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Processing speed, intelligence, creativity, and school performance: Testing of causal hypotheses using structural equation models[☆]

H. Rindermann[a,*], A. C. Neubauer[b]

[a]Institut für Psychologie, Otto-von-Guericke-Universität Magdeburg, Postfach 4120, Magdeburg D, 39016, Germany

[b]Institut für Psychologie, Karl-Franzens-Universität Graz, Germany

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Abstract

According to mental speed theory of intelligence, the speed of information processing constitutes an important basis for cognitive abilities. However, the question, how mental speed relates to real world criteria, like school, academic, or job performance, is still unanswered. The aim of the study is to test an indirect speed-factor model in comparison to rivaling models explaining the relationships between different mental abilities and performance. In this speed-factor model, basic cognitive processing is assumed to influence higher mental abilities (IQ and creativity). Intelligence and creativity themselves should be valid predictors of school performance. We computed bivariate correlations and structural equation models to test this hypothesis, using indicators of processing speed [Zahlen-Verbindungs-Test (ZVT) and Coding Test], psychometric intelligence [Kognitiver Fähigkeits-Test (KFT) and Raven's Advanced Progressive Matrices (APM)], creativity [Verbaler Kreativitäts-Test (VKT) and Verwendungs-Test (VWT)] and school performance (grades). In a sample of 271 students from German gymnasiums (Class Levels 9 to 11) the *speed-factor model* can reproduce at best the empirical relationships between processing speed, intelligence, creativity, and school performance: It assumes that processing speed influences higher mental abilities (intelligence and creativity), which, in the sequel, influence school performance. Therefore, processing speed seems to have no direct

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* Corresponding author. Tel.: +49 391 671 1919; fax: +49 391 671 1914.

E-mail address: heiner.rindermann@gse-w.uni-magdeburg.de (H. Rindermann).

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effect on school performance; the effect is indirect as it operates via mediation through higher cognitive abilities.

Keywords: Processing speed; Intelligence; Creativity; School performance; Structural equation model; Causal relationship

1. Introduction

The study of the relationship between mental speed (or speed of information processing) and cognitive ability goes back already to early notions by Galton (1883), who tried to measure reaction time, and diverse sensory and motor variables in relation to independent indicators of accomplishment or intelligence. However, after several unsuccessful attempts to replicate the idea, the speed theory was almost completely abandoned until Roth (1964) reported a significant negative relationship between reaction times in a choice reaction time task and psychometric intelligence, indicating a quicker speed of processing in brighter subjects. It took another 15 years until this findings led to considerable research efforts which now—20 years and dozens of studies later (cf. Deary, 2000; Neubauer, 1997)—provide us with a substantive base of evidence on the relationship between speed of processing as measured by so-called elementary cognitive tasks (ECTs) and human psychometric intelligence. Many studies employing such diverse tasks, like choice reaction time, inspection time (IT), Sternberg and Posner paradigms, reading rates, and coding of numbers or letters, show an average relationship between psychometric intelligence and speed of information processing of about $r=|.30|$ for single elementary cognitive tasks (ECTs), which rise to multiple relationships up to .50 or .60 when combining several ECTs (Grudnik & Kranzler, 2001; Neubauer, 1997; Neubauer & Knorr, 1998). In unrestricted samples, speed and intelligence are even correlated at up to $r=|.50|$ (Deary, 2001).

Theoretically, the relationship was initially explained referring to notions of ‘oscillation rate’ (Jensen, 1982) or ‘neural efficiency’ (Vernon, 1993); later, this concept has also been linked to findings from psychophysiological intelligence research, demonstrating short latencies in certain EP components for brighter individuals (review by Deary & Caryl, 1993) or a higher brain effectiveness in the sense of less brain glucose consumption (Haier, 1993) or weaker cortical activation as measured by means of the EEG (e.g., Neubauer, Fink, & Schrausser, 2002; Neubauer, Freudenthaler, & Pfurtscheller, 1995). Higher IQ individuals use their brain more efficiently.

In mental speed theory, the speed of information processing is considered an important basis of cognitive abilities (intelligence). These higher cognitive abilities, like intelligence (but maybe also creativity), influence cognitive performances in the real world, like school, academic, or job performance. The question to be studied here, is, if processing speed might have a direct impact on real world cognitive performances or if the effect of speed on real world performance operates indirectly via the mediation through intelligence and creativity.

Deary (1995) has regarded mental speed (as measured by IT) as a limiting factor for the development of cognitive abilities. The speed of apprehension during the early stages of perception determines the development of general intelligence; throughout years of individual development, small individual differences in processing speed might accumulate to large differences in intelligence, vocabulary, and performance (Brand, 1981; Deary, 1995; Jensen, 1982). A high speed of processing in basic brain functions makes higher cognitive operations—like intelligence or creativity—more efficient. In turn,

higher cognitive abilities, like intelligence, are known to be very important for real world performance, like in school, university, or job.

Psychometric intelligence is usually correlated around $r=|.45|$ with school performance (Süß, 2001), but processing speed correlates only around $r=|.30–.40|$ and creativity $r=|.20–.35|$ with school performance (Cropley, 1995; Hentschel, 2003; Rindermann & Neubauer, 2000). Luo, Thompson, and Detterman (2003) have shown that the relationship between intelligence and scholastic performance could be partially explained by mental speed. The relationship between speed and creativity has rarely been studied. Rindermann and Neubauer (2000) found an r around $|.30|$. All these relationships—if they could be traced back to mental speed—could support the *singularity of mind view* (cf. Neubauer & Bucik, 1996), predicting correlations between different measures of intelligence and intellectual performance presumably because of the efficiency of central nervous system operations.

Here, we use school performance as probably the most valid external criterion for intelligence. In addition to IQ, we also consider creativity as an important additional mental ability, which might be more strongly influenced by personality factors than processing speed or intelligence (Heller, 1995).

In former attempts to elucidate the relationships between speed and intelligence, almost exclusively bivariate correlations have been computed. Causal modeling using path analyses has rarely been used. One exception is the study of Nettelbeck and Young (1990), who computed *cross-lagged panel correlations* between IT and intelligence (IQ) to analyze causal relations. In their 13-month longitudinal study with thirty 7-year-old children, Nettelbeck and Young have found equal cross-lagged correlations ($r=|.40|$) between IT and IQ. They conclude that there was no evidence for a causal relationship between IT and IQ.

Deary (1995) used *structural equation modeling* to test the direction of causation between IT and IQ in a two-year longitudinal design (using IT and IQ instruments other than that employed by Nettelbeck and Young). For manifest (not latent) variables, Deary reported that an *IT-causes-IQ model* had the best fit, the worst fit had an *IQ-causes-IT model* (the fit of a reciprocal-causation model was similar, but little lower, to that for the IT-causes-IQ model).

In former research on causal effects, only the causal relationship between processing speed and intelligence was analyzed. In the theory of the mental speed approach, processing speed is seen as a major factor limiting intelligence. A rarely studied question, however, is if speed of processing constitutes a limit also for real world performances, like school grades. Kranzler, Whang, and Jensen (1994) investigated if gifted vs. nongifted junior high school students can be correctly classified on the basis of ECTs and found a discrimination function allowing for a correct classification around 80%. This rate is surprisingly high, but this might be due to the testing of extreme groups: The gifted and nongifted displayed a difference of 26 IQ points on Raven's Advanced Progressive Matrices (APM). Luo and Petrill (1999) compared if a g estimate based on ECTs as compared to one based on psychometric intelligence tests allows similar predictions of scholastic performance, which was corroborated. The authors concluded that "the predictive power of g will not be compromised when g is defined using experimentally more tractable ECTs" (p. 157).

As important as these studies are, they do not inform us if processing speed influences school performance directly or indirectly via the mediation through psychometric intelligence, a question that—to our knowledge—has not been studied before. The aim of our study is to clarify the relationships between processing speed, intelligence, creativity, and school performance using path analyses. Our assumption according to mental speed theory is that processing speed as a basic mental ability is a precondition for higher mental abilities, like intelligence and creativity, which in turn are preconditions

for performance in school. The direct effect of processing speed on school performance should be small, but the mediated effect should be significant. Unlike in the study by Deary (1995), where only observed variables were used and measurement error was not considered, we will employ structural equation modeling to specify relationships between latent variables and to identify measurement error.

To test our model with competing models, we compute different path models, modeling different mental abilities (processing speed, intelligence, and creativity) as independent or mediator causal factors for real-life school performance (school grades). Standardized path coefficients and fit indices shall allow an estimation of causal relationships and of the suitability of different models.

2. Method

2.1. Instruments

2.1.1. Speed-of-processing tests

For the measurement of speed of information processing, we employed two paper-and-pencil tests, which can be administered in groups: the Zahlen-Verbindungs-Test (ZVT; Oswald & Roth, 1978) and the Coding Test (Kodierungstest, KDT; Lindley, Smith, & Thomas, 1988; Neubauer & Knorr, 1998; Sitzwohl, 1995). In both instruments, participants have to solve easy mental tasks within a short time limit (30 s).

In the ZVT, which essentially is a trail-making test consisting of four matrices, randomly arranged numbers have to be connected in an ascending order (from 1 to 90) with a pencil within a given time limit of 30 s per matrix.

In the KDT (Coding Test), letters, numbers, or circle segments have to be copied (no coding, copy condition) or written one sequence forward (code forward: next letter in alphabet, next number/add one, enlarge the circle segment in a clockwise direction; simple coding) or one sequence backward (code backward: preceding letter or number or circle segment; complex coding). The Coding Test was originally developed by Lindley et al. (1988) using letters and digits mixed; separate forms for letters, digits, as well as using figural stimuli have been developed by Sitzwohl (1995, cf. also Neubauer & Knorr, 1998). In each version (verbal, numerical, and figural), participants were given one row of 10 items as practice and then two sheets with seven rows of 10 items (with a time limit of 30 s per page; instructions stressed speed and accuracy). The time limit per page was 30 s. The dependent variable is the number of correct items within the time limit for each condition (copy, code for, code back), aggregated over both repeated presentations of each condition.

Both the ZVT and KDT measurements were collected from 1995 to 1999. The polarity is positive: the higher the numerical result in processing speed, the quicker is the person. For all tests used in the study, the scores have been transformed to the T norm (M=50, S.D.=10).

2.1.2. Intelligence tests

Psychometric intelligence was measured using Raven's APM (Heller, Kratzmeier, & Lengfelder, 1998; Raven, 1958) and the Kognitiver Fähigkeits-Test (KFT; Heller, Gaedike, & Weinläder, 1985). The KFT (Cognitive Abilities Test) assesses verbal, numerical, and nonverbal/figural abilities. We were using six subscales: vocabulary and word analogies, comparison of quantities and number series, and classification of figures and figure analogies. The KFT is used in two parallel forms (A in Year 1 and B

in Year 2); with each class level (4, 5, 6, etc.), the tasks get more difficult (class-level adaptive testing). The APM measure reasoning using abstract figures. The APM are considered a good indicator of general intelligence (Spearman's *g*). Both intelligence tests were collected from 1995 to 1999.

2.1.3. Creativity tests

Creativity was measured using the Verbaler Kreativitäts-Test (VKT; Schoppe, 1975) and the Verwendungs-Test (VWT; Facaoaru, 1985; for a more detailed description of both tests, see Rindermann & Neubauer, 2000). In the VKT, the students must generate out of four given letters different reasonable and innovative sentences (which are evaluated according to the two subscales, verbal productivity/ quantity and verbal creativity/diversity; combined α=.96). In the VWT, students must produce different reasonable and innovative applications of given objects (three subscales: productivity, flexibility, and originality; combined α=.94).

2.1.4. Grades

Grades or marks were taken from the final-year school report (all tests and grades were individually assigned by using anonymous codes). Grades in comparison to performance tests have the advantage that they represent relevant real-life performance. Subject grades were grouped into four areas by content and by cluster analysis: languages (depending upon school type: German, English, French, Latin, Greek, or Literature), mathematics and physics, natural sciences (depending upon school type: biology, chemistry, nature, geography, or informatics), and humanities (depending upon school type: history, politics, social sciences, religion, ethics, psychology, or philosophy). Grades were collected from 1995 to 1999. Here, the polarity of school grades was reversed: the higher the score, the better the person is at school (*worst*: 1, *best*: 6).

2.2. Participants

Two-hundred seventy-one students of Classes 9, 10, and 11 in German gymnasiums (high schools), between 14 and 17 years of age, participated in the study (only persons with complete data in all variables, participants with missing data were excluded in advance). One-hundred sixty-nine students (62%) are members of four high-ability gymnasiums, where students reach the general qualification for university entrance ("Abitur") in 8 years (G8); 102 students (38%) are from two regular gymnasiums, where students reach the Abitur in 9 years (G9). Generally, German gymnasiums are for students with abilities above average (between 10% and 50% of an age group, depending from province and city). Only students from the upper 50% of ability distribution of German students are attending these schools (gymnasiums). The combination of a sample of high-ability students and a sample of average and above-average students ensures a sufficient variance in intelligence and performance measures in this study.

2.3. Procedure

Every student and every scale is used only once as a mean value in the final sample. Results of tests, which are used in Classes 9, 10, and 11 (KFT and grades), 9 and 10 (APM, ZVT, and KDT), or 9 and 11 (VKT and VWT) are averaged across class. Thus, we obtain a higher reliability of all measures. Students were tested in the morning in school at normal lesson times (order of the tests: KFT, APM, VKT, VWT,

ZVT, and KDT). Because the APM were used for the second measurement in Class 10, but creativity tests in Class 11 (different times of measurement), we waive for longitudinal analysis and use cross-sectional data. We have complete data in all variables from 271 students, but not all tests (APM vs. VKT and VWT) were applied at the same class at the same age.

2.4. Statistical analyses

In a first step, we computed correlations between observed variables for each ability and for school performance. In a second step, correlations between individuals' means of processing speed, intelligence, creativity, and school performance were calculated. These correlations are shown for the whole group, and for the above-average vs. average high school sample separately. A stepwise regression gives first evidence how much explained variance in mean school performance is explained by the three predictors.

Thirdly, structural equation models using LISREL (Jöreskog & Sörbom, 1996) were tested. Latent variables were processing speed (observed variables: KDT and ZVT), intelligence (KFT-general and APM), creativity (VKT and VWT), and school performance (languages, math–physics, sciences, and humanities). There are 55 variances and covariances with maximally 29 coefficients—to have more variances and covariances than coefficients is a necessary prerequisite for an identified model. Three latent variables had only two observed variables as indicators, we fixed one indicator of each latent variable. The models are identified, because one loading of each latent variable is fixed to one and because the latent variables correlate sufficiently among each other [Eid, 1999; Kaplan, 2000, p. 50; Nachtigall, Kroehne, Funke, & Steyer, 2003, p.13; for correlations between latent variables, see Table 2 (in parentheses)]. Error is presented as error variance, not as error path.

The following models were tested:

Three-factor model: processing speed, intelligence, and creativity influence independently and directly school performance (Model 1).

Speed-factor models: processing speed influences directly intelligence and creativity and directly and indirectly school performance; Model 2a without direct path between mental speed and school performance; Model 2b without direct path between mental speed and school performance and with correlated errors between intelligence and creativity.

Intelligence-factor model (Model 3): intelligence influences directly processing speed and creativity and directly and indirectly school performance.

Creativity-factor model (Model 4): creativity influences directly processing speed and intelligence and directly and indirectly school performance.

In the figures, we show only completely standardized path coefficients. We calculated direct and indirect effects (Cohen & Cohen, 1983, p. 358). Finally, we checked different fit indices. Structural-equation-model research has provided a nearly innumerable amount of fit indices; many researchers have developed special fit indices. In Table 3, we are displaying the root mean square residual (RMR; not normed, good for comparison of models within one data set), the standardized root mean square residual (S-RMR; standardized RMR), the common goodness-of-fit index (GFI; most-used index, comparison of model with no model), adjusted goodness-of-fit index (AGFI; like GFI, but considers degrees of freedom, rewards parsimony), parsimony goodness-of-fit index (PGFI; similar to AGFI), root mean square error of approximation (RMSEA; considers degrees of freedom), normed fit index (NFI; rewards parsimony), comparative fit index (CFI; often used, comparison of model with 0-correlations model) and

the Consistent Akaikes Information Criterion (CAIC; good for comparison of different models, considers degrees of freedom, rewards parsimony).

Hu and Bentler (1998, 1999) evaluated the sensitivity of different fit indices in Monte-Carlo studies under varied conditions of sample size and distribution. They recommend a two-index strategy with the use of the S-RMR (cutoff $\leq$.08) and one of the following indices: RMSEA (cutoff $\leq$.06) or CFI (cutoff $\geq$.95). Our interpretation here is based mainly on the S-RMR, the RMSEA, and CFI.

With structural equation models, it is possible to test complex relationships between sets of variables, which could only be interpreted as causal effects when experimental or quasi-experimental designs were used or if a distinct time succession is given and at the same time the influence of bias variables can be excluded. High path coefficients and fit values are a *necessary*, but *not sufficient* precondition for causal inference. If an indirect speed-factor model (mental speed influences higher cognitive abilities, they both influence school performance) does not fit well or if other models fit better, the model is falsified.

3. Results

3.1. Correlations between observed variables

With the exception of the creativity dimension, all observed variables, which were later used as indicators for latent dimensions, correlated highly with the other indicators of the same trait (see Table 1). For the structural equation models to be computed later, it could be expected that ZVT and KDT are good indicators for processing speed (r=.65), KFT and APM for intelligence (r=.55), and the grades in four different subjects for school performance (r=.56 to .73). The two tests of creativity correlate rather weakly, albeit significantly. Generally, creativity is difficult to measure in a reliable way. Therefore, the relatively low correlation is not surprising.

3.2. Correlations between arithmetic mean values of processing speed, intelligence, creativity, and school performance

Before computing structural equation models, we computed the zero-order relationships between all four constructs (operationalized as mean variables; see Table 2). Latent variables in structural equation models are estimated in dependence of the whole model—their values depend not only of their indicators (observed variables), because the relationship between observed and latent variables (e.g., different weights of the only two observed variables of one latent variable) is optimized in relation to the whole model (the other observed and latent variables in the model and their relationships). Table 2 shows bivariate zero-order correlations between the arithmetic means of processing speed, intelligence, creativity, and school performance, which are independent from their relationships to other variables.

The correlation between processing speed and intelligence is in the range that is reported in many studies and reviews of mental speed research ($r \approx$.30). With an r of .14, the correlation between intelligence and creativity is rather low. In view of this low correlation, it is even more surprising that processing speed and creativity correlate at r=.33. Processing speed seems to be a basic component for both higher cognitive abilities, intelligence and creativity.

Table 1
Correlations between all observed variables

Korrelationen		ZVT	KDT	KFT	APM	VKT	VWT	Lang	MP	Scien	Hum
ZVT	*r*	1.00	.65	.34	.18	.30	.11	.30	.31	.27	.24
	P		.00	.00	.00	.00	.07	.00	.00	.00	.00
KDT	*r*	.65	1.00	.24	.21	.38	.18	.30	.25	.19	.23
	P	.00		.00	.00	.00	.00	.00	.00	.00	.00
KFT	*r*	.34	.24	1.00	.55	.20	.03	.48	.51	.50	.39
	P	.00	.00		.00	.00	.58	.00	.00	.00	.00
APM	*r*	.18	.21	.55	1.00	.12	.06	.29	.44	.34	.24
	P	.00	.00	.00		.05	.31	.00	.00	.00	.00
VKT	*r*	.30	.38	.20	.12	1.00	.34	.28	.13	.22	.27
	P	.00	.00	.00	.05		.00	.00	.04	.00	.00
VWT	*r*	.11	.18	.03	.06	.34	1.00	.14	.10	.09	.22
	P	.07	.00	.58	.31	.00		.02	.11	.12	.00
Lang	*r*	.30	.30	.48	.29	.28	.14	1.00	.61	.70	.72
	P	.00	.00	.00	.00	.00	.02		.00	.00	.00
MP	*r*	.31	.25	.51	.44	.13	.10	.61	1.00	.73	.56
	P	.00	.00	.00	.00	.04	.11	.00		.00	.00
Scien	*r*	.27	.19	.50	.34	.22	.09	.70	.73	1.00	.70
	P	.00	.00	.00	.00	.00	.12	.00	.00		.00
Hum	*r*	.24	.23	.39	.24	.27	.22	.72	.56	.70	1.00
	P	.00	.00	.00	.00	.00	.00	.00	.00	.00	

N=271 students; ZVT and KDT for processing speed, KFT and APM for intelligence, VKT and VWT for creativity, languages, math–physics, science, and humanities for grades in school; exact *P* values.

The correlations of psychometric tests with school performance match with the results documented in ability–research: intelligence and school performance correlate around r=.50, processing speed and school performance r=.35, and creativity and school performance only r=.25 (see also Rindermann & Neubauer, 2000). It is noteworthy here, that the correlation between processing speed and school grades in the normal ability student sample is marginally higher than in the above average sample (r=.39 vs. .26; n.s.).

Table 2
Correlations between processing speed, intelligence, creativity, and school performance (arithmetic means)

Scale	Intelligence	Creativity	School performance
N=271 students, average IQ=119 (KFT: IQ=126, APM: IQ=112)			
Processing speed	.31**	.33**	.35**
	(.40/.39)	(.51/.50)	(.40/.39)
Intelligence		.14*	.52**
		(.21/.24)	(.61/.61)
Creativity			.25**
			(.35/.36)

IQ: age norms, *M*=100, S.D.=15; polarity, all scales positive: the higher processing speed, the quicker the person is, the higher the school grade, the better the person is at school, etc.; for *N*=271 students: correlations between latent factors (error free) in Model 2 (speed-factor model) and Model 1 (three-factor model) are in parentheses.

* *P*<.05.

** *P*<.01.

The correlations between latent variables (calculated in structural equation models) are a little bit higher because the latent variables are measurement error free.

Using psychometric intelligence, processing speed, and creativity in a stepwise regression on school performance, the IQ is the most important predictor (r=.57, shrunken r=.56, R^2=.33; standardized β for intelligence .45, P<.01, for processing speed .17, P<.01, and for creativity .13, P<.05).

3.3. Testing between structural equation models

In Model 1, we tested an independent three-factor model: processing speed, intelligence, and creativity are influencing independently school performance (see Fig. 1; all values standardized). Total explained variance of school performance is $R^2=\sum\beta r$=.43. The R^2 is higher than in stepwise regression because the relationships are analyzed in structural equation modeling at the error-free measurement level. With the exception of VWT, all observed variables are good indicators of "their" latent factors. The weights (Λ, lambda) are between β=.60 and .92. Weights between a latent factor and "its" two or more observed variables could be different (e.g., KFT β=.92 and APM β=.60 of intelligence) because the weights are fitted in relation to the whole model. Squared weights (Λ) represent explained variance or the lower bound estimate of reliability of an observed variable (e.g., the reliability of the KFT as measure for intelligence is r_{tt}=.85). In this model, the KFT is a better indicator of intelligence than the APM which might be due to its greater similarity with school performance regarding its cognitive demands (the KFT includes verbal and mathematical tasks as compared to the APM which include only figural nonverbal tasks). In addition, KFT tasks are more similar to contents of the school curriculum. As could be demonstrated by Süß (2001), the degree of similarity between intelligence-test tasks and school tasks can be an important moderator variable for relation between IQ and grades.

ZVT and KDT are good indicators of processing speed; their loadings are more or less equal. The VKT is in our model a better indicator of creativity than the VWT. Both are verbal paper-and-pencil tests of creativity, but the VKT more strongly reflects verbal abilities (it involves the reformulation of words and sentences). The correlations between VKT and the other eight observed ability and performance measures in our model are higher than the VWT correlations (mean r=.23 vs. .13; with grades in languages: r=.27 vs. .14; see Table 1).

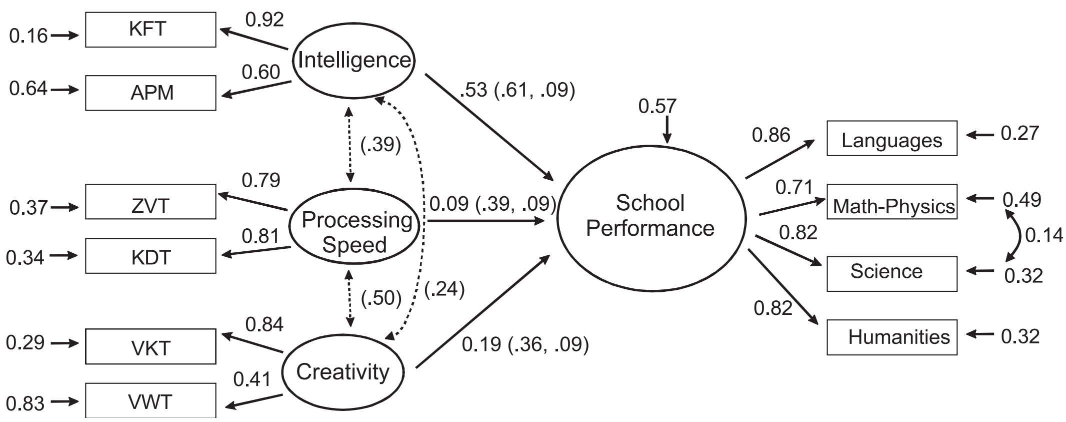

Fig. 1. Three-factor model (completely standardized solution; correlations and standard errors are given in parentheses; arrows with broken lines are correlations; here allowed correlations between three exogenous variables).

All four school subjects are good indicators of school performance. Between math–physics and sciences, we allow correlated errors in all tested models as these have more in common than is represented by the general latent factor school performance.

As expected from the correlational findings, intelligence is the best single predictor of school performance. The weight (Γ, gamma) of the path is considerably greater than the weights between creativity and school performance or between speed and school performance (β=.53 vs. .19 and .09).

As Model 2, we tested the speed-factor model (see Fig. 2). The weights between latent and observed variables (Λ) are nearly the same. Now the different paths between the independent latent variable (predictor) processing speed, the latent mediators intelligence and creativity, and the latent dependent variable school performance (criterion) are important. Like in the independent three-factor model (Fig. 1), processing speed has a small direct effect on school performance (β=.08), but processing speed has a strong direct effect on intelligence and creativity (β=.40 and .51). The whole effect of processing speed to school performance is β=(.40×.53)+.08+(.51×.20)=.39. The indirect effect of processing speed on school performance is higher (.31) than the direct effect (.08). Total explained variance of school performance is $R^2=\sum\beta r$=.43. In this model, processing speed represents an important direct determinant of higher mental abilities, and through this, an indirect (mediated by intelligence and creativity) determinant of school performance too.

The direct effect between processing speed and school performance reaches only β=.08 (standard error .09). We tested if the more parsimonious model without a direct effect is suitable (Model 2a). The fit values are nearly the same, RMSEA and CAIC are somewhat smaller (better), the small χ^2 difference is not significant, R^2 is a little bit higher (.44). A direct path between processing speed and school performance is

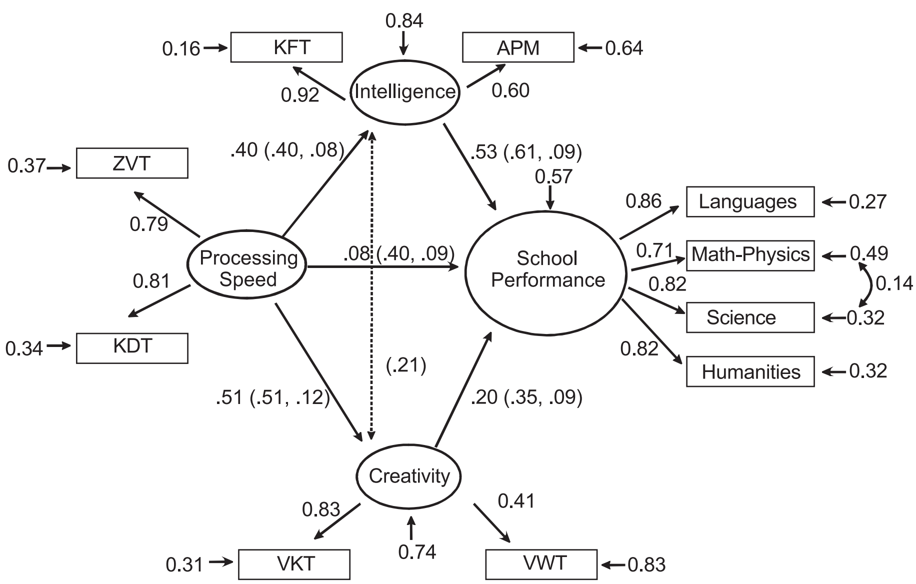

Fig. 2. Speed-factor model (completely standardized solution; correlations and standard errors are given in parentheses; arrows with broken lines are not given paths). (a) Speed-factor model without direct effect (completely standardized solution; correlations and standard errors are in parentheses; arrows with broken lines are not given paths). (b) Speed-factor model without direct effect and correlated errors between intelligence and creativity (completely standardized solution; correlations and standard errors are in parentheses; arrows with broken lines are not given paths).

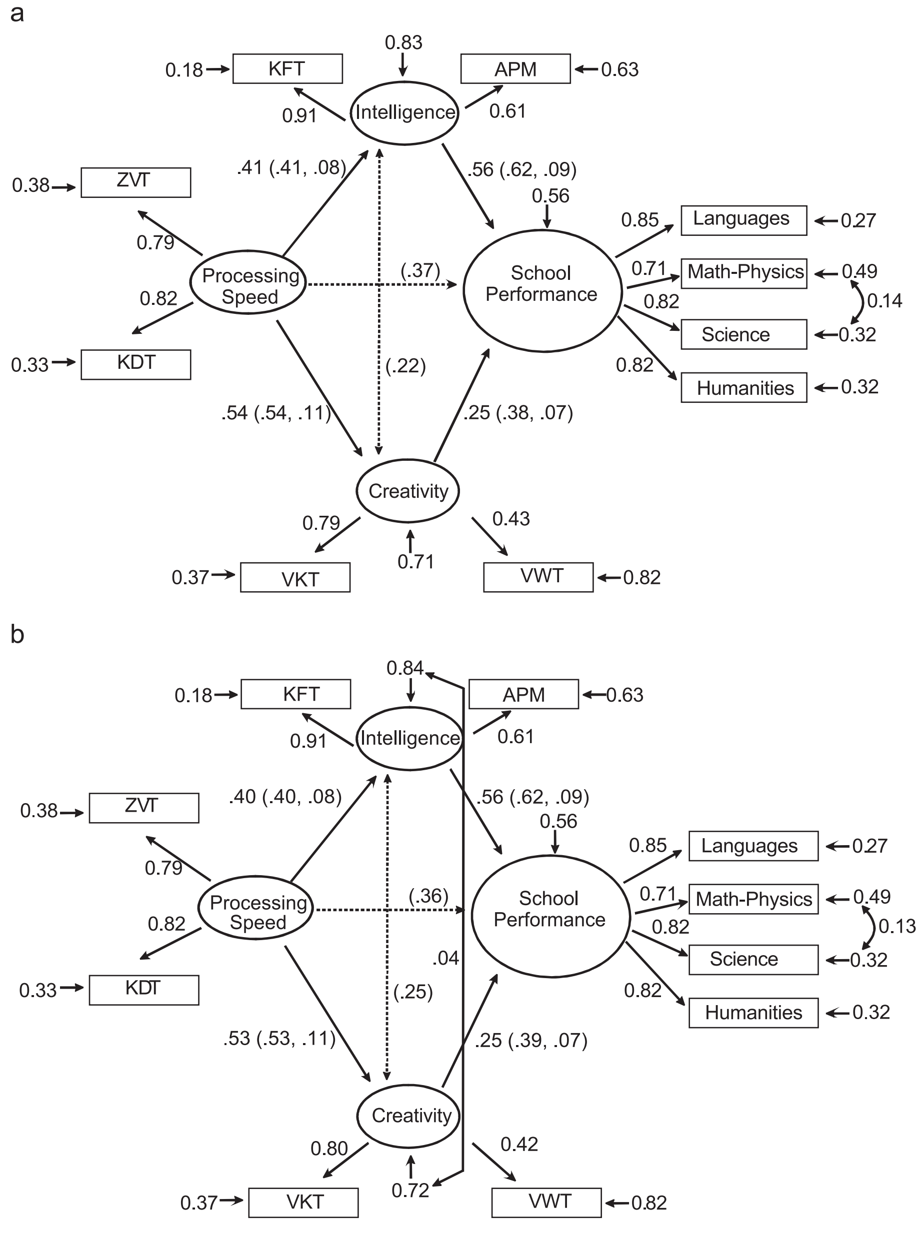

Fig. 2 (*continued*).

statistically not necessary. Additionally, we tested a processing speed model without a direct effect on school performance and with correlated errors between intelligence and creativity. The fit is worse, parsimony is lost, the theoretical basis is worse. More convincing are models without correlated errors.

As a competing model to the speed-factor models, we tested an intelligence-factor model too (see Fig. 3). Here, the total explained variance of school performance is R^2=.43. As expected, intelligence has a large direct effect on school performance (β=.54). The indirect effect is small [β=(.42×.09)+(.28×.18)=.09], the

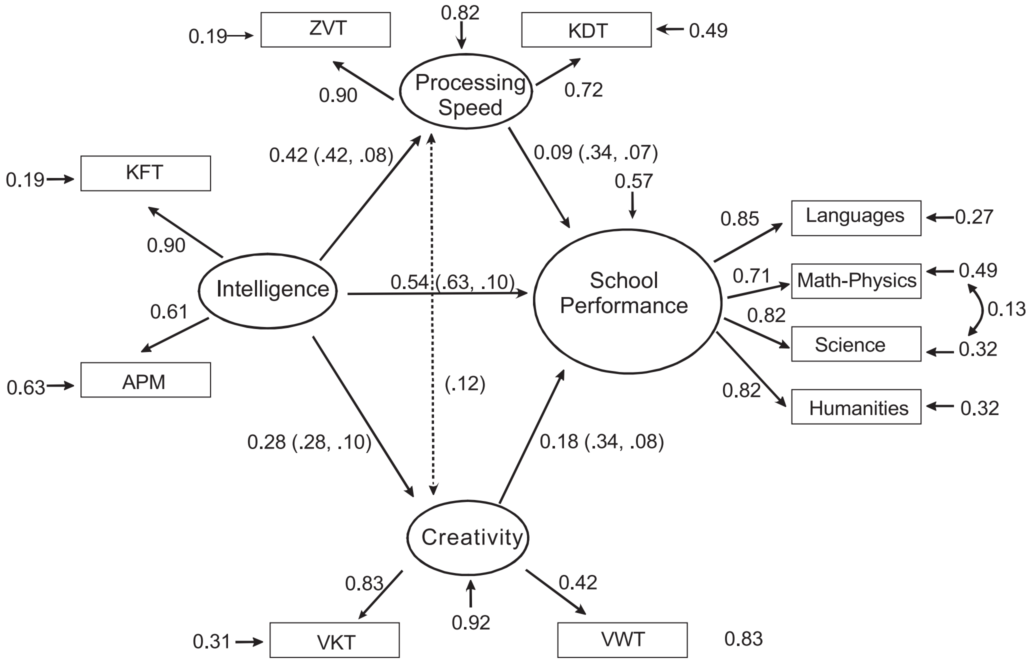

Fig. 3. Intelligence-factor model (completely standardized solution; correlations and standard errors are in parentheses; arrows with broken lines are not given paths).

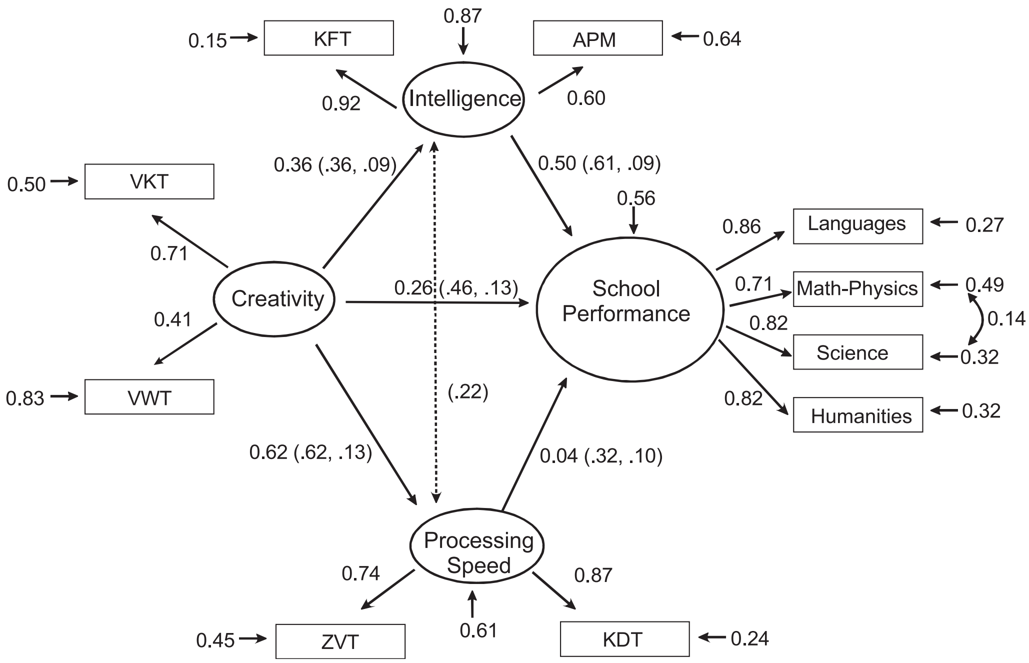

Fig. 4. Creativity-factor model (completely standardized solution; correlations and standard errors are in parentheses; arrows with broken lines are not given paths).

whole effect is β=.63. Intelligence can explain variance in processing speed and creativity, but the error variances (Ψ, Psi) of these mediator variables remain high (0.82 and 0.92). The path from processing speed to creativity in Model 2 has been stronger (β=.51 vs. here 0.28), the error variance of creativity has been smaller (0.74 vs. 0.92). The error variance of school performance remains constant (0.57). The intelligence-factor model explains school performance well because of a strong direct effect of intelligence towards school performance.

Finally, we tested a creativity-factor model (see Fig. 4). There is no reasonable theoretical basis for this model, but it should be tested in statistical comparison to the theoretically well-founded speed-factor model. Total explained variance of school performance is $R^2=\sum\beta r$=.44. Creativity has a medium direct effect on school performance (β=.26), the indirect effect is of medium size, too [β=(.36×.50)+(.62×.04)=.20], the whole effect of creativity is β=.46.

When we compare the models regarding their fit to the data (see Table 3), Models 3 and 4, that is, the intelligence-factor model and the creativity-factor model, show less good fit values. CFI is under .95 and RMSEA is over .06, only the S-RMR displays a good value. In comparison to the three-independent-factor model (Model 1) and the speed-factor model (Model 2), the S-RMR value is worse. The CFI value is lower too. In all models, the RMSEA is too high (>.06), but in the intelligence- and the creativity-factor models, the values are the worst. Only in the three-independent-factor and in the speed-factor models (Models 1 and 2) is the CFI value acceptable. When comparing the three-independent-factor model and the speed-factor model (Models 1 and 2), the speed-factor model shows somewhat better values: it is superior in two of three fit indices.

Table 3
Results of causal analyses (fit indices)

Fit indices	RMR	S-RMR	GFI	AGFI	PGFI	χ^2	$P\ (\chi^2)$	RMSEA	NFI	CFI	CAIC
Three-factor model: N=271 students, df=28											
Model 1	1.47	0.045	0.94	0.89	0.48	79,26	<.000	0.082	0.93	0.95	257.5
Speed-factor model: N=271, df=29 [(a) without direct path speed–school performance, df=30; (b) without direct path speed–school performance and with correlated errors between intelligence and creativity, df=29]											
Model 2	1.56	0.046	0.95	0.90	0.50	78,46	<.000	0.079	0.93	0.96	250.1
Model 2a	1.66	0.047	0.94	0.90	0.52	78,91	<.000	0.078	0.93	0.96	244.0
Model 2b	1.61	0.047	0.94	0.89	0.50	79,59	<.000	0.080	0.93	0.95	251.2
Intelligence-factor model: N=271 students, df=29											
Model 3	5.26	0.072	0.93	0.86	0.49	103,58	<.000	0.098	0.91	0.93	275.2
Creativity-factor model: N=271 students, df=29											
Model 4	3.32	0.063	0.93	0.87	0.49	96,80	<.000	0.093	0.92	0.94	268.5
Interpretation for fit indices											
Range?	–	–	(0)–1	(0)–1	0–1	>0	0–1	>0	0–1	0–1	>0
Good fit?	Near 0	≤0.08	≥.90	≥.90	Near 1	Small	>.05	≤0.06	≥.95	≥.95	Small
Parsimonious models preferred?	No	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes

RMR=root mean square residual; S-RMR=standardized root mean square residual; GFI=goodness-of-fit index; AGFI=adjusted goodness-of-fit index; PGFI=parsimony goodness-of-fit index; RMSEA=root mean square error of approximation; NFI=normed fit index; CFI=comparative fit index; CAIC=(Model) Consistent Akaikes Information Criterion; EQS produces for the first model χ^2=78,607.

When comparing the three speed-factor models (Models 2, 2a, and 2b), Models 2 and 2a fit slightly better. Model 2a has parsimony as advantage and therefore better values in parsimony rewarding fit indices; Model 2 has the "illustrative" advantage of demonstrating the weak direct effect of speed on school performance (β=.08). Additionally, the comparison between Models 2, 3, and 4 is easier because of the same degrees of freedom and same R^2.

In comparison of the three single-factor models with same degrees of freedom (Models 2, 3 and 4; df=29, N=271) the fit values for the speed-factor model (Model 2) are the best: S-RMR and RMSEA are the lowest, CFI the highest. In addition, χ^2, which can be used in models with same degrees of freedom and same sample size, is in Model 2 the lowest (the best). The speed-factor model fits good to the data, and in comparison to the others, it fits best.

4. Discussion

The aim of the study was to test a speed-factor model in comparison to different models that explain the relationship between three mental abilities and school performance. The speed factor hypothesis assumes processing speed as a basic mental ability, influencing higher mental abilities, like psychometric intelligence and creativity, which themselves should predict school performance. We tested this hypothesis by using correlations and structural equation models. In structural equation analysis, we compared different models in competition with the speed-factor hypothesis: the three-independent-abilities hypothesis, the intelligence-factor hypothesis, and the creativity-factor hypothesis.

The results of the study provide most support for the speed-factor hypothesis: processing speed is influencing both intelligence and creativity. Intelligence and creativity both have an impact on school performance. The total effect of processing speed on school performance is β=.39, but the direct effect is small (β=.08, bivariate r=.35) compared to the indirect effects (sum indirect: β=.31) mediated by intelligence (indirect β=.21) and creativity (indirect β=.10). The direct effect of intelligence on school performance is much higher (β=.54, bivariate r=.52), the indirect effects are small (sum indirect: β=.09). Creativity has a moderate effect on school performance (β=.26, bivariate r=.25).

When comparing the three single-factor models and the one independent three-factor model, the explained variance of school performance is logically always the same (R^2=.43). To proof the suitability of the models, we used fit indices for structural equation models, which—on the basis of Monte-Carlo analyses—are recommended by Hu and Bentler (1998, 1999). The speed-factor model has shown the best values regarding fit indices; that is, the data and a single speed-factor model match best. This model postulates that processing speed influences intelligence and creativity, which in turn, allow to predict school performance. A direct path between speed and school performance is not necessary. It should be remarked, that we inferred cause–effect relationships from cross-sectional data. Of course, a direct proof of cause–effect relationships between processing speed, intelligence, creativity, and school performance in a longitudinal design involving repeated measurements of these variables at different ages would provide additional support.

4.1. A model of mental abilities and performance: the central core intelligence

In a recent study (Rindermann & Neubauer, 2001), we have shown that personality factors, like self-concept, motivation, anxiety, learning, working, and cognitive styles, have a larger impact on school

performance (r=.69) than on psychometric intelligence (r=.51) or processing speed (r=.32). Traits, attitudes, and self-concept can influence—in a positive or negative way—more strongly school performance and psychometric intelligence than mental speed. On the contrary, speed of processing is barely predictable by personality scales. School performance is much more dependent on knowledge acquired at school and by education. And for the acquisition of knowledge, personality attributes, like motivation and learning styles, are very important.

Processing speed as a basic mental ability seems less "biased" or even almost independent of these factors (Rindermann & Neubauer, 2001). It should be remarked, however, that this study focused on processing speed as one basic mental ability; recent research has shown that especially working memory capacity could be another important basic source of individual differences in human cognitive performance (e.g., Kyllonen & Christal, 1990; Schweizer & Koch, 2002; Schweizer & Moosbrugger, 1999; Wittmann & Süß, 1999). In the study of Kyllonen and Christal (1990), processing speed and working memory capacities correlated with $r \approx .42$, and like in our study, processing speed had no direct "effect" on a criterion variable (here, general knowledge), but a rather strong indirect effect (effect is put in quotation marks here, because the authors used only correlations and confirmatory factor analysis).

It could be concluded that mental speed tests seem to measure cognitive ability in a less, by culture, learning, or personality, influenced form than intelligence tests. But processing speed cannot substitute psychometric intelligence or g as it is not identical with intelligence. Knowledge and personality are two additional important determinants that should not be neglected for understanding and explaining intelligence and school performance. On this basis, we cannot expect the correlation between processing speed and school performance to be as high as the correlation between psychometric intelligence and school performance. In conformity with the Roberts and Stankov (1999) model of processing speed and intelligence, who regard processing speed as correlated with fluid, but not crystallized intelligence, our results demonstrate only an indirect influence of processing speed on the heavily "crystallized" competence of school performance.

In confirmation of our hypotheses, the speed-factor model has not only shown empirical superiority over an independent three-factor model or competing intelligence and creativity models in fit indices, but the speed-factor model also has a large advantage in its theoretical persuasiveness: the mental speed theory regards speed and efficiency of information processing in ECTs as an important basis of individual differences in other cognitive abilities. The capacity of working memory is limited, information in working memory decays rapidly; therefore, a high speed of mental operations is advantageous because an overload of working memory can be avoided. Former research has shown (for a review, see Neubauer, 1997; cf. also Rindermann & Neubauer, 2000) that the relationship between processing speed and intelligence could not be explained by motivation or other "top–down" explanations like strategies or concentration ability. Explanations referring to a biological substrate (efficiency of biologically determined central nervous system, "bottom–up" approaches) seem to be more adequate. The results of this study conform to such a view: processing speed is an important basic resource of intelligence.

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