Predicting school achievement from self-paced continuous performance: Examining the contributions of response speed, accuracy, and response speed variability

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Abstract

Trial-to-trial fluctuations in self-paced performance have long been considered an important aspect of an individual's performance. Whereas average response speed has been considered a cognitive factor indexing the speed of mental processing, response speed variability has been considered an energetic factor indexing an individual's capability to sustain mental processes over prolonged time periods. Here we investigated whether there is an incremental contribution of response speed variability, compared to mental speed, in predicting school achievement. A sample of 89 individuals was tested with the Serial Mental Addition and Comparison Task (SMACT) twice within a retest-interval of three days. In addition to the conventional performance measures speed (M_{RT}) and accuracy (error percentage, EP), we evaluated two intraindividual response speed variability measures, standard deviation (SD_{RT}) and coefficient of variation (CV_{RT}), with regard to their power to statistically predict secondary- and high-school achievement. In general, school performance was best predicted by M_{RT} and not at all by EP. Response speed variability, especially CV_{RT}, appeared to be a good predictor of school performance, especially mathematics performance. The combined intake of M_{RT} and CV_{RT} as predictors in a multiple linear regression model, however, did not yield additional predictive value compared to the single-predictor model that contained only M_{RT}. A further interesting finding was that the performance measures were differentially predictive across genders. In sum, we suggest that response speed variability as indexed by CV_{RT} is a candidate dimension for the assessment of sustained concentration performance. Before applying CV_{RT} in practical assessment settings, however, additional research is required to elucidate effects of different task factors (e.g., task length, task complexity, content domain, etc.) on the predictive power of this performance measure.

Key words: concentration, attention, school achievement, reaction time variability, distractibility

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Although several studies have related intellectual ability, personality, and motivational variables to school achievement (e.g., Bratko, Chamorro-Premuzic, & Saks, 2006; Di Fabio & Busoni, 2007; Rindermann & Neubauer, 2004; Spinath, Spinath, Harlaar, & Plomin, 2006), very few have investigated concentration despite the fact that the ability to sustain and regulate mental focus over extended periods of time is an important prerequisite in almost every domain of learning and skill acquisition (cf. Ackerman, 1987). Most educational and school psychologists agree that concentration plays a pivotal role in intentional learning at school and elsewhere (e.g., Baillargeon, Pascual-Leone, & Roncadin, 1998; Bühner, Mangels, Krumm, & Ziegler, 2005; Cattell, Barton, & Dielman, 1972; Chang & Burns, 2005).

This study is concerned with the use of self-paced choice reaction tasks to predict school achievement. Such tasks usually require the speeded categorization of stimuli according to a fixed rule (Pieters, 1985). A variety of such tasks has been constructed as so-called concentration tests, which have a long tradition in cognitive-psychometric research and are currently used by numerous researchers and practitioners all over the world (e.g., Flehmig, Steinborn, Langner, & Westhoff, 2007a; Hagemeister, 2007; Pieters, 1985; Smit & Van der Ven, 1995; Van Breukelen, 1989; Van Breukelen et al., 1996; Van der Ven, Smit, & Jansen, 1989; Westhoff & Graubner, 2003). Notably, current research and practice has mainly focused on conventional measures such as average response speed and error percentage to index performance but largely neglected measures of response speed variability. Since in doing so some valuable information might be missed (Rabbitt, Osman, Moore, & Stollery, 2001), a more comprehensive approach would be to extract several competing aspects of task performance and relate them to different aspects of school achievement (Van Breukelen et al., 1996). Besides the conventional measures speed and accuracy, we here examined whether there is an incremental contribution of intraindividual response speed variability to statistically predict secondary and high-school achievement, exemplarily using the Serial Mental Addition and Comparison Task (Restle, 1970; Steinborn, 2004).

Psychometric assessment of sustained concentration

The assessment of elementary cognitive abilities has a long tradition in experimental and applied psychology (Moosbrugger & Goldhammer, 2006). Tests of concentration or mental speed have been widely used since the beginning of the 20th century (cf. Flehmig, Steinborn, Langner, Scholz, & Westhoff, 2007; Van Breukelen et al., 1996; Westhoff & Kluck, 1984, for a review). The term "mental speed test" was mainly used in the Anglo-American tradition of intelligence measurement (Peak & Boring, 1926; Spearman, 1927), whereas the term "sustained concentration test" was preferred in the European tradition (Kraepelin, 1902; Pauli, 1938). Conventional tests measuring the ability to sustain concentration over prolonged time periods are comprised of relatively easy and homogeneous items, which require individuals to engage in a speeded self-paced repetitive activity (Moosbrugger & Goldhammer, 2006; Westhoff & Kluck, 1984). The most frequently used tasks include continuous letter cancellation and mental addition (Smit & Van der Ven, 1995; Van Breukelen et al., 1996). In order to keep a high level of speed and accuracy over time, individuals must shield themselves against competing, task-unrelated thoughts to prevent distraction, which becomes more difficult the longer the task (Sanders & Hoogenboom, 1970; Van der Ven et al., 1989).

A distinct feature of serial choice response tasks is that performance can be registered by various measures for distinct aspects of behavior, including the average speed of responding, the accuracy of performance (error percentage) but also the constancy of performance, as reflected by measures of response speed variability. Actually, the possibility to extract several distinct dependent measures from the same overt behavior is indeed the major advantage of concentration tests, which makes them economic and versatile instruments in every kind of assessment situation (Pieters, 1985). With this regard, Westhoff and colleagues (e.g., Westhoff, 1985; Westhoff & Graubner, 2003; Westhoff & Hagemeister, 1992; Westhoff & Kluck, 1984) conducted a long series of studies showing that concentration speed and accuracy are largely independent dimensions of performance with differential predictive power in both educational and work-related settings (cf. Van Breukelen et al., 1996, for a similar view).

Besides response speed and accuracy, there is a third dimension of performance with potential informational value: response speed variability. These trial-to-trial response speed variations in self-paced choice tasks are a well known empirical phenomenon and have been extensively discussed since the beginning of the 20th century (cf. Van Breukelen et al., 1996, for a review). Kraepelin (1902) who pioneered in investigating the "work curve" phenomenon already observed that his participants had difficulties to permanently keep a high level of response speed during a testing session, but instead showed considerable variations in their performance. After conducting a long series of experiments, he concluded that continuous performance may not solely be determined by mental processing speed, which he referred to as the "quickness of thought", but also by some kind of mental discipline, which he referred to as "will persistence", a rather non-intellectual ability required to overcome the continuous accumulation of resistance against further proceeding with the task.

Subsequent research was largely influenced by Kraepelin's work, and the view that self-paced choice performance is not solely determined by cognitive speed but to a considerable degree by an energetic component raised common acceptance by many researchers (e.g., Bäumler, 1967; Bills, 1937; Fiske & Rice, 1955; Pauli, 1938; Poffenberger & Tallman, 1915; Sanders & Hoogenboom, 1970; Weaver, 1942; Yerkes, 1904). Sanders (1998, chap. 9) summarized the results of many studies on self-paced performance within the context of his cognitive-energetic model, arguing that lowered energetic states (as induced by situational variables, e.g., sleep deprivation, etc.) or individual differences in volitional control (referred to as the willingness and/or ability to invest mental effort during demanding tasks) often affect average response speed only indirectly, via an increase response speed variability. For example, it has been shown that individuals with attention-deficit hyperactivity disorder have particular problems to volitionally increase effort during mentally demanding tasks (e.g., Sanders, 1998, p. 411; Sergeant, 2000). At the behavioral level, ADHD is strongly related to response speed variability but not to average response speed (e.g., Castellanos et al., 2005; Leth-Steensen, Elbaz, & Douglas, 2000) even when motivation is controlled (Sergeant, 2000)[4]. It is thus suggested to use a mean-corrected variability measure, in particular, the reaction time coefficient of variation (CV_{RT}) instead of the reaction time standard deviation

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[4] Notably, individuals with ADHD are considered average in cognitive ability but to have particular difficulties with continuously energizing cognition. This is especially observed when performance is to be maintained over a relatively long time period and when the task is monotonous and/or repetitive. It should be noted at this point that the construct underlying the ability to volitionally increase and maintain an optimal level of mental effort during attention and concentration tasks is different from motivation.

(SD_{RT}) to index response speed variability (cf. de Zeeuw et al., 2008; Flehmig et al., 2007; Sanders, 1998, chap. 9; Segalowitz, Poulsen, & Segalowitz, 1999; Weaver, 1942).

To account for performance fluctuations in self-paced tasks, formal models have been developed that are based on the assumption that the response time distribution of an individual is composed of a mixture between two operating mental states, a state of preparation and a state of non-preparation (Falmagne, 1965; Falmagne & Theios, 1969; Pieters, 1985; Theios & Smith, 1972). Importantly, a two-state view of self-paced performance considers response speed variability not as resulting from a symmetric variation around the mean of the response time distribution but as arising from an asymmetric increase in the proportion of very long reaction times. This was first reported by Bills (1931) who identified the occurrence of incidental extra-long responses (called "mental blocks") after periods of normal work speed in self-paced color naming. The frequency of blocking increased as a function of task length thus resulting in a more skewed (sometimes bimodal) distribution of response times (e.g., Bäumler, 1967; Bertelson & Joffe, 1963; Bunce, Warr, & Cochrane, 1993; Weaver, 1942)[5].

Whereas the aforementioned models can account for experimental effects on the average individual, models of sustained concentration take the ubiquitous differences between the individuals into account (cf. Bäumler, 1967; Jansen & Glas, 2005; Smit & Van der Ven, 1995; Van Breukelen et al., 1996; Van der Ven, 1998; Van der Ven et al., 1989). The general assumption is that any continuously performed mental act that requires a certain amount of mental effort actually consists of a sequence of alternating periods of attention (i.e., active information processing) and distraction (i.e., task-unrelated processing, due to mental blocks). In periods of attention the individual is actually working on the tasks whereas in periods of distraction (blocking) the individual is not working on the task. In the context of the aforementioned concentration models, mental blocks are involuntary resting pauses that arise from a cognitive overload that accumulates during periods of deliberate information processing. Because a state of active attentional control is a transient process (Smallwood, McSpadden, Luus, & Schooler, 2008; Weissman, Roberts, Visscher, & Woldorff, 2006), optimal sustained performance requires a mechanism that stabilizes or reactivates attentional control and thus ensures continuous task engagement. This stabilization, termed sustained concentration, is considered an active and effortful process of self-regulation (Posner, Cohen, Choate, Hockey, & Maylor, 1984; Rothbart, Ellis, Rueda, & Posner, 2003; Tucker &

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[5] The mechanism underlying mental blocks is considered different from motivation and cognitive fatigue. At the surface level, there are some similarities but the constructs are not equivalent. For example, blocking frequency has been shown to decrease when short resting breaks (of 5 to 30 seconds) are given and further can be reduced when the interval between subsequent trials (i.e., response-stimulus interval) is optimally choosen (Van Breukelen et al., 1996, for a review; Wilkinson, 1990). The finding that accumulated overload dissipates quickly during rests is taken as evidence that blocks are different from cognitive fatigue (Sanders & Hoogenboom, 1970). Moreover, blocks are largely prevented when a warning signal is given in advance of the imperative stimulus in order to establish preparation (i.e., considered a timed state of "peak concentration", Los & Schut, 2008; Posner et al., 1984; Steinborn et al., 2008). The use of a warning signal at the beginning of a trial is common practice in research on the relationship between mental speed and intelligence, isolating the effects of noise as the remaining source of response speed variability (e.g., Jensen, 1992; Larson & Alderton, 1990). In addition, this is considered a distinctive feature between concentration tests and mental speed tests. Another important fact is that motivational variables (e.g., instruction, incentives, knowledge of results, etc.) have only short-term benefits on performance; in prolonged work tasks, however, the major effect of motivation is on the individual's speed-accuracy tradeoff (Pailing & Segalowitz, 2004; Wickelgren, 1977, for a review).

Williamson, 1984), different from mental speed (cf. Pieters & Van der Ven, 1982; Van Breukelen, 1989) and thus to be indexed by a relative measure of response speed variability (cf. de Zeeuw et al., 2008; Flehmig et al., 2007; Van Breukelen et al., 1996). This study therefore examines whether, by including variability measures, the prediction of school achievement can be improved over the prediction from conventional measures.

Prediction of school achievement

A great body of research has shown that achievement can be predicted from performance in general intelligence tests (e.g., Colom, Escorial, Shih, & Privado, 2007; Deary, Strand, Smith, & Fernandes, 2007; Krumm, Ziegler, & Bühner, 2008; Laidra, Pullmann, & Allik, 2007; Luo, Thompson, & Detterman, 2006; Spinath, 2006). In most of the studies, performance in a variety of standard ability tests is positively related to school achievement, and general intelligence is usually observed to be the best predictor of secondary and high-school grades (Jensen, 1998, chap. 8, for a review). For example, Spinath et al. (2006) recently reported correlations between general intelligence and math grades ($r = .49$), but also with English as foreign language ($r = .44$). Among the various study courses (i.e., mathematics, physics, chemistry, biology, native language, foreign languages, etc.), mathematics grades are typically best predicted by standard ability tests, with correlation coefficients from around $r = .30$ to .70 (Jensen, 1998, pp. 277-282; Sherman, 1979). Moreover, a gender-related predictability effect is often found, showing that females' school achievement is better predicted by ability tests than males' (e.g., Harackiewicz, Barron, Tauer, & Elliot, 2002; Robbins et al., 2004; Sherman, 1979). Finally, the observed relationships are stronger for early stages of schooling (i.e., elementary and secondary school) than for later ones (i.e., high school, university college) – a finding that is often explained as a selection effect caused, for example, by school dropouts (Battin-Pearson et al., 2000). Another explanation is that high-school/college students can choose/omit a certain part of their courses according to their personal interests or abilities (Jensen, 1998, pp. 277-279; Robbins et al., 2004; Schmitt et al., 2007).

Experimental research has isolated the cognitive processes underlying performance in specific ability tests and their individual contributions to predicting achievement. Broadly speaking, the empirical evidence suggests that working memory capacity and mental speed are strong predictors of school achievement (Gathercole, Pickering, Knight, & Stegmann, 2004; Krumm et al., 2008; Lehto, 1995; Luo et al., 2006; Maybery & Do, 2003). Results from experimental studies show that mental speed and executive working memory is involved in tasks that are indicative of school achievement, such as tests of reading comprehension and mental arithmetic (Bull & Scerif, 2001; Clair-Thompson & Gathercole, 2006), or attention switching (de Jong & das-Smaal, 1995). For example, Rindermann and Neubauer (2004) observed positive correlations between mental speed (i.e., Zahlen-Verbindungstests, ZVT, a German version of the trail-making test) and natural science grades (math and physics, $r = .31$) but also with language grades ($r = .30$). More recently, Luo et al. (2006) showed that the relationship between basic cognitive parameters (simple and choice reaction time, short-term memory, etc.) and school achievement (measured via a standardized test, the Metropolitan Achievement Test) is rather complex and may depend on the particular task and paradigm used; the observed correlations between cognitive perform-

ance with math achievement ranged from $r = .36$ to $r = .50$. It has also been shown that several nonintellectual factors are of substantial predictive value, for example, self-discipline (Duckworth & Seligman, 2005), motivation and personality variables (Noftle & Robins, 2007; O'Connor & Paunonen, 2007, for a summary of findings).

Of special interest for the present study are individual differences in self-paced performance, in particular, response speed variability. Proceeding from the cognitive-energetic model (Sanders, 1998, chap. 9) and the formal models of concentration (Jansen, 2007; Pieters, 1985; Pieters & Van der Ven, 1982; Smit & Van der Ven, 1995; Van Breukelen, 1989; Van Breukelen et al., 1996; Van der Ven et al., 1989) that can be viewed as an application of the cognitive-energetic model to cognitive-psychometric assessment, individual differences in average response speed (i.e., M_{RT}) is considered the best estimate to assess mental speed whereas mean-corrected response speed variability (i.e., CV_{RT}) is considered to reflect individual differences in distractibility and self-regulatory effort control (cf. de Zeeuw et al., 2008; Leth-Steensen et al., 2000; Muraven & Baumeister, 2000; Pieters & Van der Ven, 1982; Robinson, Wilkowski, & Meier, 2006; Sergeant, 2000). Actually, distractible individuals show poorer performance as schoolchildren (Rabiner, Murray, Schmid, & Malone, 2004) and reduced efficiency in the workplace as adults (Wallace & Vodanovich, 2003). Furthermore, distractibility in real life can produce errors with all kinds of different negative consequences (Flehmig, Steinborn, Langner, & Westhoff, 2007b). In tasks of sustained concentration, distractible individuals usually differ from nondistractible ones in response speed variability but to a much lesser degree in average response speed (Flehmig et al., 2007a).

Several studies have examined the criterion validity of tasks that tap sustained concentration. For example, Westhoff and Graubner (2003) reported correlations between performance speed and math grades in the Complex Concentration Test ($r = .40$), the Test d2 of Attention ($r = .36$), and the Konzentrations-Leistungs-Test ($r = .24$), a test of continuous mental arithmetic. More recently, Petrat (2008) examined the utility of a short and a long version of the Serial Mental Addition and Comparison Task (SMACT) to predict school achievement. Response speed in the SMACT predicted secondary math performance better (short version: $r = .42$; long version: $r = .26$) than standard predictors such as the test d2 of attention $(r = .21)$ and the Wiener Matrices Test ($r = .30$). Surprisingly, the short (i.e., about four minutes lasting) version of the SMACT was a better predictor than the long (i.e., about 50 minutes lasting) version. In a subsequent study, Osterburg (2008) examined the role of task complexity in sustained concentration performance, comparably for an easy and a difficult version of the SMACT. Secondary math performance was best predicted by the Advanced Progressive Matrizen Test ($r = .31$) but also to a considerable degree by response speed in the SMACT (easy version: $r = .29$; difficult version: $r = .24$). Since these studies did not examine the combined predictive power of several performance measures, the results raise the question whether response speed variability contributes to the conventional indices of performance, speed and accuracy, in predicting school achievement.

Research plan

Here we examined the incremental power of two behavioral facets of self-paced continuous performance, response speed and response speed variability, to predict school achievement. We measured the speed and accuracy at which individuals carry out a concentration task and the persistence with which they maintain their work speed; these measures were then related to school grades. To this end, the Serial Mental Addition and Comparison Task (Restle, 1970; Steinborn, 2004) was used, a self-paced task that requires individuals to engage in continuous mental addition of digit pairs and subsequent comparison of the result with another digit value. Average speed in the SMACT has been shown to have a relative high g-loading, with correlations ranging from $r = .33$ to $r = .45$. Further, SMACT response speed predicted school grades to about the same degree as control measures of general intelligence and attention (Osterburg, 2008; Petrat, 2008). Since the construct and criterion validity of SMACT response speed can be sufficiently determined from previous studies, we here considered response speed as control predictor and examined whether there is a validity increment in response speed variability to predict school grades. The task is described in more detail in the Method section.

For each individual, we computed four indices of performance, namely average response speed (i.e., M_{RT}), error percentage (i.e., EP) absolute response speed variability (i.e., reaction time standard deviation, SD_{RT}) and relative (mean-corrected) response speed variability (i.e., reaction time coefficient of variation, CV_{RT}). M_{RT} was used as an estimate of processing speed and EP to measure an individual's tendency to keep a certain standard of quality. CV_{RT} is used as an estimate of distractibility (de Zeeuw et al., 2008; Segalowitz et al., 1999). We expected to predict school grades, in particular math grades, from M_{RT} (Osterburg, 2008; Petrat, 2008). In addition, we asked whether CV_{RT} possesses any incremental predictive value, besides M_{RT}. In addition, we examined whether there is a differential predictability of school achievement across genders. We hypothesized a generally better predictability for female participants' achievement than for male participants' (Furnham, Chamorro-Premuzic, & McDougall, 2002; Keith, 1999; Stetsenko, Little, Gordeeva, Grasshof, & Oettingen, 2000). Moreover, we speculated that M_{RT} is more powerful in predicting school achievement for females whereas CV_{RT} is more powerful in predicting school achievement for males (Byrnes, Miller, & Schafer, 1999; Greene, DeBacker, Ravindran, & Krows, 1999; Hyde, Fennema, & Lamon, 1990).

Method

Participants. Eighty-nine individuals (38 male, 51 female; mean age = 24.5 years, SD 5.2 years) participated in the study, which took place on two separate dates three days apart. Most participants were right-handed (6 left-handed), and all of them had normal or corrected-to-normal vision. The participants were requested to bring their last secondary- or high-school report along to the first testing session to provide evidence of their grades, which have a range between 1 (excellent) and 6 (insufficient) in Germany.

Description of the SMACT. The serial mental addition and comparison task (SMACT) was administered twice within a retest interval of three days. In each trial, participants were presented with an addition term and with a single number, which were spatially separated by

a vertical bar (e.g., "4+5 | 10"). Participants were required to solve the addition and then to compare the number value of their calculated result with the number value of the presented digit. In all trials, the value of the digit was either one point smaller or one point larger than the value of the addition term but never of equal value. Participants were instructed to indicate the larger number value by pressing either the left or the right Shift key: when the number value on the left side was larger (e.g., "2+3 | 4"), they were to respond with the left key, and when the number value on the right side was larger (e.g., "5 | 2+4"), they were to respond with the right key. Participants self-paced their responding, since each item in a trial was presented until response and was replaced immediately after the response by the next item. No feedback was given, neither in case of an erroneous response, nor in case of too slow responses. To prevent individuals from building up item-specific stimulus-response (S-R) associations, a large set of 148 items was used, with a problem size ranging from 4 to 19. In an experimental session, each item was presented four times, amounting to a total of 592 randomly presented trials. The task lasted about 30 min. The construct validity of the SMACT has been demonstrated (Flehmig et al., 2007a; Osterburg, 2008; Petrat, 2008; Steinborn, 2004): correlations have been reported between SMACT response speed and general intelligence, measured via the Advanced Progressive Matrices Test and the Wiener Matrizen Test (ranging from $r = .33$ to .45), the Test d2 of Attention (ranging from $r = .40$ to .58), and self-reported everyday life attention, measured via the Cognitive Failures Questionnaire (ranging from $r = .18$ to .30).
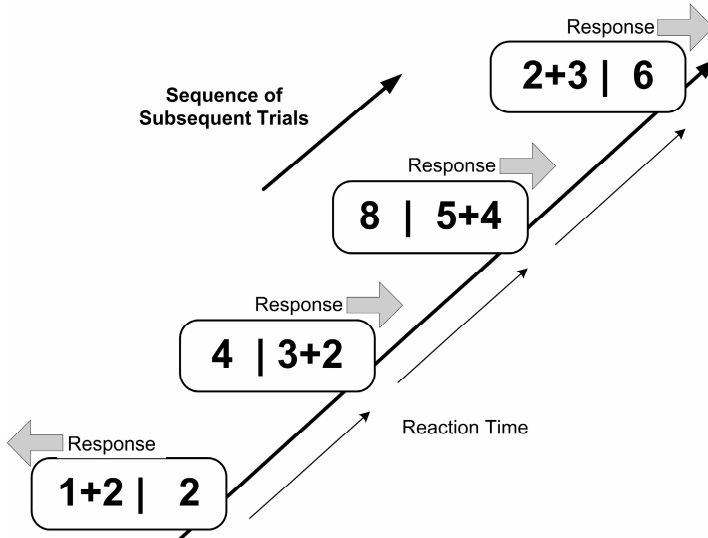

Figure 1 :
Example of a typical sequence of trials in the Serial Mental Addition and Comparison Task (SMACT). Participants have to indicate which side contains the larger numerical value, by pressing either the left or the right response key. As characteristic for sustained concentration tests, the task is self-paced since the presentation of a stimulus follows immediately after the response to the previous stimulus.

Procedure. The experiment took place in a noise-shielded room and was run on a standard IBM-compatible personal computer with color display (19", 150 Hz frequency), using the software package Experimental Runtime System (Behringer, 1987) for stimulus presentation and response recording. Participants were seated at a distance of about 60 cm in front of the computer screen, and the stimuli were presented at the centre of the screen.

Results

Preanalysis. Correct responses longer than 100 ms and shorter than two standard deviations above the individual mean were used to compute M_{RT} as a measure of speed. Erroneous responses were computed as index of accuracy (error percentage, *EP*). SD_{RT} and CV_{RT} were computed as measures of absolute and relative (i.e., mean-corrected) response speed variability. SD_{RT} was computed as the individual standard deviation of response times, and CV_{RT} was computed as the individual standard deviation of response times divided by the individual mean of response times and multiplied by 100 (Guilford, 1956, pp. 78-103). Mean scores, standard deviation, and range of scores for both performance measures of the SMACT as well as school achievement grades are displayed in Table 1.

Table 1:

Descriptive Statistics for School Achievement and Performance in the Serial Mental Addition and Comparison Task (SMACT)

	School Achievement	Secondary School		High School	
		M	*SD*	*M*	*SD*
1	*Average*	1.87	0.57	1.70	0.60
2	*Mathematics*	2.01	0.74	1.91	0.81
3	*Physics*	1.99	0.79	1.94	0.83
4	*Chemistry*	2.10	0.76	1.83	0.81
5	*Biology*	1.71	0.63	1.64	0.68
6	*Native Language (German)*	1.74	0.68	1.78	0.73
7	*Foreign Language (English)*	1.86	0.75	1.79	0.79
	Performance (SMACT)	Session 1		Session 2	
		M	*SD*	*M*	*SD*
8	M_{RT}	1674	351	1411	297
9	*EP*	3.02	2.34	2.42	2.75
10	SD_{RT}	906	460	683	352
11	CV_{RT}	47	13	42	13

Notes: M_{RT} = mean reaction time (in ms); *EP* = error percentage; SD_{RT} = standard deviation of reaction times; CV_{RT} = coefficient of variation of reaction times.

Correlational Analysis. Table 2 displays the correlations between the facets of concentrative performance and secondary-school achievement. Response speed (M_{RT}) and response speed variability (CV_{RT}) appeared to be substantially related to average school grades and, in particular, mathematics and physics grades. However, there were no relationships between performance accuracy (EP) and school performance at all. As displayed in Table 2, average secondary-school grades were best predicted by M_{RT} ($r = .26$; retest: $r = .25$) but also significantly by CV_{RT} ($r = .27$; retest: $r = .20$). As expected, M_{RT} was observed to be the most powerful predictor of mathematics grades ($r = .42$; retest: $r = .35$), however, mathematics grades were also predicted by CV_{RT} ($r = .31$; retest: $r = .22$), even though to a lesser degree. In sum, the results suggest a considerable contribution of response speed variability, besides response speed, in predicting secondary-school achievement.

Table 3 displays the correlations between concentrative performance and high-school achievement. As expected, concentration was less powerful in predicting high-school performance compared to secondary-school performance. As displayed in Table 3, average high-school grades were solely predicted by M_{RT} ($r = .19$; retest: $r = .18$) but not any more by CV_{RT}. M_{RT} was again observed to be the most powerful predictor of mathematics grades ($r = .31$; retest: $r = .25$), whereas CV_{RT} had no power to predict high-school achievement at all. These results leave speed as the main predictor for high-school achievement, as is typically reported in the literature.

Table 2:

Correlations between Secondary-School Achievement and Performance in the Serial Mental Addition and Comparison Task (SMACT)

		Secondary-School Achievement						SMACT - Session 1			
		Aver	*Math*	*Phys*	*Ch*	*Bio*	*Ger*	*Eng*	M_{RT}	*EP*	SD_{RT}	CV_{RT}
		1	2	3	4	5	6	7	8	9	10	11
	1	-	**.68**	**.70**	**.66**	**.59**	**.67**	**.72**	**.26**	-.04	**.30**	**.27**
	2	-	-	**.62**	**.54**	**.46**	**.29**	**.40**	**.42**	-.05	**.39**	**.31**
	3	-	-	-	**.58**	**.40**	**.43**	**.42**	.21	.01	**.22**	**.22**
	4	-	-	-	-	**.33**	**.41**	**.41**	.15	-.05	**.18**	.16
	5	-	-	-	-	-	**.42**	**.34**	.21	-.08	**.24**	**.23**
	6	-	-	-	-	-	-	**.64**	.04	-.03	.13	.14
	7	-	-	-	-	-	-	-	**.21**	.02	**.21**	**.20**
Session	8	**.25**	**.35**	**.18**	.14	**.20**	.04	**.23**	**.96**	-.11	**.85**	**.66**
2	9	-.02	-.02	.11	.01	-.08	.02	-.09	-.17	**.80**	-.06	.00
	10	**.22**	**.28**	.16	.12	.15	.10	.17	**.82**	-.07	**.89**	**.94**
	11	**.20**	**.22**	.17	.12	.13	.11	.14	**.62**	-.03	**.94**	**.84**

Notes: Courses: average grade, mathematics, physics, chemistry, biology, native language (German), foreign language (English); Performance indices: M_{RT} = mean reaction time; EP = error percentage; SD_{RT} = standard deviation of reaction times; CV_{RT} = coefficient of variation of reaction times. Test-retest reliability is shown in the main diagonal (denoted grey); correlations for the first session are shown above, for the second session below the main diagonal. Significant correlations ($p < .05$) are denoted in bold.

Table 3:

Correlations between High-School Achievement and Performance in the Serial Mental Addition and Comparison Task (SMACT)

		High-School Achievement						SMACT - Session 1			
		Aver 1	*Math* 2	*Phys* 3	*Ch* 4	*Bio* 5	*Ger* 6	*Eng* 7	M_{RT} 8	*EP* 9	SD_{RT} 10	CV_{RT} 11
	1	-	**.67**	**.66**	**.58**	**.74**	**.72**	**.66**	**.19**	.01	.14	.10
	2	-	-	**.74**	**.46**	**.47**	**.30**	**.34**	**.31**	-.05	.14	.04
	3	-	-	-	**.52**	.05	**.42**	**.27**	-.08	.10	-.16	-.19
	4	-	-	-	-	**.34**	**.44**	.19	.16	.02	**.27**	**.26**
	5	-	-	-	-	-	**.53**	**.57**	.08	.13	.13	.17
	6	-	-	-	-	-	-	**.49**	.05	-.04	.13	.16
	7	-	-	-	-	-	-	-	.15	**.23**	.09	.09
Session 2	*8*	**.18**	**.25**	-.09	.10	.06	.10	.17	**.96**	-.11	**.85**	**.66**
	9	.11	.05	**.28**	.08	.08	-.03	**.21**	-.17	**.80**	-.06	.00
	10	.08	.06	-.19	.21	.03	.10	.12	**.82**	-.07	**.89**	**.94**
	11	.03	-.02	-.21	-.21	.03	.10	.10	**.62**	-.03	**.94**	**.84**

Notes: Courses: average grade, mathematics, physics, chemistry, biology, native language (German), foreign language (English); Performance indices: M_{RT} = mean reaction time; *EP* = error percentage; SD_{RT} = standard deviation of reaction times; CV_{RT} = coefficient of variation of reaction times. Test-retest reliability is shown in the main diagonal (denoted grey); Correlations for the first session are shown above, for the second session below the main diagonal. Significant correlations ($p < .05$) are denoted in bold.

Regression Analysis. To examine the incremental predictive validity of CV_{RT} with regard to school achievement, multiple linear regression analyses were performed. The main results can be summarized such that the combined intake of M_{RT} and CV_{RT} as predictors in a multiple linear regression model for school performance (separately for average school grades, mathematics, physics, etc.) as criterion did not reveal any increased predictive power compared to a single-predictor model (i.e., when M_{RT} or CV_{RT} were separately taken as predictors). This indicates that average speed, as reflected by M_{RT}, remains the most powerful factor in predicting school achievement, and distractibility, as reflected by CV_{RT}, does not deliver additional information beyond M_{RT}.

Analysis of Gender Effects. Finally, we analyzed whether performance in the SMACT is differentially predictive with regard to gender. A multivariate ANOVA revealed that females and males did not differ in their average speed and error percentage [M_{RT}: $F < 0.79$; *EP*: $F < 0.03$], and did also not differ in average secondary-school performance [$F < 2.9$] and average high-school performance [$F < 3.9$]. Table 4 and 5 display the correlations between the facets of SMACT performance and school achievement, separately for female and male participants. Since *EP* appeared not to be useful in predicting school achievement, only the correlations of school grades with M_{RT} and CV_{RT} are displayed.

When inspecting Table 4 and 5 it becomes apparent that school grades are best predicted by M_{RT} and only to a lesser degree by CV_{RT}. Broadly speaking, M_{RT} is a powerful predictor in the female group but not (or to a lesser degree) in the male group. To statistically verify

Table 4:

Correlations between Secondary-School Achievement and Performance in the Serial Mental Addition and Comparison Task (SMACT), Separately for Female and Male Participants

Gender	Session	Measures	Secondary-School Achievement						
			Aver	*Math*	*Phys*	*Chem*	*Bio*	*Ger*	*Eng*
Female	1	M_{RT}	**.41**	**.55**	**.37**	.16	**.30**	.18	.16
		CV_{RT}	**.37**	**.29**	**.32**	.17	**.34**	**.25**	.14
	2	M_{RT}	**.40**	**.51**	**.36**	.18	**.25**	.17	.16
		CV_{RT}	**.37**	**.27**	**.35**	.20	.19	**.24**	.14
Male	1	M_{RT}	.20	**.27**	.03	.15	.11	-.01	**.31**
		CV_{RT}	**.26**	**.32**	.10	.17	.10	.13	**.30**
	2	M_{RT}	.16	.20	.00	.11	.15	-.04	**.31**
		CV_{RT}	.11	.15	-.03	.04	.05	.08	.21

Notes: M_{RT} = mean reaction time; CV_{RT} = coefficient of variation of reaction times; Courses: average grade, mathematics, physics, chemistry, biology, native language (German), foreign language (English). Significant correlations ($p < .05$) are denoted in bold.

Table 5:

Correlations between High-School Achievement and Performance in the Serial Mental Addition and Comparison Task (SMACT), separately for Female and Male Participants

Gender	Session	Measures	High-School Achievement						
			Aver	*Math*	*Phys*	*Chem*	*Bio*	*Ger*	*Eng*
Female	1	M_{RT}	**.41**	**.54**	.22	.25	.13	.05	.19
		CV_{RT}	**.28**	.19	-.14	.15	.22	.18	.18
	2	M_{RT}	**.36**	**.46**	.20	.13	.10	.06	.19
		CV_{RT}	.15	.12	-.07	.06	.08	.11	.18
Male	1	M_{RT}	.03	.06	-.24	.00	.14	.15	.11
		CV_{RT}	.00	-.10	-.21	**.41**	.15	.23	-.03
	2	M_{RT}	.04	.01	-.25	.04	.09	.20	.16
		CV_{RT}	-.03	-.15	**-.29**	**.42**	.02	.17	-.01

Notes: M_{RT} = mean reaction time; CV_{RT} = coefficient of variation of reaction times; Courses: average grade, mathematics, physics, chemistry, biology, native language (German), foreign language (English). Significant correlations (p < .05) are denoted in bold.

the interacting influence of gender on the relationship between M_{RT} and school grades, we dichotomized M_{RT} across the sample via median split, resulting in a 2 × 2 design, and tested the speed (fast group vs. slow group) × gender (female vs. male) interaction effect on average achievement and math achievement (note that for simplicity, secondary- and high-school grades were aggregated). There was a significant speed × gender interaction effect on average grades [$F(1,85) = 4.7$, $p < .05$] and on math grades [$F(1,85) = 6.6$, $p < .05$] at the first testing session (Figure 2, Panel A and B). The overall pattern of interaction was about simi-
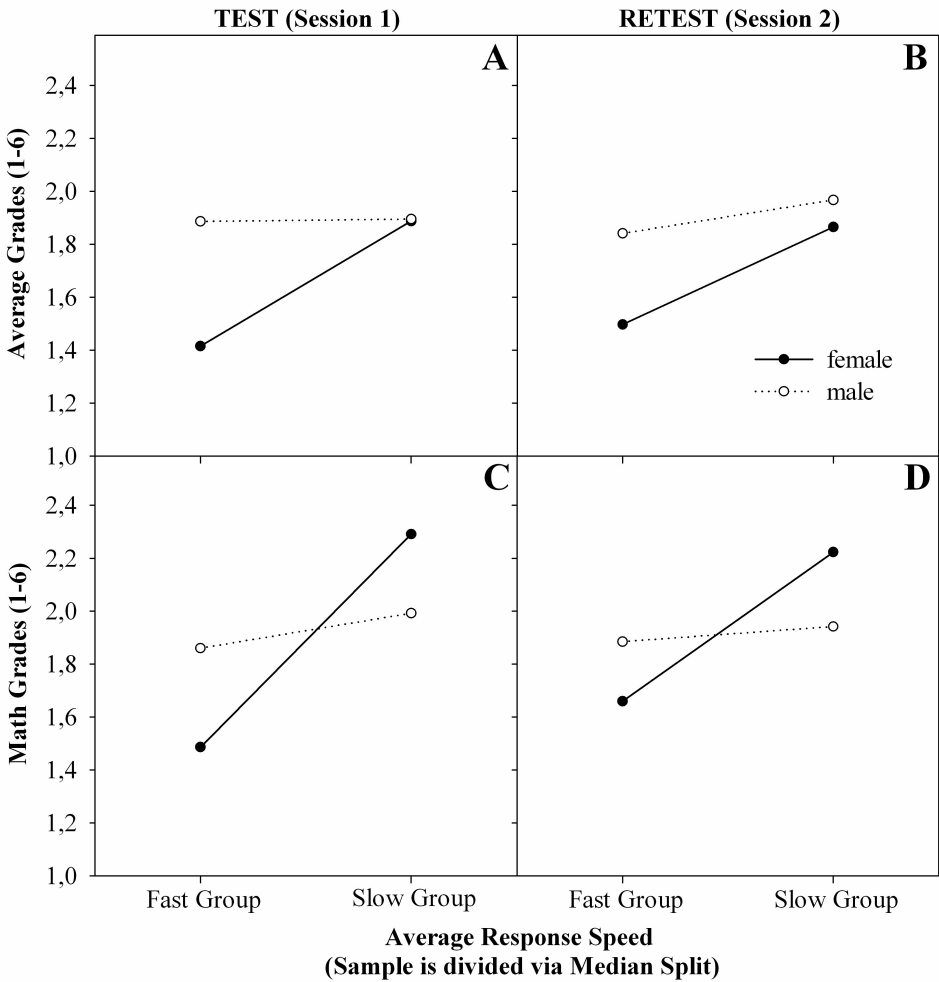
Figure 2:
Interaction between task performance (average speed, M_{RT}) and gender in predicting school achievement. For simplicity, secondary and high school average (Panel A, B) and math grades (Panel C and D) are aggregated into a single index. Data are separately displayed for the test (session 1) and the retest (session 2) session.

lar in the second testing session (Figure 2, Panel C and D) although there was only a tendency towards significance at retest. Therefore, the statistical analyses support the argument that performance in concentration tests might be more predictive for females than for males, with regard to school achievement.

Discussion

We examined whether school achievement can be predicted from self-paced continuous performance, using the Serial Mental Addition and Comparison Task (SMACT). In particular, we examined the question of whether relative response speed variability, as indexed by CV_{RT}, contributes to the predictive value usually obtained with measures of average response speed, as indexed by M_{RT}. The results can be summarized as follows: (1) We observed a substantial relationship between M_{RT} and school achievement, indicating that the faster an individual's work speed, the better the school grades. In particular, M_{RT} appeared to be the best predictor of average secondary- and high-school grades, and in addition, mathematics and physics grades. (2) Accuracy (error percentage) did not reveal any relationship with school achievement. (3) Response speed variability as indexed by CV_{RT} was positively correlated with secondary-school grades (especially mathematics grades), but not with high-school grades. Individuals exhibiting performance inconsistency in the SMACT were also less successful in secondary-school achievement. Notably, the predictive power of CV_{RT} was less than that of M_{RT}, leaving processing speed as the principal predictor of school achievement. (4) The combined intake of M_{RT} and CV_{RT} as predictors in a multiple linear regression model predicting school achievement did not reveal any additional predictive power compared to a single-predictor model that only included M_{RT}. (5) The interaction between average speed (M_{RT}) and gender in predicting school grades indicates that females can be better predicted than males (Figure 2).

The present results are consistent with studies suggesting that elementary cognitive ability, namely mental speed, is the most powerful predictor of school achievement (Luo, Thompson, & Detterman, 2003; Rindermann & Neubauer, 2004; Sheppard & Vernon, 2008). The height of correlations observed between M_{RT} and school grades (average grades and mathematics) in the present study varied between $r = .25$ and $r = .42$, which is in about the same range as is typically observed with (larger) intelligence test batteries (e.g., Colom et al., 2007; de Jong & das-Smaal, 1995; Di Fabio & Busoni, 2007; Furnham et al., 2002). Among the study courses that comprise the curriculum in secondary- or high-school, the correlations were highest between M_{RT} and mathematics/physics grades, a finding that has been repeatedly observed before (e.g., Jensen, 1998, chap. 9; Maybery & Do, 2003; Robbins et al., 2004; Sherman, 1979).

The aim of this study was to examine the utility of intraindividual response speed variability for predicting school achievement. Response speed variability was related to school achievement but did not deliver additional information beyond average response speed. This may be due to collinearity between M_{RT} and CV_{RT} in the present task (i.e., SMACT). That is to say, M_{RT} and CV_{RT} were substantially correlated in the SMACT ($r = .66$; retest: $r = .62$), indicating that fast individuals were also more constant in their performance, compared to slow individuals. This is in contrast to other studies, showing that M_{RT} and CV_{RT} were virtually independent of each other (e.g., Flehmig et al., 2007; Hayashi, 2000; Segalowitz et al., 1999; Stuss, Murphy, Binns, & Alexander, 2003). However, the specific relationship between measures of speed and variability in self-paced tasks is far from resolved, and their contribution in predicting school achievement should be subject to further research, especially with regard to several factors, among them item complexity and task length (e.g., Stuss, Meiran, Guzman, Lafleche, & Willmer, 1996; Westhoff & Graubner, 2003), and per-

haps intertrial item sequential effects (e.g., Jentzsch & Leuthold, 2005; Steinborn, Rolke, Bratzke, & Ulrich, 2008).

Consistent with current research, the relationship between test performance and school grades was stronger for secondary- than for high-school grades. This finding is typically explained by assuming selection effects that occur in the course of schooling. For example, high-school students can choose or omit a certain part of their courses according to their personal interests, their self-estimated ability structure, and individual preferences (Jensen, 1998, pp. 277-282). This kind of selection effects results in a greater homogeneity of students in a particular high-school course, for example mathematics or physics, thus reducing the predictability of achievement from cognitive performance data. An alternative hypothesis is that students develop individual learning styles and specific strategies to cope with several difficulties, for example, to establish learning motivation (Carey, 1998; Lehtinen, Vauras, Salonen, Olkinuora, & Kinnunen, 1995), or to sustain attention and mental focus over prolonged time periods (Ramseier, 2001; Schaefer & McDermott, 1999). The present data fit well with studies showing better predictability of school achievement for female than for male individuals. These findings support the somewhat speculative explanation that mental speed may be sufficient to predict females' school achievement, but other variables are additionally beneficial to predict males' school achievement (e.g., Harackiewicz et al., 2002; Keith, 1999; Robbins et al., 2004; Sherman, 1979).

A limitation of the present study is that the sample size is relatively small and may not be representative with regard to the population mean and variance. This, however, may not be a serious limitation because the greater homogeneity of our sample may lead to an underestimation of correlative relationships rather than to an overestimation. For that reason, the criterion validity of CV_{RT} may be much greater in a population-based sample that also contains individuals with learning disabilities or attention deficits (Sergeant, 2000). A further limitation may be that there are no established control predictors (i.e., intelligence) available that could be compared with SMACT performance in the present study. Nevertheless, we think that this may not affect our research goal which was to examine the incremental validity of CV_{RT} in predicting school grades. Since construct validity and criterion validity of the SMACT can be sufficiently determined, based on previous studies (Osterburg, 2008; Petrat, 2008; Steinborn, 2004), the alternative measures, in particular CV_{RT} and SD_{RT}, were compared against the conventional measure M_{RT} as control predictor.

General conclusion

Using a serial mental addition and comparison task (SMACT), requiring self-paced continuous choice responding over a period of about 30 minutes, we showed that school achievement can be predicted by average response speed. Although intraindividual variability did not provide additional predictive information beyond average speed, the present results do not disqualify the potential usefulness of variability measures in predicting achievement. Instead, the present findings raise further questions of how to construct self-paced speed tests and how to evoke intraindividual variability for purposes of prediction in applied testing situations. Indices of variability are especially useful in situations in which energetic factors play a crucial role (Sanders, 1998, chap. 9). Although the issue of what exactly is reflected in mean-corrected response speed variability is not yet resolved, there is agreement

that the consistency of an individual's performance in self-paced tasks reflects distractibility (e.g., Appleton, 1967; Castellanos et al., 2005; de Zeeuw et al., 2008; Pieters & Van der Ven, 1982; Smallwood et al., 2008; Smit & Van der Ven, 1995; Van Breukelen et al., 1996; Wagenmakers & Brown, 2007). In addition, the ability to shield the cognitive system against distraction during an attention-demanding task, and to self-regulate (i.e., to attain and maintain an appropriate energetic level) is considered an energetic prerequisite for achieving optimal information processing efficiency.

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