcel to the school grades parcel yielded an insignificant path coefficient ($\lambda = .21$, $p = .084$). Using the residual of the dependent variable after controlling for PISA 2004 ranking led to similar results.

The model applied to predict the language grades parcel is depicted in Fig. 3. It revealed an acceptable to good overall model fit (χ^2 [44] = 77.18, $p<.05$, RMSEA = .069 [.042–.094], SRMR = .044, CFI = .96). Altogether, 8% of variance in the language grades parcel was explained. As expected, the latent short-term storage variable significantly predicted the language grades parcel ($\lambda = .19$, $p<.05$). However, an additional contribution was observed for the latent mental speed variable ($\lambda = .17$, $p<.05$). Relational integration did not significantly predict the language grades parcel ($\lambda = .09$, $p = .391$). Using the residual of the dependent variable after controlling for PISA 2004 ranking revealed similar results.

In sum, results of the confirmatory factor analyses provided support for Hypotheses 1 and 2, thereby attesting to the differential validity of relational integration and short-term storage. Hypothesis 3 (no significant contribution of mental speed) was only supported for the prediction of the science grades parcel but not for the language grades parcel.

As an alternative approach to the data, we attempted to predict school grades in a structural equation model that did not specify orthogonal but correlated mental speed and short-term storage factors. In order to focus on basic cognitive abilities and to avoid colinearity issues, this model (see Fig. 4) did not include a relational integration factor, which also covered reasoning. Fit indices suggested an acceptable overall model fit (χ^2 [18] = 35.86, $p<.05$, RMSEA = .079 [.040–.116], SRMR = .055, CFI = .97). Neither the latent mental speed nor the latent short-term storage variable yielded a significant path to the science grades parcel. However, short-term storage showed a significant path to the language grades parcel ($\lambda = .17$, $p<.05$).[6]

6.3. Hierarchical regression analysis

Three dependent variables were employed in individual hierarchical regression analyses. Altogether, 9.8% of the language grades parcel, 11.9% of the science grades parcel, and 20.1% of the statistic exam scores parcel were predicted.

The first set of hierarchical regression analyses examined the incremental contribution of short-term storage tasks over and above mental speed and relational integration tasks (cf. Table 2). As expected such a validity increment was not evident in predicting the science grades parcel ($\Delta R^2 = .006$, $p = .617$). Contrary to our expectation, no additional contribution of short-term storage tasks was observed in predicting the language grades parcel ($\Delta R^2 = .011$, $p = .395$). However, the validity increment was evident in predicting the statistics exam scores parcel ($\Delta R^2 = .082$, $p<.05$).

The second set of hierarchical regression analyses tested for incremental contribution of relational integration tasks over and above short-term storage tasks and mental speed tasks (cf. Table 3). In line with our expectations, the validity increment ($\Delta R^2 = .085$, $p<.01$) was evident in predicting the science grades parcel, but not in predicting the languages grades parcel. However, contrary to our expectations, no incremental contribution was observed in predicting the statistics exam grades parcel ($\Delta R^2 = .048$, $p = .151$).

The third set of hierarchical regression analyses was employed to investigate the incremental contribution of mental speed tasks to the prediction of the language grades parcel, the science grades parcel, and the statistics exam scores parcel, while controlling for relational integration and short-term storage tasks (cf. Table 4). As expected, mental speed tasks did not incrementally predict either one of the dependent variables (ΔR^2's ranging from .016 to .028, *ns.*).

In sum, Hypotheses 1, 2, and 3 were only partially supported by the hierarchical regression analyses.

7. Discussion

The current study examined the relevance of cognitive functions for academic performance. In particular, a model of cognitive functions was

[6] We thank the anonymous reviewer for valuable comments suggesting this alternative approach.

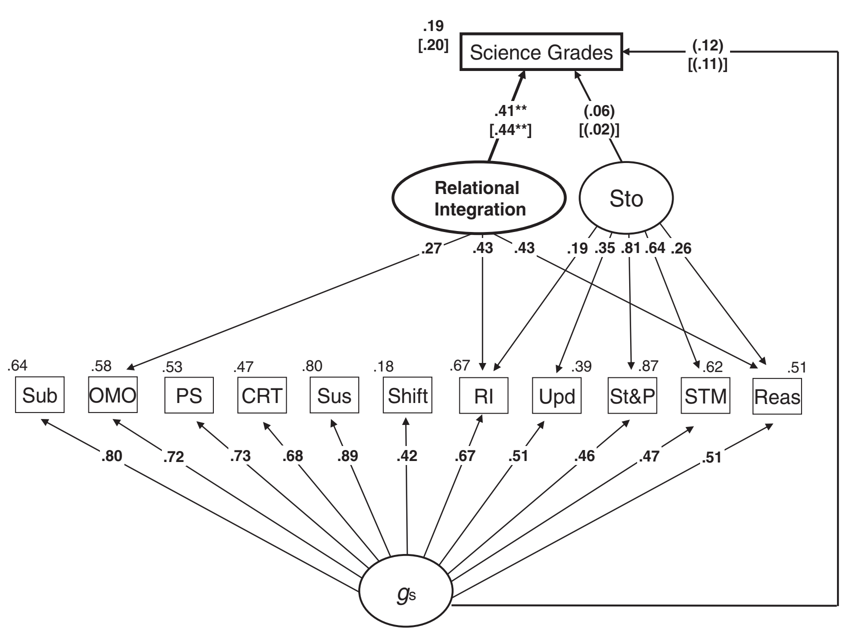
Table 1
Means, standard deviations, reliability estimates, and bivariate correlations of the applied variables.

	Variables	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Storage in the context of processing (number of correct responses)	3.77	0.41	.87 [a]													
2	Relational integration (hits minus false alarms)	1.67	0.52	.46	.85[a]												
3	Shifting (reaction time difference in ms)	271.60	127.71	.26	.26	.93[a]											
4	Short-term memory (number of correct responses)	3.92	0.55	.73	.40	.31	.88[a]										
5	Updating (proportion of correct responses)	0.69	0.09	.52	.50	.18	.46	.72[a]									
6	Perceptual speed (number of correctly edited items)	21.65	3.26	.30	.46	.23	.28	.37	–[b]								
7	Odd-man-out (number of correctly edited items)	56.61	8.85	.31	.62	.22	.33	.34	.58	–[b]							
8	Substitution (number of correctly edited items)	90.71	12.60	.43	.46	.44	.38	.38	.57	.51	–[b]						
9	Sustained attention (number of correctly edited items)	109.05	16.00	.37	.61	.37	.39	.48	.66	.64	.72	.98[a]					
10	Computerized choice reaction time (reaction time in ms)	609.26	71.62	.41	.53	.30	.44	.32	.47	.56	.58	.57	.99[a]				
11	Reasoning (number of correct answers)	13.78	2.23	.44	.57	.19	.40	.41	.30	.45	.42	.48	.38	.76[a]			
12	School grades: language (grades ranging from 15 to 1)	10.06	2.40	.23	.20	.04	.20	.18	.16	.08	.12	.15	.21	.25	.95[c]		
13	School grades: science (grades ranging from 15 to 1)	10.04	2.32	.10	.24	.06	.06	.20	.07	.19	.05	.11	.15	.29	.58	.94[c]	
14	Statistic exam score (grades ranging from 1 to 5)	2.63	1.00	.28	.28	.09	.09	.28	.09	.07	.08	.19	.09	.29	.37	.35	.57[d]

Notes. All the variables represent task parcels, with statistic exam score being the exception. Scores were re-coded for correlation analyses so that high scores expressed high performances. a = reliability of parcels as provided by Krumm et al. (2009) who used the same data set; b = could not be calculated; c = Cronbach's alpha; d = split-half reliability obtained from two exams.

applied to simultaneously predict school performance and university exam grades with mental speed, short-term storage, and relational integration task parcels. Our hypotheses were largely supported with regards to the prediction of school performance. Science course grade variance was exclusively explained by relational integration tasks, whereas language course grade variance was best (but not exclusively) explained by short-term storage tasks. In the latter case, mental speed tasks also revealed explanatory power. Hierarchical regression analysis demonstrated that relational integration tasks incrementally predicted science course grades variance but not language course grades variance. Short-term storage tasks did not act as an incremental predictor for any one of the school grade measures. Contrary to our presumptions, statistics exam grades were not predicted by relational integration tasks when all the other cognitive tasks were held constant. Rather, these grades were incrementally predicted by short-term storage tasks.

Although previous studies have reported findings that are in line with the results hereby presented (cf. Gathercole et al., 2004), most of these studies had not simultaneously examined the three factors and focused exclusively on one of the variables. For example, Rindermann and Neubauer (2004) examined the relevance of mental speed in predicting school grades. Other researchers focused on specific aspects of working memory in explaining variance in school grades (e.g., D'Amico & Guarnera, 2005). Yet others applied a broad concept of working memory but did not consider mental speed and executive functions (e.g., Krumm, Ziegler, & Bühner, 2008). Hence, the current research spans many recent studies on cognitive abilities that attempted to predict academic performance. Our study revealed that student performance in science courses predominantly requires cognitive ability to build a mental representation of several elements that are related to each other and to integrate new elements into it (i.e., relational integration, cf. Oberauer et al.,



χ^2=76.26 [44], p<.05, RMSEA=.068 [.041, .093],
SRMR=.045, CFI=.96

Fig. 2. *Three orthogonal factors explaining variance in science grades. Notes*. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content). Abbreviations: Sub = substitution, OMO = odd-man-out, PS = perceptual speed, CRT = choice reaction time, Sus = sustained attention, Shift = shifting, RI = relational integration, Upd = updating, St&P = storage in the context of processing, STM = short-term memory, Reas = reasoning, gs = general (mental speed) factor, Sto = storage. Coefficients in squared brackets refer to analysis in which we controlled for PISA results.

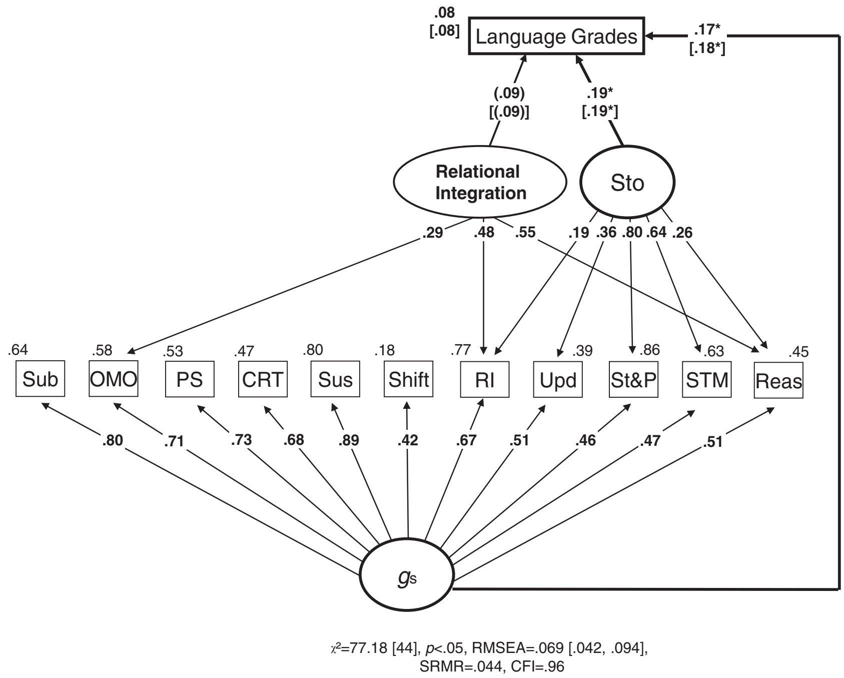


Fig. 3. *Three orthogonal factors explaining variance in language grades. Notes*. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content). Abbreviations: Sub = substitution, OMO = odd-man-out, PS = perceptual speed, CRT = choice reaction time, Sus = sustained attention, Shift = shifting, RI = relational integration, Upd = updating, St&P = storage in the context of processing, STM = short-term memory, Reas = reasoning, gs = general (mental speed) factor, Sto = storage. Coefficients in squared brackets refer to analysis in which we controlled for PISA results.

2003). Conversely, performance in language courses mostly rely on one's ability to temporarily store and retrieve information (i.e., short-term storage) — for instance, when drawing inferences from texts or when reading sentences with many nested clauses (cf. Baddeley et al., 1985; Colom, Escorial, Shih, & Privado, 2007).

The current study also yielded some unexpected findings. First, confirmatory factor analysis revealed that student performance in language courses was also determined by mental speed, i.e., the speed of mental information processing. However, this was only the case when mental speed was applied as a broad factor that was orthogonal to short-term storage and relational integration. When applied as a correlated factor, no significant paths from latent mental speed to language grades occurred. These seemingly contradictory results may indicate that performance on short-term storage tasks is — in addition to storage demands — to some extent contingent on mental speed, such that high mental speed can act as a compensatory mechanism for poor short-term storage, and vice-versa. Thus, mental speed may not have acted as a significant predictor in addition to short-term storage. The explanation as to why a broad, orthogonal mental speed factor might be

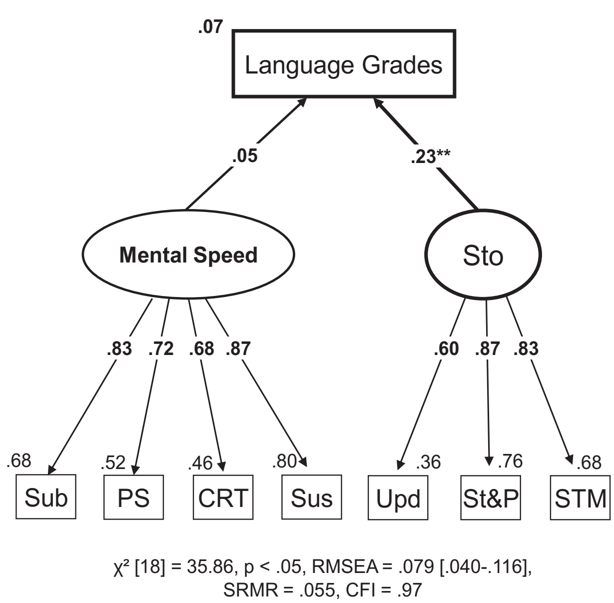


Fig. 4. *Alternative approach explaining variance in language and science grades. Notes*. The same model was applied to predict science grades. No significant paths from either latent storage or latent mental speed to science grades were observed. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content). Abbreviations: Sub = substitution, PS = perceptual speed, CRT = choice reaction time, Sus = sustained attention, Upd = updating, St&P = storage in the context of processing, STM = short-term memory, Sto = storage.

Table 2
Hierarchical regression analysis predicting academic performance with short-term storage controlling for mental speed and relational integration.

Independent variables	Dependent variables					
	Language grades		Science grades		Statistic exams	
	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1						
Choice reaction time	.18		.15		−.01	
Perceptual speed	.09	.048	−.01	.028	−.04	.047
Sustained attention	.02		.11		.32	
Substitution	−.05		−.12		−.13	
Step 2						
Relational integration	.03	.039*	.15	.085**	.21	.072
Reasoning tasks	.22*		.27**		.19	
Step 3						
Storage and processing	.12	.011	.00	.006	.46*	.082*
Short-term memory	.01		−.09		−.32	
Overall R^2		.098		.119		

Notes. Step 1 included tasks with the highest loadings on the mental speed factor, step 2 consisted of tasks with the highest loadings on the relational integration factor, and step 3 comprised tasks with the highest loadings on the short-term storage factor. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content).

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Table 3
Hierarchical regression analysis predicting academic performance with relational integration controlling for mental speed and short-term storage.

Independent variables	Dependent variables					
	Language grades		Science grades		Statistic exams	
	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1						
Choice reaction time	.18	.048	.15	.028	.01	.047
Perceptual speed	.09		−.01		−.04	
Sustained attention	.02		.11		.32	
Substitution	−.05		−.12		.13	
Step 2						
Storage and processing	.16	.025	.11	.005	.51**	.107*
Short-term memory	.03		−.08		−.29	
Step 3						
Relational integration	.00	.024	.15	.085**	.13	.048
Reasoning tasks	.19		.28**		.20	
Overall R^2		.098		.119		.201

Notes. Step 1 included tasks with the highest loadings on the mental speed factor, step 2 consisted of tasks with the highest loadings on the short-term storage factor, and step 3 comprised tasks with the highest loadings on the relational integration factor. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content).

relevant in language grades is similar to the mental speed hypothesis relating mental speed to intelligence (cf. Deary, 2000): The faster information is processed the less information may decay. It seems plausible that this ability is relevant in language courses, in which information is acquired constantly and only accessible for a limited amount of time (e.g., listening and reading).

Secondly, contrary to our assumption, short-term storage tasks did not act as incremental predictors of language course grades in the hierarchical regression analysis. Please note that the two approaches of analyzing our data (confirmatory factor analysis vs. hierarchical regression analysis) differ in one important aspect: In the confirmatory factor analysis we used orthogonal latent variables to predict academic achievement. In the hierarchical regression analysis, we entered single task parcels which were correlated with each other. Thus, mental speed tasks and short-term storage tasks might have prevented each other from showing significant incremental contributions in the regression analysis, whereas this was not the case when orthogonal latent variables were applied in the confirmatory regression analysis.

Third, the prediction of the statistics exam scores showed a reversed and unexpected pattern such that relational integration tasks did not act as incremental predictors, whereas short-term storage tasks did act as incremental predictors. To date, only few studies examined the relevance of working memory in performances at college or university. For instance, Gropper and Tannock (2009) provided preliminary evidence showing that working memory span (which we labeled short-term storage) is related to college performance. Examining a small sample of attention-deficit/hyperactivity disorder patients and normal controls, the researchers found a significant correlation between (auditory) working memory span and college GPA. In the current research, however, we surmised that statistics exams would fall into the science course cluster and thus predominantly require relational integration. However, bivariate correlations revealed that statistics exam scores were similarly related to both science and language course grades, thereby drawing a more differentiated picture of the validity of statistics exams. We can only speculate whether students did not deeply elaborate information but memorized single statistical facts. Future research should be concerned with relating specific cognitive functions to both global measures of success at the university and success in specific courses.

7.1. Significance

The current study contributed to the existing body of research in manifold ways. First, basic cognitive functions were applied that were derived from a model covering a variety of simple and complex cognitive tasks (Krumm et al., 2009). Second, a broad set of basic cognitive tasks classes were considered, with task classes consisting of verbal, numerical, and figural tasks each. Third, the current study assessed real life criteria of academic achievement, whereas most studies on the relevance of cognitive abilities in academic achievement are based on academic achievement tests. Although the latter approach has advantages (e.g., reducing the impact of context-related influences on academic achievement, such as teacher–student interaction), one can also assume that the relevance of some cognitive abilities is overestimated. Gathercole et al. (2004) speculated that the applied tests per se require reading, writing, and spelling — and, thus, are related to working memory. In our opinion, assessing academic achievement with tests and with real life criteria represent supplementary approaches. Finally, the current study assessed achievement in both secondary and tertiary education and distinguished two important performance clusters in secondary education, i.e., science and language courses (cf. Denig & Weis, 1970; Rindermann & Neubauer, 2004).

7.2. Limitations and future directions

We assessed academic performance retrospectively and, thus, cannot draw causal conclusions. Additionally, we analysed a homogeneous student sample in which the range of the applied variables was restricted. A heterogeneous sample would most likely have led to higher proportion of explained variance and more significant path coefficients. So, our results do not generalize to samples with lower school grades or learning disabilities (Ruban, McCoach, McGuire, & Reis, 2003). We controlled for PISA 2004 ranking in order to account for clustered data. Future studies should examine larger samples using multi-level analysis.

The current study contributed to research on the relevance of distinct cognitive abilities in a single aspect of academic achievement (i.e., grades). Future research might extend this approach by considering additional aspects of academic achievement such as academic attainment. Furthermore, additional insights might be gained by longitudinal studies as well as meta-analysis. Finally, we could gain

Table 4
Hierarchical regression analysis predicting academic performance with mental speed controlling for relational integration and short-term storage.

Independent variables	Dependent variables					
	Language grades		Science grades		Statistic exams	
	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1						
Relational integration	.08	.068*	.11	.095**	.16	.101*
Reasoning tasks	.21*		.23*		.20	
Step 2						
Storage and processing	.11	.014	−.02	.007	.40*	.071
Short-term memory	.03		−.08		−.33*	
Step 3						
Choice reaction time	.13	.016	.10	.016	−.04	.028
Perceptual speed	.10		.01		−.02	
Sustained attention	−.05		−.05		.17	
Substitution	−.11		−.14		−.25	
Overall R^2		.098	.119			.201

Notes. Step 1 included tasks with the highest loadings on the relational integration factor, step 2 consisted of tasks with the highest loadings on the short-term storage factor, and step 3 comprised tasks with the highest loadings on the mental speed factor. The analyses were based in task parcels containing three individual tasks (with verbal, numerical, and figural content).

further insights by linking the cognitive variables examined in the current study with non-cognitive predictors of academic achievement (cf. Lipnevich, MacCann, Krumm, Burrus, & Roberts, 2011).

7.3. Practical implications

These findings are not only relevant from a theoretical point of view but have several practical implications. The most obvious implication is that learning strategies may be adapted according to the specific cognitive abilities of individuals. This could be done, for example, by making relationships between different knowledge domains more explicit in science courses. Individuals with low working memory span may be encouraged to summarize short text sequences or to mark crucial elements of a text. An implication for a learning strategy may also be to rehearse shorter pieces of information more often. On a motivation level it is less stigmatizing to trace back school problems to distinct cognitive functions rather than intelligence in general and may improve students' attitudes towards school and school related activities (e.g., homework).

Overall, the current study highlights the importance of relating specific cognitive functions to academic achievement. In doing so, we contribute to improved understanding of cognitive variables underlying academic performance. This in turn may help students and instructors to adaptively choose the most effective strategies and materials to foster utmost success in school.

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