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The causal factor underlying the correlation between psychometric *g* and scholastic performance

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Abstract

Structural equation models were fitted to covariances among 9 Cognitive Abilities Test (CAT) variables, 11 Wechsler Intelligence Scale for Children—Revised (WISC-R) subtest scores, and 3 Metropolitan Achievement Test (MAT) scaled scores, administered to a sample of 532 primary school children who participated in the Western Reserve Twin Project. The models were designed to test the hypothesis that factors representing basic cognitive processes, extracted from the nine CAT variables, were the main causal determinants for the observed correlation between psychometric *g* and scholastic performance, which were represented, respectively, by a general factor extracted from the WISC-R and a factor from the MAT. Structural relations between the CAT factors as the primary independent variables, psychometric *g* as a secondary independent variable, and scholastic performance as the dependent variables were estimated, and the R^2 change indicating the higher-order shared variability between *g* and scholastic performance was evaluated. After the influence of a CAT general factor was controlled, the WISC-R general factor accounted for about 6% of the variability in the MAT scholastic factor, as opposed to as much as 30% of the zero-order variability shared by the two variables. The results were not seriously affected by the exclusion of nonchronometric measures of the cognitive tasks from the model, suggesting that individual differences in mental speed are a main causal factor underlying the observed correlation between

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general intelligence and scholastic performance in children between the ages of 6 and 13.

Keywords: Scholastic performance; Elementary cognitive tasks; Mental speed; Psychometric *g*; Structural equation modeling

1. Introduction

The nature of the relationship between intelligence and scholastic achievement has been frequently debated among psychologists and educators. There is a substantial correlation between measures of intelligence and measures of scholastic performance, but the source of the correlation is not clear. Intelligence, particularly its general factor, or *g*, has been thought by some as precedent to scholastic performance in the causal chain, because *g* is commonly acknowledged as more pervasive in intellectual tasks, and appears to be more biologically rooted than school achievement (Jensen, 1998). From this perspective, *g* reflects an individual's potential, whereas scholastic performance is one of the intellectual activities to which the *g*-potential can be applied. Opponents of this view contend that most intellectual abilities, *g* included, are partly a product of education; therefore, the assertion that *g* causally precedes scholastic performance is misleading. Rather, scholastic performance as a measure of education can causally determine *g* (Ceci, 1991, 1992).

In recent decades, studies have applied a reductionist approach to the issue (Deary, 1980, 1986; Detterman, 1987; Frearson & Eysenck, 1986; Jensen, 1982a,b, 1985, 1987; Nettlebeck & Lally, 1976; Raz & Willerman, 1985; Raz, Willerman, Ingmundson, & Hanlon, 1983). These studies relate intelligence to basic cognitive processes, which are measured using tasks such as simple reaction time, stimulus discrimination time, inspection time, and memory recall and recognition tasks. Cognitive processes involved in these tasks, such as mental speed and memory processing, have been found to be strongly related to psychometric *g*, and can account for 50% or more of the variance in *g* (Jensen, 1982a,b; Luo & Petrill, 1999; Miller & Vernon, 1992; Vernon, 1987).

Studies directly relating basic cognitive processes to scholastic performance have been rare. The effort made by J.M. Cattell and his associates (Cattell & Farrand, 1890; Wissler, 1901) a century ago relating basic psychological processes to Columbia University students' school performance resulted in disappointingly near zero correlations between the two classes of variables, and discouraged researchers from further studies in the same direction. The renewal of interest in decomposing complex intellectual abilities into basic cognitive processes has led to a few studies involving scholastic achievement. Carlson and Jensen (1982) measured reaction time with the Hick paradigm (Hick, 1952) and found a substantial correlation between reaction time and reading comprehension. In a recent analysis by the present authors (Luo, Thompson, & Detterman, 2000a,b), a general factor extracted from a set of elementary cognitive task variables was found to contribute up to 30% of variance in

scholastic performance, and was primarily genetically mediated. Furthermore, the extracted component appears to represent mental speed.

These findings suggest that the correlation between *g* and scholastic performance may be rooted in basic cognitive processes. However, it is not clear whether the basic cognitive processes involved in scholastic performance are *qualitatively* equivalent to those involved in psychometric *g*. In previous studies, substantial correlations between mental speed and *g* were typically observed when the mental speed component was defined by multiple elementary cognitive tasks (Kranzler & Jensen, 1992a,b; Luo & Petrill, 1999; Miller & Vernon, 1994; see also Vernon, 1992; Jensen, 1998 for a comprehensive review). In these studies, the component was derived either as a latent factor or as a linear composite from mental speed tasks, with considerable variation in task selection. The variation in task selection in these studies makes the nature of the mental speed component ambiguous: the component may pertain to different cognitive functions in different studies. The same ambiguity also exits in the studies where a substantial correlation between mental speed and scholastic performance was observed, as these studies also used different sets of elementary task variables to define mental speed. Because of this ambiguity, it is possible that the correlation between mental speed and *g* is determined by one set of cognitive functions, and that between mental speed and scholastic performance is controlled by quite another. In other words, there may not be a common set of mental speed functions that determine both *g* and scholastic performance even though substantial correlations have been observed, respectively, between mental speed and *g* and between mental speed and scholastic performance . To avoid such an ambiguity, one needs to relate psychometric *g* and scholastic performance to a mental speed component defined by the same set of elementary tasks, and evaluate the extent to which the variability shared between *g* and scholastic performance can be ascribed to the mental speed component.

Statistically, the mediating role of mental speed in the correlation between psychometric *g* and scholastic performance can be assessed by calculating the correlation between psychometric *g* and scholastic performance with the influence of mental speed controlled. If the variability shared between *g* and scholastic performance is substantially reduced after mental speed is taken into consideration, then mental speed evidently mediates most of the correlation between *g* and scholastic performance. On the other hand, if some unknown, more complex processes are shared by *g* and scholastic performance, then the higher-order variability shared by *g* and scholastic performance will remain strong after the influence of mental speed is factored out.

The present study assesses the higher-order variability shared between psychometric *g*, which was indicated by the Wechsler Intelligence Scale for Children—Revised (WISC-R) subtests and scholastic performance, as measured by the Metropolitan Achievement Test (MAT), while controlling for basic cognitive processes measured by the Cognitive Abilities Test (CAT) tasks using the structural equation modeling (SEM) method. The method of SEM provides a means of estimating structural relations between latent constructs, which are theoretically independent of the error terms and therefore do not need correction for unreliability. The magnitude of the higher-order shared variability between *g* and scholastic performance while controlling the influence of basic cognitive processes is in essence the R^2

change relating *g* as a secondary independent variable to scholastic performance as the dependent variable. The influence of the elemental cognitive components on *g* and scholastic performance, on the other hand, can be represented statistically as regression weights relating these components to *g* and scholastic performance, and figuratively as one-way paths from the former to the latter. The higher-order variability shared between *g* and scholastic performance controlling for mental speed was the focus of the present study, and the assessment of this shared variability would answer directly the question of whether or not basic cognitive processes are the main mediators of the observed correlation between *g* and scholastic performance.

2. Method

2.1. Participants

Participants were drawn from the Western Reserve Twin Project, a study of cognitive abilities and scholastic achievement in twins. The twins were recruited through public, private, and parochial schools within a six county area surrounding the city of Cleveland, OH. All participants were in the first through sixth grade at the time of participation. The sample consisted of 568 participants. In the present study, all twin pairs were split and randomly assigned into two nonoverlapping subsamples. Covariances were pooled from the two subsamples so that participants were treated as though they were unrelated individuals. Covariances between all variables were based on 532 observations after list-wise deletion of cases with missing values, and model testing and parameter estimation in the present study were conducted on the basis of these covariances.

The data in the present study had a score dispersion that was not restricted, and did not require correction procedures for correlation attenuation due to the restriction in range of test scores. Range restrictions often compromised results from studies relating elemental cognitive skills to more global intellectual abilities. Although correction procedures have been proposed to overcome the resulting attenuation of correlation, it is desirable to directly assess correlations in a representative sample. The present study used data collected from 284 identical and fraternal twin pairs of primary school age representing the full range of individual differences in general intelligence with a WISC-R Full Scale IQ mean of 104.5 and a standard deviation of 15.8.

2.2. Measures

Each child in the study was tested a total of 8.5 h over three sessions.

2.2.1. Elementary cognitive tasks

Six tasks from the CAT (Detterman, 1988) were administered to all participants. They were: learning (LR), probe recall (PR), reaction time (RT), stimulus discrimination (SD), self-paced probed recall (SP), and tachistoscopic threshold (TT).

Stimulus presentation was similar in LR, PR, and SP. In each trial, a participant was presented with a row of blank windows slightly below the center of the computer screen, and a probe window centered above this row. Matrix diagrams were shown one by one as stimulus items in each blank window. Each diagram appeared and disappeared before the presentation of the next diagram. After the last diagram disappeared on the screen, one of the previously presented diagrams reappeared in the probe window and participants were asked to indicate which bottom window contained the probed diagram.

In LR, each of the presented diagrams were probed and participants were asked to respond to all of them. In PR, only one of the presented diagrams appeared as the probe stimulus during each trial. SP was the same as LR, except that participants could control the presentation time of each stimulus diagram.

In the RT task, an array of one, two, four, six, or eight empty windows appeared on the screen and one of the windows would light up in each trial. The participant was required to touch the lit window as quickly as possible.

Participants in SD were presented with six blank windows in the bottom portion of the screen and a probe window in the upper portion of the screen. The six windows each displayed a different diagram and the probe window presented a diagram identical to one of the six diagrams below it. The participant's task was to find the match to the probe and touch it as quickly as possible.

In TT, two diagrams were presented simultaneously for a very brief duration and were then masked and participants were asked to determine whether they were the same. The presentation time varied until a threshold duration for correct identification was determined.

All participants during the CAT sessions used a touch screen device to make their responses to the stimuli and both their response times and response choices were automatically recorded by a computer.

Nine variables from the CAT were used in the current analyses: percentage-correct from LR (LRPC), percentage-correct from SP (SPPC), percentage-correct from the PR (PRPC) task, reaction time for correct responses from PR (PRRT), decision time from RT (RTDT), decision time from SD (SDDT), decision time from TT (TTDT), movement time from TT (TTMT), and threshold time from TT (TTTH). Decision times in the RT, SD, and TT tasks represent the time from the onset of the stimulus presentation to the time the participant's finger leaves the home button on the touch screen. Movement time in TT represents the time required by the participant to move a finger from the home button to the response button on the touch screen. Reaction time in PR is the time needed by the participant to touch the target position after the presentation of the probe stimulus. Threshold time of the TT task indicates the minimum stimulus presentation time needed for a participant to respond correctly 75% of the times for the task. All nine variables were corrected for age and gender differences.

The CAT variables analyzed in the present study are valuable because important information may be provided when the variables are subjected to experimental analysis. The stimulus presentation and the task demands of these tasks can be manipulated and responses to these manipulations can reveal mechanisms of information processing. For example, the number of windows presented in the reaction time task varies complexity systematically (one, two, four, six, or eight choices) within a relatively simple task. In the SD

Table 1
Observed correlations between CAT, WISC-R, and MAT variables

	IN	SI	AR	VO	COMP	PC	PA	OA
IN	*9.5998*							
SI	0.6258	*10.4967*						
AR	0.5242	0.4657	*9.3928*					
VO	0.6599	0.6466	0.4821	*10.3331*				
COMP	0.5744	0.5973	0.4795	0.6906	*10.3195*			
PC	0.3701	0.3512	0.3244	0.3953	0.3392	*7.6965*		
PA	0.4000	0.3927	0.3115	0.4062	0.3947	0.3730	*9.7041*	
OA	0.3845	0.3754	0.3382	0.3915	0.3563	0.5022	0.4907	*10.5108*
BD	0.4429	0.4296	0.5027	0.4109	0.4115	0.4462	0.4363	0.6305
CD	0.1974	0.1582	0.3121	0.1659	0.1494	0.1525	0.1551	0.2154
DS	0.4254	0.3751	0.4893	0.4004	0.4034	0.2779	0.2599	0.2244
LRPC	0.3371	0.3057	0.3457	0.2988	0.2955	0.3425	0.2511	0.3851
PRPC	0.2663	0.2331	0.3268	0.2287	0.2648	0.1630	0.1997	0.2993
SPPC	0.2992	0.2977	0.3834	0.3048	0.3052	0.2501	0.2035	0.3339
PRRT	0.1996	0.1216	0.1512	0.0785	0.1002	0.0703	0.1055	0.0612
RT	0.2775	0.2281	0.2377	0.2086	0.2264	0.1779	0.1673	0.1818
SD	0.3414	0.2539	0.2521	0.2725	0.2154	0.2489	0.2470	0.2808
TTMT	0.0779	0.0892	0.1396	0.1540	0.0953	0.1192	0.0290	0.1181
TTDT	0.1675	0.1715	0.1103	0.1378	0.1684	0.1601	0.0311	0.1213
TTTH	0.2307	0.2331	0.2430	0.2475	0.2386	0.2966	0.3201	0.3127
LANG	0.3693	0.3774	0.4338	0.3153	0.3788	0.1770	0.1422	0.2175
MATH	0.3218	0.3778	0.4510	0.2664	0.3913	0.1535	0.1265	0.2130
READ	0.4098	0.4202	0.4650	0.3665	0.4089	0.2167	0.1914	0.2754

	BD	CO	DS	LRPC	PRPC	SPPC	PRRT	RT
BD	*11.2609*							
CD	0.2728	*12.1636*						
DS	0.3377	0.1910	*10.0118*					
LRPC	0.4189	0.2356	0.2918	*0.9958*				
PRPC	0.3160	0.2345	0.2864	0.3407	*0.9930*			
SPPC	0.4049	0.2367	0.3672	0.4652	0.4050	*0.9736*		
PRRT	0.1292	0.1669	0.1672	0.1190	0.2187	0.0478	*0.9883*	
RT	0.1906	0.2584	0.2561	0.2759	0.2485	0.2062	0.4862	*0.9654*
SD	0.2902	0.2873	0.1988	0.3177	0.3333	0.2156	0.3820	0.4973
TTMT	0.1548	0.1541	0.1163	0.0891	0.0813	0.1601	0.0415	0.1695
TTDT	0.1352	0.0663	0.1406	0.1395	0.1266	0.1306	0.0442	0.1762
TTTH	0.3160	0.1790	0.2082	0.3181	0.2335	0.2746	0.0366	0.1837
LANG	0.3078	0.2434	0.3846	0.2807	0.2286	0.2848	0.1496	0.2464
MATH	0.3279	0.2347	0.3726	0.2621	0.2470	0.3005	0.1058	0.2117
READ	0.3664	0.2430	0.4305	0.2930	0.2820	0.3109	0.1916	0.2820

	SD	TTMT	TTDT	TTTH	LANG	MATH	READ
SD	*0.8981*						
TTMT	0.2154	*0.9870*					
TTDT	0.1493	0.0364	*1.0061*				
TTTH	0.3196	0.2234	0.1446	*1.0296*			

Table 1 (*continued*)

	SD	TTMT	TTDT	TTTH	LANG	MATH	READ
LANG	0.2360	0.1369	0.1589	0.2100	*1.3020*		
MATH	0.2137	0.1305	0.1270	0.2187	0.8739	*1.8196*	
READ	0.2632	0.1524	0.1922	0.2212	0.8850	0.8660	*2.0399*

Italic diagonal values are variable variances. Acronyms for the CAT variables are: percent-correct for learning (LRPC), percent-correct for probe memory (PRPC), percent-correct for self-paced learning (SPPC), mean reaction time for probe memory (PRRT), mean decision time for simple reaction time (RT), mean decision time for stimulus discrimination (SD), movement time for inspection time (TTMT), decision time for inspection time (TTDT), and threshold time for inspection time (TTTH). Acronyms for the WISC-R variables are: information (IN), similarity (SI), vocabulary (VO), comprehension (COMP), picture completion (PC), picture arrangement (PA), object assembly (OA), block design (BD), arithmetic (AR), digit span (DS), and coding (CO). Acronyms for the MAT variables are: language (LANG), mathematics (MATH), and reading (READ).

task, the additional demand of matching complex target stimuli is added. The nature of the stimulus presentations and the task demands of LR, PR, and SP are specifically controlled to provide leverage on isolated processes.

2.2.2. Battery of psychometric intelligence

Scale scores of 11 subtests from the WISC-R (Wechsler, 1974): information (IN), similarity (SM), arithmetic (AR), vocabulary (VO), comprehension (COMP), digit span (DS), picture completion (PC), picture arrangement (PA), object assembly (OA), block design (BD), and coding (CO) were used to construct psychometric *g*.

2.2.3. Scholastic measures

Three-scaled scores from the MAT were used to construct the scholastic performance factor: the total reading scale score (READ), the total mathematics scale score (MATH), and the total language scale score (LANG). The three MAT variables were rescaled to have variances comparable to those of the CAT and WISC-R variables (variances scaled to 1/33 of their original magnitudes). The pooled covariance/correlation matrix for all the 23 variables is presented in Table 1.

2.3. Analysis

Factor analysis models were first fitted separately to the covariance matrices of the CAT, WISC-R, and MAT batteries. These factor models were then used as submodels in a combined model, and structural relations between the CAT factors, the psychometric *g* factor, and the MAT variables were then estimated. The structural relations relating independent elemental cognitive components to psychometric *g* and scholastic performance indicate the contributions from the elemental components to *g* and scholastic performance. A higher-order correlation between WISC-R *g* and scholastic performance was also specified and estimated in the combined model. Such a higher-order correlation between the residual of *g* and the residual of scholastic performance can be used to calculate the R^2 change relating the secondary independent variable, *g*, to the dependent variable of scholastic

performance when the primary independent variables, the elemental cognitive components, are statistically controlled.[1]

Two kinds of model fits were evaluated in the analyses of the study, i.e., evaluation of the overall models and evaluation of specific parameters. The former ensured that the overall factor analysis models fit the data reasonably well, whereas the latter was used to test the importance of specific aspects of the models. Chi-square values were reported for the

[1] To estimate the R^2 change representing the higher-order shared variability between *g* as a secondary independent variable and scholastic performance as the dependent variable, one can specify an additional model in which *g* and the elemental cognitive components are all treated as the independent variables for scholastic performance. The standardized estimate of the residual variance of scholastic performance from this model can be compared to that from the model treating only the elemental components, but not *g*, as independent variables, and the difference between the two residual variances of the scholastic performance factor gives an estimate of the R^2 change induced by the secondary independent variable *g*.

An alternative approach is to calculate the semipartial correlation using the structural equation model estimates from the model in which both *g* and scholastic performance are treated as correlated dependent variables to the elemental cognitive component independent variables, and square the semipartial correlation for the R^2 change described above. We adopted the second approach because it allows us to test the significance of the correlation between the residuals of the WISC-R *g* and the scholastic performance factor, and thus the significance of the semipartial correlation and R^2 change, by fixing the correlation at zero in a reduced model and gauging the chi-square difference caused by the fixed parameter. The specific formulas to calculate the semipartial correlation using the structural relation estimates vary according to the correlations among the independent variables.

When independent variables are not intercorrelated, as in the case of CAT G and M, the formula to calculate the semipartial correlation using the estimated correlation between two residual variances and the standardized regression weights is:

$$r_{1(2.34)} = \frac{r_{12} - \beta_{13}\beta_{23} - \beta_{14}\beta_{24}}{\sqrt{1 - \beta_{23}^2 - \beta_{24}^2}} = \frac{r_{\text{resid1 resid2}}}{\text{Proportion of Variability in 2 Unexplained by 3 and 4}},$$

where r_{12} is the estimated zero-order correlation between variables 1 and 2; β_{13} and β_{23} are the estimated standardized regression weights relating the independent variable (variable 3) to the two dependent variables (variables 1 and 2), and β_{14} and β_{24} are the standardized regression weights relating an additional independent variable (variable 4) to dependent variables 1 and 2.

For example, the correlation between the residual variances of the WISC-R *g* (variable 2) and the MAT scholastic performance factor (variable 1) was estimated to be $r_{\text{resid1 resid2}}$=.151 for the combined baseline model (see Table 4). The standardized regression weights indicating the contributions from the CAT G (variable 3) and M (variable 4) factors to the WISC-R *g* were estimated to be β_{23}=.761 and β_{24}=.225, respectively. The regression weight relating the CAT M factor to the MAT scholastic factor was not specified in the model, so β_{14}=0. Consequently, the semipartial correlation reflecting the unique contribution from the WISC-R *g* to the MAT scholastic factor controlling the influence from the CAT G and M factors is

$$r_{1(2.34)} = \frac{r_{12} - \beta_{13}\beta_{23}}{\sqrt{1 - \beta_{23}^2 - \beta_{24}^2}} = \frac{r_{\text{resid1 resid2}}}{\text{Proportion of Variability in 2 Unexplained by 3 and 4}}$$

$$= \frac{0.151}{\sqrt{1 - 0.761^2 - 0.225^2}} = 0.248$$

When there is only one independent variable, as in the case of the CAT submodel without the working memory percent correct variables, the parameters related to variable 4 vanish from the formula above, and the formula is simplified to that for a first-order semipartial correlation.

assessment of model fit along with the Non-Normed Fit Index (NNFI; Bentler & Bonnet, 1980; Marsh, Balla, & MaDonald, 1988; Tucker & Lewis, 1973), the Comparative Fit Index (CFI; Bentler, 1990), and the Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980). For NNFI and CFI, values below 0.9 are usually considered as indicative of an unsatisfactory model fit and, for RMSEA, a value of about 0.05 or lower indicates a reasonable fit. The indexes used to test the importance of specific model parameters were based on chi-square differences between models with and without constraints on the parameters in question.

2.3.1. Factor analysis submodels

The final factor analysis submodel for the CAT consisted of three group factors, i.e., a response time (RST) factor indicated by RTDT, SDDT, and PRRT; a memory (M) factor defined by PRPC, LRPC, and SPPC; and an inspection time (IT) factor represented by the three inspection time variables, TTMT, TTDT, and TTTH; and one general factor (G). Fit indexes for the model were 0.94, 0.97, and 0.052 for NNFI, CFI, and RMSEA, respectively, indicating an adequate fit.

For the WISC-R, the commonly adopted model with one general factor (g) and three group factors, the verbal factor (V), the performance factor (P), and the freedom from distraction factor (FD), was found to fit the data satisfactorily. The freedom from distraction group factor, however, appeared to be weakly defined in the factor structure, and had near zero loadings for two of its indicators, i.e., DS and CO. To overcome this problem within the confines of the three-group-factor model, the three indicators, AR, DS, and CO, were constrained to be equivalent in factor loadings. The model was still consistent with the three-factor structure and its fit was not significantly worsened by the constraints (chi-square increment for df=2 was 3.962). The WISC-R general factor in this submodel represents psychometric g in the present study.

The three MAT variables were apparently indicators of the same scholastic factor, as intercorrelations between them were all quite high, and loadings on the factor all above 0.90. With the three manifest variables to indicate one scholastic latent factor, the submodel was just identified. Tables 2 and 3 display the standardized loading estimates and the fit indexes of these submodels.[2]

2.3.2. Combined structural equation models

The submodels of the CAT, WISC-R, and MAT were combined into a series structural equation models, in which paths and factorial correlations between latent variables of different submodels were specified. The combined models were built upon the submodels and were specified on two levels: the baseline level, on which all important pathways and factorial correlations of interest between latent variables were freed for estimation and the

[2] The three MAT variables, LANG, MATH, and READ, had intercorrelations near .90. Models specified on the basis of the individual MAT variables yielded essentially the same results as those obtained from the models using all three MAT variables to define the scholastic performance factor. The results based on individual MAT variables were thus omitted in the paper to avoid redundancy.

Table 2
Standardized parameter estimates for the CAT, WISC-R, and MAT factor analysis model

Indicators	CAT factors			
	General	Memory	Response time	Inspection time
LRPC	0.553 (0.043)	0.379 (0.054)		
PRPC	0.466 (0.042)	0.319 (0.047)		
SPPC	0.560 (0.043)	0.384 (0.055)		
PRRT	0.343 (0.037)		0.455 (0.036)	
RT	0.452 (0.041)		0.610 (0.038)	
SD	0.420 (0.040)		0.558 (0.036)	
TTMT	0.260 (0.047)			0.177 (0.050)
TTDT	0.234 (0.047)			0.159 (0.047)
TTTH	0.488 (0.042)			0.332 (0.093)
Indicators	WISC-R factors			
	g	V	P	FD
IN	0.752 (0.030)	0.226 (0.061)		
SI	0.718 (0.031)	0.262 (0.062)		
VO	0.705 (0.033)	0.565 (0.069)		
COMP	0.695 (0.033)	0.349 (0.067)		
PC	0.488 (0.039)		0.341 (0.048)	
PA	0.509 (0.038)		0.310 (0.047)	
OA	0.504 (0.039)		0.758 (0.058)	
BD	0.625 (0.033)		0.415 (0.047)	
AR	0.698 (0.029)			0.309 (0.041)
CO	0.273 (0.046)			0.309 (0.041)
DS	0.554 (0.036)			0.309 (0.041)
Indicators	MAT factor			
	Scholastic factor			
LANG	0.938 (0.008)			
MATH	0.918 (0.009)			
READ	0.937 (0.008)			

Values in parentheses are estimated standard errors.

reduced level, on which one of the pathways or correlations was reduced to test the significance of the reduced paths.

In our previous analyses (Luo & Petrill, 1999; Luo et al., 2000a,b), only the CAT general and memory factors were significantly correlated with the WISC-R *g*, and only the CAT general factor had a significant correlation with the MAT variables. The correlations of the CAT RST and IT factors with the WISC-R *g* and with any of the MAT variables were trivial, and only the WISC-R FD group factor had stable, positive correlations with the MAT variables. These results were used to build the comprehensive model used in the current analyses in which the submodels of the CAT, WISC-R, and MAT were combined. In the model, two of the CAT factors, the CAT general factor and the CAT memory factor, were

Table 3
Model fit indexes of submodels and combined models

Model	Baseline and reduced models				
	χ^2	*df*	NNFI	CFI	RMSEA
Submodels					
CAT submodel	42.936	18	0.943	0.973	0.052
WISC-R submodel	55.968	33	0.986	0.991	0.034
Model providing zero-order correlation estimates					
	162.281	67	0.970	0.977	0.052
Model without CAT percent-correct variables					
	310.670	151	0.961	0.968	0.044
Combined baseline model					
	412.829	207	0.955	0.962	0.043

The baseline model above frees the correlations between the WISC-R *g* and the MAT scholastic performance factor in addition to the paths from the CAT factors to the WISC-R *g* and to the MAT scholastic performance factor.

allowed to be related through one-way paths, respectively, to the WISC-R *g*. One CAT factor, the CAT general factor, contributed to the MAT scholastic factor via a one-way path. Two WISC-R factors, the *g* and FD factors, were specified to have correlations with the scholastic factor. The correlation between the WISC-R *g* factor and the scholastic factor was represented as a correlation between the residual variances of the two factors with the influences from the CAT factors controlled. Fig. 1 depicts this comprehensive baseline model. Table 2 lists model-fit indexes for all the combined baseline models. The indexes suggest that all models fit the data reasonably well.

For the combined baseline model, three reduced models were constructed to assess the importance of specific model parameters. In the first reduced model, the correlation between the residuals of the WISC-R *g* and the scholastic performance factor was fixed at zero, and the chi-square difference between the reduced model and the baseline model showed the impact of the reduced parameter, i.e., the higher-order shared variability between the WISC-R *g* and the scholastic performance factor beyond the influence of the CAT general factor. In the second reduced model, the path from the CAT general factor to the WISC-R *g* was constrained to zero, and the chi-square difference indicated the importance of the CAT G to the WISC-R *g*. Finally, the reduced model deleting the path from the CAT G to the MAT revealed the influence of the CAT G on the scholastic performance factor.

2.3.3. *Model providing zero-order correlation estimates*

This model estimated the zero-order correlation between the WISC-R *g* and the scholastic performance factor. The model included only the WISC-R submodel and the scholastic performance factor, and the factorial correlations between the two sets of variables could indicate the zero-order correlation between the WISC-R *g* and scholastic performance, and could be compared with the corresponding higher-order shared variability between the two

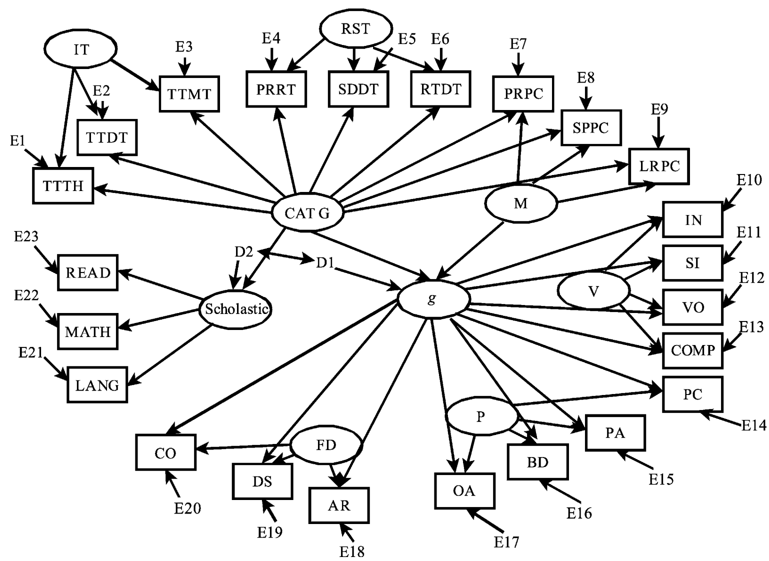

Fig. 1. Path diagram depicting combined baseline model including all CAT, WISC-R and MAT variables. D1 and D2 are residuals to the endogenous latent variables, i.e., WISC-R *g* and the scholastic factor, and E1 through E23 are residuals to the observed variables. The three one-way paths (the two that lead from the CAT G and CAT M factors to the WISC-R *g*, and the one from the CAT G to the scholastic factor) represent contributions of the CAT factors to the two intellectual variables. The two-way path between D1 and D2, highlighted for emphasis, describes the correlation between the residual variances of he WISC-R *g* and the scholastic factor beyond the CAT influence. The other two-way path, the one that connects WISC-R FD and the residual to the scholastic factor, is the factorial correlation between the two latent variables.

factors from the baseline models consisting of the CAT, the WISC-R, and the scholastic performance factors. One minus the ratio of the higher-order shared variability to the zero-order shared variability between the WISC-R *g* and the scholastic performance factors gives the proportion of the variability shared between the two factors mediated by the elemental cognitive factors.

2.3.4. Model without the CAT percent-correct variables

Evidence from previous analyses (Luo & Petrill, 1999) suggested that the CAT general factor largely reflects speed of information processing; however, larger than average loadings on the factor as shown in Table 2 of the three CAT percent-correct measures (LRPC, SPPC, and PRPC), which presumably reflect processes other than mental speed, suggest that other influences may also be operating. A thorough investigation of the mechanisms of the factor was beyond the scope of the present study, but the incorporation of the CAT submodel without the percent-correct variables into the combined models may shed some light on the issue. In these models, the CAT submodel consisted of a general factor, defined by the six chronometric measures (PRRT, RTDT, SDDT, TTMT, TTDT, and TTTH), a RST group factor indicated by the three reaction time measures, and a IT group factor for the three inspection time variables. The CAT general factor, therefore, was exclusively chronometric in

nature and would be more convincingly understood as a mental speed component. This factor was again related to the WISC-R *g* and the scholastic performance factor, and the higher-order shared variability between the WISC-R *g* and the scholastic performance factor was evaluated once more to show that the exclusion of the percent-correct measures did not seriously alter the basic findings of the study.[3]

2.3.5. SEM program

The SAS Proc CALIS program was used for the analyses. The COSAN option (Fraser & McDonald, 1988) of the program allows one to standardized parameter estimates, together with their standard errors, by scaling parameters on the basis of variable variances (Krane & McDonald, 1978). These standardized estimates were, in essence, correlation and standardized regression coefficients, and their standard errors could be used to evaluate the importance of these correlations and regression coefficients. The properties of the COSAN option were valuable for the present study, because the evaluation on standardized estimates, including those of the higher-order shared variability between psychometric *g* and scholastic performance, was of particular interest for the present study.

3. Results and discussion

The standardized path coefficient estimates from the model combining the CAT, the WISC-R, and the MAT scholastic performance factor are presented in Table 4. The size of coefficient estimates, together with the estimate-to-standard-error *t* ratio, indicates the importance of each path in the model. The importance of individual paths is also indicated in Table 5, which displays the chi-square difference between the baseline model and the reduced models.

The paths from the CAT general factor to the WISC-R *g* and to the scholastic performance factor in the baseline model, as shown in Table 4, is substantial, accounting for just under 60% of the variance in the WISC-R *g* and about 25% of the variance in the scholastic performance factor. It can be seen in Table 5 that the reduction of each of these paths from the baseline model also led to very large increases of the chi-square value.

The most notable of the outcomes is the higher-order shared variability between the WISC-R *g* and the scholastic performance factor, with the influence from the CAT factors held constant. The correlation between the residuals of the WISC-R *g* and the scholastic performance factor in the combined baseline model displayed in Table 4 is below .2, equivalent to semipartial correlations below .25.[1] The estimate-to-standard-error *t* ratio for

[3] The submodels of the CAT and WISC-R factor structures could also be specified as hierarchical models with the Schmid–Leiman transformation (Schmid & Leiman, 1957). These submodels could then be included into the combined models analogous to the combined models described here. Since the outcomes using the transformed submodels were basically the same as those reported in the article, descriptions and results based on these submodels were omitted to avoid redundancy.

Table 4
Standardized path coefficient and correlation coefficient estimates

Models	Path/correlation parameters				
	CAT G to WISC-R *g*	CAT M to WISC-R *g*	CAT G to MAT	WISC-R *g* and MAT	WISC-R FD and MAT
Model providing zero-order correlation estimates					
				.533 (.039)	.377 (.076)
Model without CAT percent-correct variables					
	.707 (.051)		.457 (.053)	.213 (.055) **.301**	.382 (.085)
Combined baseline model					
	.761 (.043)	.225 (.076)	.506 (.045)	.151 (.045) **.248**	.404 (.108)

Values in parentheses are estimated standard errors. The boldface values are the semipartial correlations computed from the estimated correlations between residual variances (see [1]).

the correlation between the residual variances exceeds the conventional 2.00 criterion, and the chi-square difference between the baseline model and the model reducing such a higher-order shared variability is statistically significant. On the other hand, the zero-order correlation for WISC-R *g* and the scholastic performance factor of .53 equivalent to a shared variance close to 30%, reduces to a semipartial correlation of .248, equivalent to about 6% of the variance. In other words, the CAT general factor explains a great deal of the common variability between these two variables, and leaves only a little room for other possible explanatory factors to exert their influence.

Removing the CAT percent-correct variables from the combined model weakened the impact of the CAT G on both the WISC-R *g* and scholastic performance, and raised the higher-order shared variability between the WISC-R *g* and the scholastic performance factor, but the effect was only moderate. Table 3 indicates that, when the CAT percent-correct variables were excluded from the related full combined model, the path relating the CAT G to the scholastic performance factor decreased from .506 to .457, and the correlation between the WISC-R *g* and the scholastic performance factor residuals increased from .151 to .213 (converted to semipartial correlations, from .248 to .301). In other words, the variability

Table 5
Chi-square differences between baseline and reduced models

Reduced parameter	χ^2 for reduced model	χ^2 difference (*df*=1)
Correlation between WISC-R *g* and scholastic	443.199	20.378**
Path from CAT G to WISC-R *g*	582.073	159.252**
Path from CAT G to scholastic	514.508	91.687**

Reduced parameters include the correlation between the residual variances of the WISC-R *g* and the MAT scholastic performance factor, the path from the CAT G to the WISC-R *g*, and the path from the CAT G to the MAT scholastic performance factor.

** Significance at $P<.01$.

contributed by the CAT G to the scholastic performance factor decreased by no more than 5%, and the variability of scholastic performance explained by the WISC-R *g* increased by <3%. The relationship between the CAT G and the WISC-R *g* remains strong after the deletion of the CAT percent-correct variables. The estimated contribution from the former to the latter is about 50% in variability. The basic finding from the full baseline models, that the CAT G is the main determinant of the observed relationship between the WISC-R *g* and scholastic performance, still holds even though the CAT G is characterized completely by the chronometric measures.

The above findings have intriguing implications. The elementary tasks employed in the present study require only minimum formal tuition and a rudimentary ability to educe correlates and relations, and are experimentally manipulable. The underlying mechanisms of these basic tasks can therefore be more readily explicated than those of conventional ability tests. In previous studies, some of the elemental cognitive functions measured by these tasks were found to play a salient role in psychometric *g* and some were found to be functional in scholastic performance, but it was not certain whether the same set of elemental cognitive functions can determine both *g* and scholastic performance. The findings in the present study indicate that the observed correlation between seemingly complex *g* and scholastic performance is indeed mostly mediated by a set of elemental cognitive functions.

The exact nature of the elemental functions mediating most of the correlation between *g* and scholastic performance is an issue that calls for further investigations. The elementary tasks used in our study presumably represent a mental speed component, but the component is elemental only in a relative sense. It is likely to involve more fundamental processes, some of which may not be speed-related. Alternative mechanisms could also explain individual differences in both the speed and stability of response time (Luo et al., 2000a,b). Mental speed may not be the only elemental cognitive component mediating the correlation between *g* and scholastic performance either. Other elemental cognitive components, such as those of memory processing, may also contribute to such a correlation. In the present study, some nonchronometric, memory processing measures had high loadings on the mental speed component, and the cognitive underpinnings that tied them to the component need to be clarified.

Additional studies are needed to determine if the current findings will generalize to other age groups, other measures of academic achievement, and other cognitive tasks batteries. In particular, the sample in our study was comprised of only primary school children. It is not clear how the development of mental speed interacts with the growth of intellectual abilities during this period of development. The fundamental role of this elemental cognitive component in complex intellectual tasks has implications for the construction of new instruments for intelligence testing. Currently, among the numerous revisions and new versions of IQ tests, only a few new instruments have attempted to measure some of these elemental cognitive processes (Carroll, 1993). The available test batteries of elementary cognitive tasks, such as the CAT, were largely designed for research purposes and not fully equipped for practical testing of intelligence. More effort should be dedicated to the development of test batteries that not only employ elementary cognitive tasks, but also have psychometric properties comparable to those of traditional intelligence tests.

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References

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*, 238–246.

Bentler, P. M., & Bonnet, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*, 588–606.

Carlson, J. S., & Jensen, C. M. (1982). Reaction time, movement time, and intelligence: a replication and extension. *Intelligence*, *6*, 265–274.

Carroll, J. B. (1993). *Human cognitive abilities: a survey of factor-analytic studies*. New York, NY: Cambridge Univ. Press.

Cattell, J. M., & Farrand, L. (1890). Physical and mental measurements of the students of Columbia University. *Psychological Review*, *3*, 618–648.

Ceci, S. J. (1991). How much does schooling influence intellectual development and its cognitive components? A reassessment of the evidence. *Developmental Psychology*, *27*, 703–722.

Ceci, S. J. (1992). Schooling and intelligence. *Psychological Science Agenda*, *5*, 7–9.

Deary, I. J. (1980). *How general is the mental speed factor in "general" intelligence: an attempt to extend inspection time to the auditory modality.* BS honors thesis, University of Edinburgh, Scotland.

Deary, I. J. (1986). Inspection time: discovery or rediscovery? *Personality and Individual Differences*, *7*, 625–632.

Detterman, D. K. (1987). What does reaction time tell us about intelligence? In P. Vernon (Ed.), *Speed and information processing and intelligence*. Norwood, NJ: Ablex.

Detterman, D. K. (1988). Manual for the cognitive abilities tests battery.

Fraser, C., & McDonald, R. P. (1988). COSAN: covariance structure analysis. *Multivariate Behavioral Research*, *23*, 263–265.

Frearson, W. M., & Eysenck, H. J. (1986). Intelligence, reaction time (RT) and a new "odd-man-out" RT paradigm. *Personality and Individual Differences*, *7*, 807–817.

Hick, W. E. (1952). On the rate of gain of information. *Quarterly Journal of Experimental Psychology*, *4*, 11–26.

Jensen, A. R. (1982a). Reaction time and psychometric *g*. In H. J. Eysenck (Ed.), *A model for intelligence* (pp. 93–132). New York: Springer.

Jensen, A. R. (1982b). The chronometry of intelligence. In R. J. Sternberg (Ed.), *Advances in the psychology of human intelligence*, *vol. 1* (pp. 255–310). Hillsdale, NJ: Erlbaum.

Jensen, A. R. (1985). Methodological and statistical techniques for the chronometric study of mental abilities. In C. R. Reynolds, & V. L. Wilson (Eds.), *Methodological and statistical advances in the study of individual differences* (pp. 57–116). New York: Plenum.

Jensen, A. R. (1987). Individual differences in the Hick paradigm. In P. A. Vernon (Ed.), *Speed of information-processing and intelligence*. Norwood, NJ: Ablex.

Jensen, A. R. (1998). *The g factor.* Westport: Praeger Publishers (CT 06881).

Krane, W. R., & McDonald, R. P. (1978). Scale invariance and the factor analysis of correlation matrices. *British Journal of Mathematical and Statistical Psychology*, *31*, 217–228.

Kranzler, J.H., & Jensen, A.R. (1991a). The nature of psychometric *g*: unitary process or a number of independent processes? *Intelligence*, *15*, 397–422.

Kranzler, J.H., & Jensen, A.R. (1991b). Unitary *g*: unquestioned postulate or empirical fact? *Intelligence*, *17*, 437–448.

Luo, D., & Petrill, S. (1999). Elementary cognitive tasks and their roles in psychometric *g*. *Intelligence*, *27*(2), 157–174.

Luo, D., Thompson, L. A., & Detterman, D. K. (2000a). *Phenotypic and behavioral genetic covariation between elemental cognitive components and scholastic performance.* Submitted manuscript.

Luo, D., Thompson, L. A., & Detterman, D. K. (2000b). On the mechanisms of cognitive determinants in *g. Presented at the First Annual Conference of the International Society for Intelligence Research.*

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indexes in confirmatory factor analysis: the effect of sample size. *Psychological Bulletin*, *103*, 391–410.

Miller, L. T., & Vernon, P. A. (1992). The general factor in short term memory, intelligence, and reaction time. *Intelligence*, *16*, 5–30.

Nettlebeck, T., & Lally, M. (1976). Inspection time and measured intelligence. *British Journal of Psychology*, *67*, 17–22.

Raz, N., & Willerman, L. (1985). Aptitude-related differences in auditory information processing: effects of selective attention and tone duration. *Personality and Individual Differences*, *6*, 299–304.

Raz, N., Willerman, L., Ingmundson, P., & Hanlon, M. (1983). Aptitude-related differences in auditory recognition masking. *Intelligence*, *7*, 71–90.

Schmid, J., & Leiman, J. (1957). The development of hierarchical factor solutions. *Psychometrika*, *22*, 53–61.

Steiger, J. H., & Lind, J. C. (1980). Statistically based tests for the number of common factors. Article presented at the annual meeting of the Psychometric Society, Iowa City, IA.

Tucker, L. R., & Lewis, C. (1973). The reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, *38*, 1–10.

Vernon, P. A. (1987). *Speed of information processing and intelligence*. Norwood, NJ: Ablex.

Vernon, P.A. (1988). Intelligence and speed of information processing. *Human Intelligence Newsletter*, *9*, 8–9.

Wechsler, D. (1974). *Manual for the Wechsler Intelligence Scale for Children—Revised*. New York: Psychological Cooperation.

Wissler, C. (1901). The correlates of mental and physical tests. *Psychological Review*, (Monograph Supplements 3 (6, 16).