

Phenotypic and Behavioral Genetic Covariation Between Elemental Cognitive Components and Scholastic Measures

Dasen Luo,^{1,3} Lee Anne Thompson,² and Douglas K. Detterman²

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The study subjected nine elementary cognitive task variables from the Cognitive Assessment Tasks (CAT) and three scholastic measures from the Metropolitan Achievement Test (MAT) to phenotypic and behavioral genetic structural equation modeling based on data for 277 pairs of same sex monozygotic (MZ) and dizygotic (DZ) twins from the Western Reserve Twin Project. Phenotypic and behavioral genetic covariation between certain elemental cognitive components and scholastic performance was examined to determine (a) whether these elemental cognitive components contribute substantially to the variance of scholastic performance; (b) whether such contributions vary across different domains of school knowledge or from specific domains to a general aptitude; (c) the behavioral genetic composition of the elemental cognitive components and the scholastic variables; and (d) how the association between the cognitive components and scholastic performance is genetically and environmentally mediated. The results of the study showed that as much as 30% of the phenotypic variance of scholastic performance was accounted for by the CAT general factor, which was presumably related to mental speed. A mainly genetic covariation was found between the mental speed component and scholastic performance, although each of the two variables was strongly influenced by both heritability and common family environment. The magnitude and etiology of the covariation were largely invariant whether mental speed was related to a common scholastic aptitude or to individual achievement measures covering different knowledge domains. Taken in conjunction with previous findings that mental speed has a substantial genetic correlation with psychometric *g*, and psychometric *g* has a mostly genetic covariation with scholastic achievement, the findings of the present study seems to point to a more global picture; namely, there is a causal sequence that starts from mental speed as the explanatory factor for both psychometric *g* and scholastic performance, and the etiology of the causal link is chiefly genetic.

KEY WORDS: Behavioral genetic mediation; twins; scholastic performance; elementary cognitive tasks; mental speed; structural equation modeling; intelligence.

INTRODUCTION

Nearly a century ago, J. M. Cattell made a widely known attempt to relate basic psychological functions to scholastic performance. His attempt, however, was undermined by near zero observed correlations between

his tasks of basic psychological functions, e.g., reaction time, sensory discrimination, etc., and the academic performance of Columbia University students, and such disappointingly low correlations discouraged further efforts in the following decades to decompose global intellectual abilities into elemental cognitive functions. The endeavor of reducing intellectual abilities into elemental cognitive processes was thereafter commonly considered as futile, and attention was mostly directed toward the measurement and classification of more complex psychometric traits. The consequence of focusing on global, complex ability traits

¹ Indiana University of Pennsylvania.

² Case Western Reserve University.

³ To whom correspondence should be addressed at Department of Psychology, Indiana University of Pennsylvania, Indiana, Pennsylvania 15705. Tel: (724) 357-4518. Fax: (724) 357-2214. e-mail: dluo@grove.iup.edu

was that there was a persistent ambiguity about the psychological underpinnings of these traits, as most of these traits are essentially statistical entities, and are not subject to experimental analysis. The lasting ambiguity about the nature of intellectual traits has given rise to criticisms on notions of intelligence, scholastic aptitude, etc., as non-meaningful constructs, and has led to a strong dissatisfaction for the entire research discipline of human abilities. It was not until recent years that the renewed interest in reducing intellectual abilities to elemental cognitive processing has revitalized the search for the underlying mechanisms of these ability traits.

During the last few decades, there has been a spate of research activities that attempted to relate elemental cognitive components to more global intellectual abilities (Deary, 1980, 1986; Frearson and Eysenck, 1986; Jensen, 1982a, b, 1985, 1987; Nettlebeck and Lally, 1976; Raz *et al.*, 1983; Raz and Willerman, 1985). These components, unlike psychometric ability traits, are subject to experimental analysis and are hence more tractable in their cognitive mechanisms. They are usually measured in relatively simple tasks such as reaction time tasks and stimulus discrimination tasks, but functions of these components often account for a considerable variability in complex intellectual abilities. Mental speed, as indicated by tasks like reaction time, inspection time, and memory processing time measures; and memory processing, as measured by certain memory tasks, are two such components. These components contribute significantly to the general intellectual ability, or *g*, and can explain as much as 50% of variance in *g* (Jensen, 1982a, 1982b; Vernon, 1987; Miller and Vernon, 1992; Luo and Petrill, 1999). Such a substantial contribution to psychometric *g* notwithstanding, questions may still arise whether these components are an indispensable part of global intellectual abilities.

The prime merit of psychometric *g* is its prevalence in various intellectual activities, yet it is possible that the elemental cognitive components found to be salient in *g* do not play a comparable role in other intellectual activities. One example of such intellectual activities is that of scholastic performance. Scholastic performance has been continuously shown to have a substantial correlation with intelligence, particularly the general factor of intelligence. Apparently, certain more fundamental psychological processes underlie both scholastic performance and *g*, but these shared fundamental processes are not necessarily the elemental components of mental speed or memory processing, despite their prominent roles in psychometric *g*. Some other psychological processes; for example, meta-

processes, motivational processes, etc., could be the source of the association between the two intellectual constructs, and these processes, instead of mental speed and memory processing, could be the only properties that the two constructs have in common.

The issue of whether or not the same elemental cognitive components found in *g* are also an indispensable part of scholastic performance has theoretical and practical significance. Theoretically it is a part of a broader issue that has been incendiary and controversial in social science for decades; namely, the causal sequence regarding the relationship between intelligence and scholastic achievement. Whereas proponents of general intelligence, or *g*, posit that *g* causally precedes scholastic performance because it represents a more pervasive intellectual potential, and can be applied to various intellectual activities such as those of scholastic achievement (Jensen, 1998), skeptics of *g* contest that *g* is at least partly a product of school education, and is therefore not necessarily a causal precedent to scholastic achievement (Ceci, 1991, 1992). The considerable ambiguities about the issue largely stem from the lack of knowledge about the psychological underpinnings shared by the two intellectual constructs. To the extent that certain elemental cognitive components are indispensable in both *g* and scholastic performance, the source of covariation between the two constructs is no longer a metaphysical entity, but a set of mental processes subject to experimental analysis, and can be determined in a reductive manner.

Determining the elemental cognitive components functioning in scholastic performance also has a theoretical value in its own right. From its inception, standardized scholastic aptitude tests have been designed with the intent to measure both the concrete knowledge acquired in school, and the potential of school students (Wechsler, 1977). Over the years this dual goal has been controversial, and the psychological mechanism of scholastic aptitude has been hotly debated. The effort to relate scholastic performance to cognitive elements may clear the obscurities about the construct.

The premise that certain elemental cognitive components are active in scholastic performance leads to another question, that is, whether such components actually function as a reductive, bottom-up explanatory factor for scholastic performance. It is possible for some basic cognitive skills to be acquired in educational settings and then applied to test settings. For example, attentional management skills may be acquired through school work, and then used in test settings to facilitate performance. Under such a circumstance, the explana-

tory factor is formal instruction in school work rather than the elemental cognitive components, and the direction of the relationship is not bottom-up, but top-down. One important type of research that could help to clarify the causal direction of the relationship between the elemental cognitive components and global intellectual capacities is behavioral genetic analyses of the covariation between elemental cognitive skills and global intellectual traits. While a mainly environmental etiology of the covariation may not be decisive evidence for either the bottom-up or top-down causal direction, a mostly genetic covariation would render education much less likely to be the explanatory factor for the cognitive components.

In the last few years, studies of twins and families have provided an important insight into the etiology of the correlations between elemental cognitive components and more complex intellectual capacities, including psychometric *g* and scholastic performance. Behavioral genetic studies relating global ability traits, psychometric *g* included, to scholastic performance suggest that, whereas common environment is important for both the ability traits and scholastic performance, mediation of the correlations between these traits and scholastic performance is basically genetic (Brooks *et al.*, 1990; Cardon *et al.*, 1990; Thompson *et al.*, 1991). A primarily genetic mediation was also found between speed of information processing and IQ measures (Baker *et al.*, 1991; Ho *et al.*, 1988). These studies, however, focused on the mediation either between global ability traits and scholastic performance, or between mental speed and intelligence, and little is known about the etiology of the mediation between elemental cognitive components and scholastic performance. In the absence of evidence for a genetic covariation between the relevant cognitive components and scholastic performance, the causal direction of the relationship between the two classes of variables is indeterminate. The global picture describing how certain fundamental psychological processes serve as the adhesive force to tie the more complex intellectual capacities of intelligence and scholastic performance together is thus incomplete.

Understanding how certain elemental cognitive skills are associated with scholastic performance also has practical importance. Compared to intelligence tests that educators have traditionally used as diagnostic criterion measures for children with learning difficulties, elemental cognitive skills have more tractable psychological mechanisms. Such skills, if found to be associated with school performance, can provide diagnosis of cognitive problems on a more reductive level. Moreover,

knowledge about the etiology of the relationship between these cognitive skills and scholastic performance is useful to differentiate genetically rooted cognitive deficiencies from those with environmental sources, and may aid in the identification of specific genetic and/or environmental factors influencing scholastic performance.

The present study was an attempt to investigate the phenotypic and behavioral genetic covariation between certain elemental cognitive components and scholastic performance. Nine elementary cognitive task variables and three achievement test scores were employed to represent the two constructs of interest, i.e., elemental cognitive components and scholastic performance. A series of specific issues were addressed in the present study using the structural equation modeling approach.

In the phenotypic phase of the analysis, the main issues to be addressed were (a) which elemental cognitive components substantially account for the variance of scholastic performance and (b) whether the relationship between these components and scholastic performance varies from one specific scholastic knowledge domain to another, or from specific domains to a more general aptitude. To approach these issues, submodels were first constructed and tested to closely map the relationship between observed and latent variables within the cognitive variable set and the achievement variable set, respectively, and the tested submodels were then incorporated into combined models in which structural relations between elemental cognitive components and scholastic measures were estimated and evaluated. These structural relations were in essence regression weights indicating contributions from different elemental cognitive components, treated as independent or exogenous variables in the models, to scholastic measures as dependent or endogenous variables. The combined models were specified according to the scholastic measures employed, so that the influence from elemental cognitive components on scholastic measures was assessed not only with respect to a common scholastic aptitude, but also with respect to specific knowledge domains.

The behavioral genetic phase of study comprised examinations on the additive genetic, common environmental, and specific environmental aspects of the models. First, models were tested within the cognitive and scholastic variable sets separately to examine genetic and environmental influences on factor loadings and residuals of the within-set factor structures. The tested submodels were then combined into the models in which the structural relations between the elemental cognitive components and scholastic measures were partitioned into genetic and environmental covariances.

The roles of these partitioned covariances were then evaluated accordingly. Once again, different elemental cognitive components were evaluated with respect to either a common scholastic factor or specific knowledge domains.

Two methodological issues are worth noting for the objective of the present study. Early findings relating elemental cognitive skills and scholastic performance were typically compromised by two methodological problems, i.e., attenuation of correlations due to restriction of range of talent, and attenuation of correlations due to imperfect test reliability. Although correction procedures can be used to overcome the attenuation to a certain extent, more direct assessments of such correlations in a representative sample and between variables less contaminated by measurement errors are desirable. The present study used data and analytical methods that did not require correction procedures, and therefore provided a more direct assessment of theoretical relations. Data for the present study were collected from 284 monozygotic (MZ) and dizygotic (DZ) twin pairs of primary school children and displayed no apparent restriction of ability range (the sample mean and standard deviation of the WISC-R full scale IQ are 104.5 and 15.8, respectively). Correlations between elemental cognitive skills and scholastic performance in the present study were attained on the basis of factorial components extracted from a set of elementary cognitive task measures on one hand, and some scholastic measures on the other. Because the factorial components are theoretically not compounded with measurement errors in the factor analysis model, correlations thus attained between the two classes of variables are less susceptible to attenuation due to reliability than those between observed variables. Results of the study, therefore, can provide a more direct assessment of the true linear relationship between the two classes of variables.

METHODS

Participants

Participants of the study were 146 MZ and 138 DZ twin pairs from the Western Reserve Twin Project, all of whom were primary school students ranging from age 6 to age 12 in the Greater Cleveland area. Zygosity of each twin pair was determined by two raters using the Nichols and Bilbro (1966) zygosity questionnaire, and, for uncertain pairs, blood tests were conducted by the Minneapolis Memorial Blood Bank for accurate di-

agnoses. All participants took a series of intelligence tests, a battery of elementary cognitive tasks, and an achievement test battery. Only 142 MZ and 135 DZ twin pairs had observations for the variables included in the present study, so analyses of the study were based on the sample of 277 twin pairs.

Measures

Six tasks from the Cognitive Assessment Tasks (CAT) (Detterman, 1990) battery were used as the set of elementary cognitive tasks for the present study. They were Learning, Probe Memory, Self-Paced Probe Learning, Simple Reaction Time, Stimulus Discrimination Time, and Inspection Time.

Learning, Probe Memory, and Self-Paced Probe Learning were similar in the stimulus presentation. In each trial, a subject would first see a row of blank windows slightly below the center of the computer screen, and a probe window centered above this row. Matrix diagrams would be shown one by one in all blank windows. Each diagram would appear and disappear before the presentation of the next diagram. After the last diagram disappeared on the screen, one of the previously presented diagrams would appear in the probe window, and subjects would be asked to indicate which bottom window contained the probed diagram.

In Learning, each of the presented diagrams would be probed, and subjects were asked to respond to all of them. In Probe Memory, only one of the presented diagrams would appear as the probe stimulus during each trial. Self-Paced Probe Learning was the same as Learning, except that subjects could control the presentation time of each stimulus diagram.

In the Simple Reaction Time 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 subject was required to indicate the lit window as quickly as possible.

Subjects in the Stimulus Discrimination Task 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 would each display a different diagram, and the probe window would present a diagram identical to one of the six diagrams below. The subject's task was to find the match to the probe in the windows below, and indicate it as quickly as possible.

In Inspection Time, two diagrams were presented simultaneously for a very brief duration and were then masked. Subjects were then asked to determine whether they were the same. The presentation time varied

until a threshold duration for correct identification was determined.

All subjects during the CAT sessions used a touch screen device to respond to the stimuli. Both their response times and response choices were automatically recorded by the computer through the screen.

Nine variables were obtained from the six CAT tasks: Mean Decision Time for the Simple Reaction Time task (RT); Mean Decision Time for the Stimulus Discrimination Time task (DT); Mean Reaction Time for the Probe Memory task (PRRT); Percent Correct for the Probe Memory task (PRPC); Percent Correct for the Learning task (LRPC); Percent Correct for the Self-Paced Probe Learning task (SPPC); Decision Time; Movement Time; and Threshold Time for the Inspection Time task (ITDT, ITMT, and ITTH). To partial out possible effects of age and gender on the original scores, standardized residuals were taken for each of the nine variables from a regression model with age and gender as predictors.

The scholastic measures for the study were the Language (LANG), Reading (READ), and Mathematics (MATH) subtest scores of the Metropolitan Achievement Test (MAT). All MAT measures were grade-normed scores. The test was designed to ensure that each subtest measures the same scholastic skill across different grades.

Analyses

Covariances between the CAT and the MAT variables were used in both the phenotypic phase and the behavioral genetic phase of the analysis. In the phenotypic phase of analyses, all members of the twin sample were included in the sample as individual participants. Since individuals in the twin sample are not truly independent of each other, members of each twin pair were separated and randomly assigned into two subsamples. Each of the two subsamples therefore contains completely independent individuals. Covariances between variables were then pooled from the two subsamples for phenotypic analyses. After listwise deletion of missing observations, the pooled covariance matrix for the phenotypic analysis was computed from 532 individuals.

Listwise deletion of pedigrees during the behavioral genetic phase of the analysis left 125 MZ twin pairs and 129 DZ twin pairs with complete data for the variables included in the study. Within- and between-MZ and -DZ covariances among the CAT and the MAT measures were computed for these twin pairs and behavioral genetic models were fitted to these covariances. Because the patterns of missing versus non-

missing observations were somehow variable in the overall sample, and the loss of pedigrees caused by the listwise deletion could lead to bias in the analysis, a maximum raw data procedure was also utilized to analyze every data point available in the sample (Lange *et al.*, 1976). The behavioral genetic models fitted to covariances of complete data were also fitted to the raw data, and model parameters were estimated and tested using both data procedures.

Two kinds of model fit were evaluated in the analyses of the study, evaluation of the overall models and evaluation of specific parameters. The former ensured that the overall factor analysis submodels and the combined structural relationship models fit the data reasonably well, whereas the latter was used to test the importance of certain aspects of the models. For the phenotypic analysis and behavioral genetic analysis using covariances of the complete data, chi-square values from the maximum-likelihood estimation were reported for the assessment of model fit. To overcome the problem with the chi-square values, which tend to inflate in larger samples, three derived indices less susceptible to the sample size effect were also used. They were the Non-Normed Fit Index (NNFI; Tucker and Lewis, 1973; Bentler and Bonett, 1980; Marsh *et al.*, 1988), the Comparative Fit Index (CFI; Bentler, 1990), and the (RMSEA; Stiger and Lind, 1980). For NNFI and CFI, values below 0.9 are usually considered as indicative of a unsatisfactory model fit, and for RMSEA a value of about 0.05 or lower indicates a reasonable fit. Indexes used to test the importance of certain model parameters in these analyses were based on chi-square differences between models with and without constraints on the parameters in question. For the behavioral genetic analysis using the raw data, more constrained and less constrained models were compared by taking twice the difference between the two log-likelihoods produced by the respective minimization processes. The difference index is distributed asymptotically as chi-square, and has degrees of freedom equivalent to the difference in degrees of freedom between the two models.

Phenotypic Submodels

The most basic submodels for the phenotypic phase of analysis were the hierarchical factor analysis model of the nine CAT variables and the common factor model of the three MAT scores. The CAT model consisted of three primary factors: the response time (RST) factor indicated by RT, DT, and PRRT; the memory (M) factor defined by PRPC, LRPC, and SPPC; and the

inspection time (IT) factor represented by the three inspection time variables; and one second-order factor. Fit indexes for the model were 0.87 for NNFI, 0.91 for CFI, and 0.077 for RMSEA. Although the NNFI index was slightly below 0.90, the factor structure is consistent with the known nature of the CAT variables, and yielded better fit indexes than alternative models. Thus the model was selected as the “best-fitting” model for the CAT variables. In a previous study, Luo and Petrill (1999) found that the CAT general and memory factor both had substantial correlations with psychometric *g*, whereas correlations of the response time and the inspection time group factors with psychometric *g* were negligible. The CAT RST and IT group factors appear to be largely method factors, whereas the mental speed component indicated by the CAT chronometric measures is basically represented by the CAT general factor.

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.

SAS Proc CALIS was used for the phenotypic analyses. The program allows one to reparameterize the hierarchical factor model in the fashion of Schmid-Leiman (Schmid and Leiman, 1957), i.e., transforming the hierarchical structure into one with orthogonal general and group factors. The reparameterized CAT sub-

model thus have a general factor and three group factors, all orthogonal to each other. Standardized parameter estimates, together with their standard errors, were obtained for the phenotypic analyses using the COSAN option of the SAS program (Fraser and McDonald, 1988), which scales parameters on the basis of variable variances (Krane and McDonald, 1978). These standardized estimates are, at heart, correlation coefficients, and their standard errors can be used to evaluate the importance of these correlations. Table I lists the standardized parameter estimates and their estimated standard errors of the submodels.

Phenotypic Combined Models

Based on the CAT submodel, combined models were built to include into analyses the MAT measures either all three simultaneously as indicators of a scholastic factor or one at a time to cover specific domains of school knowledge. Reduced, baseline, and extended models were constructed to evaluate the importance of the CAT factors to the scholastic variables. In the reduced models, no paths were specified from any of the CAT factors to the MAT variables. In the baseline models, only the CAT general factor was allowed to have a path to either an individual MAT variable or, when all the three MAT variables were included, to the scholastic factor. Chi-square differences between the reduced models and the baseline models, along with the *t* ratios

Table I. Standardized Parameter Estimates for the CAT and the MAT Factor Analysis Models

Indicators	CAT factors				Scholastic factor
	General	Memory	Response time	Inspection time	
LRPC	0.547 (0.052)	0.387 (0.066)			
PRPC	0.470 (0.0499)	0.333 (0.058)			
SPPC	0.546 (0.052)	0.386 (0.066)			
PRRT	0.359 (0.042)		0.439 (0.039)		
RT	0.476 (0.048)		0.582 (0.045)		
SD	0.443 (0.047)		0.542 (0.042)		
ITMT	0.279 (0.054)			0.166 (0.060)	
ITDT	0.232 (0.0525)			0.138 (0.0526)	
ITTH	0.514 (0.0518)			0.306 (0.1159)	
LANG					0.938 (0.008)
MATH					0.918 (0.009)
READ					0.937 (0.008)

Note: Values in parentheses are estimated standard errors. 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 (ITMT), Decision Time for Inspection Time (ITDT), and Threshold Time for Inspection Time (ITTH). Acronyms for the MAT variables are: Language (LANG), Mathematics (MATH), and Reading (READ).

between path estimates and their standard errors in the baseline models, were used to assess the contribution of the CAT general factor to the MAT variables. In the extended models, additional paths were specified to relate the CAT orthogonal group factors to the MAT variables. The strength of these additional paths could reveal the impact of each of the CAT group factors on scholastic measures. Figure 1 shows an example of such extended models. The model underwent a Schmid-Leiman transformation implemented by SAS Proc CALIS in the phenotypic analysis, so that paths such as B1, B2, etc., were directed from the orthogonal CAT general and group factors to the MAT variable(s) rather than from the secondary factors of the CAT.

There is a limitation to the extended models. Paths from some of the CAT group factors to the MAT variable have to be fixed to make the models identifiable. Appendix 1 provides a more explicit explanation of the issue. To test the importance of the paths from the CAT group factors to the MAT variables, which was one of the goals of the study, paths from the CAT group factors were assessed one at a time according to both the chi-square difference between the extended and the baseline models, and the *t* ratio between the path estimate and the standard error in the extended model.

Behavioral Genetic Submodels

The phase of behavioral genetic analysis consisted of two steps. The first step was the behavioral genetic analysis of the CAT factor structure submodel and the MAT factor structure submodel. The behavioral genetic submodel of the CAT variables adopted the same factor structure used in the phenotypic analysis, but expanded to observations of twin pedigrees to enable the estimation of the additive genetic and environmental components (see Cardon *et al.*, 1992, for a detailed description of the model specification). The behavioral genetic submodel for the MAT variables partitioned the latent scholastic factor and residuals of the three MAT measures into their respective genetic and environmental components. Care was taken for the parsimony of each submodel by exploring the influences of heritability and environmentality on factor loadings and residuals of the factor structure and constraining the most trivial genetic and environmental parameters.

Combined Behavioral Genetic Models

The tested behavioral genetic submodel of the CAT was combined with the MAT variables, either one at a time or all three simultaneously. The behavioral

genetic paths from the CAT factors to the scholastic variables were examined. The focus of the analysis on the combined models was the mediation of behavioral genetic influences of the CAT general factor on the scholastic variables. Baseline, extended, and reduced models were postulated to test a series of structural-relation parameters. In the baseline model, the CAT general factor was allowed to relate to the scholastic variables via a genetic, a common environmental, and a specific environmental path. Magnitude of each path would indicate the strength of genetic or environmental mediation underlying the two classes of variables. Extended models were specified to test whether the CAT memory group factor makes any non-negligible genetic or environmental contribution to the scholastic measures beyond the contribution made by the CAT general factor. In each reduced model, one of the behavioral genetic paths from the CAT general factor to the scholastic measures would be reduced, and the effect of reduction on the association between the CAT general factor and scholastic variables would be gauged. Graphically, the model drawn in Figure 1, after being expanded to a behavioral genetic model, would consist of three analogous substructures, the genetic substructure, the common environmental substructure, and the specific environmental substructure. In the baseline models, only path B1 in each of the three substructures was estimated, whereas in the extended models each substructure would also have a path B2. In a reduced model, B1 of a particular substructure, e.g., genetic, common environmental, or specific environmental, would be fixed to zero and the effect of the path removal on the overall model fit would be appraised.

The MX (Neale, 1991) multigroup option was used to specify and test all the behavioral genetic models. The program provides estimation procedures both for covariances of complete data and for raw data with missing observations. In the analysis of the raw data, the variable means need to be modeled. In the present study they were all fixed at the observed values to reduce the number of estimated parameters. Appendix 2 provides a description of the combined baseline and extended models used in the study, with an example of the MX script.

RESULTS

Phenotypic Analyses

In the phenotypic analysis, contributing paths from the CAT factors to scholastic variables were assessed one at a time to test the importance of individual ele-

Table II. Model Fit Indices of Baseline Phenotypic Models and Chi-Square Changes of Reduced and Extended Models from Baseline Models

Model	Baseline and reduced models				
	χ^2	<i>df</i>	TLI	CFI	RMSEA
CAT factor structure	96.534	24	0.872	0.914	0.077
CAT G to LANG	99.653	32	0.891	0.922	0.064
Reduced	185.040	33			
CAT G to MATH	99.073	32	0.891	0.923	0.064
Reduced	179.014	33			
CAT G to Reading	102.967	32	0.889	0.921	0.066
Reduced	211.486	33			
CAT G to Scholastic	131.0836	50	0.957	0.968	0.056
Reduced	231.1813	51			

Note: Reduced models above are models nullifying all paths from the CAT factors to the MAT variables, and chi-square differences between the baseline and reduced models show the importance of CAT G to the MAT variables in question.

and, as is displayed, all of the combined baseline models fit the data reasonably well. In the reduced models, no contributing path from the CAT factors to the relevant MAT measure was specified.

The importance of the contributing paths from the CAT general factor in the baseline models can be evaluated according to decrements in the chi-square value from the reduced models. As can be seen, all of the decrements in the chi-square value from the reduced models are quite substantial, indicating non-negligible contributions from the CAT general factor to the MAT variables. The importance of CAT general factor to the MAT variables can also be assessed according to the standardized path coefficients and their *t* ratios to the estimated standard errors. Table III presents these coefficients and their standard errors.

Table III. Chi-Square Change of Extended Models from Baseline Models (*df* = 1)

Scholastic measures	CAT contributing group factors		
	M	RST	IT
Language	0.173	0.076	0.482
Math	0.338	0.339	0.169
Reading	0.120	0.360	0.884
Scholastic	0.314	0.031	0.000

Note: The extended models are models with a free path from one of the CAT group factors to the MAT variables in addition to the path from the CAT general factor. Chi-square differences between the baseline and extended models indicate the strength of relationship between the CAT group factors, M, RST, and IT, respectively, and the MAT variables.

In Table IV, the path coefficients representing correlations between the CAT general factor and the MAT variables range from 0.477 to 0.553, suggesting that about 25% to 30% of the MAT variances can be accounted for by the CAT general factor. The *t* ratios between these path coefficient estimates and their estimated standard errors all exceed 2.0, again indicating substantial contributions from the CAT general factor to the MAT variables. It is also noteworthy that the CAT general factor has substantial relations not only with the common scholastic factor, but also with each of the specific knowledge domain measures.

The influence of each CAT group factor on scholastic performance can be illustrated in a similar manner, both in terms of the path coefficient estimates and in terms of the chi-square difference between the

Table IV. Standardized Phenotypic Path Coefficients Relating CAT Factors to Scholastic Measures

MAT variables	CAT general	CAT M	CAT RST	CAT IT
Language	0.494 (0.046)	0.048 (0.109)	0.019 (0.067)	-0.106 (0.169)
Math	0.477 (0.047)	0.115 (0.102)	-0.040 (0.068)	-0.052 (0.140)
Reading	0.553 (0.044)	0.042 (0.112)	0.043 (0.068)	-0.153 (0.196)
Scholastic	0.544 (0.046)	0.069 (0.111)	0.013 (0.069)	0.000 (0.141)

Note: Path coefficients relating the CAT general factor to the MAT variables were obtained from the baseline models, whereas those related to the CAT group factors were obtained from the extended models, in which an additional free path from one of the CAT group factors was specified to the MAT variables.

baseline and extended models. Table III displays decrements in the chi-square value of the extended models from the baseline models. Freeing the path relating each of the CAT group factors to the MAT variables does not lead to any significant change in the chi-square value. The lack of connection between the CAT group factors and the MAT variables is also evident in Table IV, where path coefficient estimates relating the CAT group factors to the MAT variables in the extended models are all near zero. Apparently, the CAT group factors do not make substantial contributions to any of the scholastic variables.

Behavioral Genetic Analysis

Behavioral Genetic Submodel

The behavioral genetic composition of both the CAT factor structure and the MAT factor structure was analyzed. The MAT submodel used all three MAT variables to define the scholastic factor, and the model fitted quite closely to the data. The exploration of genetic and environmental aspects of the model showed that, but for the genetic residuals, the factor loading and residual components are all non-negligible, indicated by the significant chi-square increments of the MAT submodel constraining the relevant sets of loading or residual parameters (see Table V for details).

Table V also presents model fit indexes of the CAT behavioral genetic submodel. Model fit indexes of the CAT behavioral genetic submodel shown in Table V indicate that the submodel can be simplified. A closer scrutiny of the model estimates showed that loadings of the two CAT group factors, the RST and the IT, were extremely small, indicating that the two group factors largely vanished among the CAT variables when the between- and within-MZ and- DZ covariances were computed. The instability of the two group factors confirms the early conjecture about the nature of the two factors, i.e., that they are merely method factors. The model also appeared to be reducible with regard to certain residual parameters, particularly the common environmental residuals, and with regard to the common environmental component of the memory group factor. Based on such observations, a simplified model was specified, which fixed to zero all the second-order loadings corresponding to the RST and IT group factors (Q2 and Q3 of Figure 1 in the genetic, common environmental, and specific environmental substructures), and all the first-order common

environmental residuals (E1 through E9 in the common environmental substructure of the model). The simplified model gained 15 degrees of freedom, 6 of which were from the RST and IT genetic, common-environmental, and specific-environmental group factors, and 9 from the first-order common-environmental residuals. The resultant increment of the chi-square value was rather trivial (chi-square change: 1.661 for the analysis of covariances, and 1.106 for the analysis of raw data), and the model had NNFI as 0.902, CFI as 0.906, and RMSEA as 0.052, indicating a reasonable fit. The subsequent behavioral genetic analyses were therefore based on the simplified submodel of the CAT. The memory genetic loadings, although also quite trivial, were retained in the simplified submodel owing to the consideration that the importance of the CAT memory group factor to scholastic performance was to be assessed next in the extended behavioral genetic models. Table IV also indicates that the CAT general factor has substantial genetic and common-environmental loadings, and relatively weak specific-environmental loadings. Zero constraints on the additive genetic and common-environmental loading components of the general factor lead to serious worsening of the model fit, causing chi-square changes of 26.837 and 17.797, respectively, according to the analysis of complete data covariances, and 17.264 and 17.677, according to the analysis of raw data, with 3 degrees of freedom. The memory group factor, on the other hand, is partly genetic and partly specific-environmental. The subsequent behavioral genetic analyses were therefore based on the simplified submodel of the CAT.

Table VI shows the standardized estimates from the CAT and MAT submodels. The standardization was accomplished by dividing the unstandardized estimates by the expected standard deviations of the related variables. The standardized estimates are congruent with what are indicated by the chi-square changes resulting from the model constraints, i.e., both the CAT general factor and the scholastic factor are mostly determined by the genetic and common environmental influences, with the CAT memory factor more influenced by heritability and specific environment.

Combined Behavioral Genetic Models

These combined models included the baseline models, the extended models, and the reduced models. Baseline models and extended models were built and tested to evaluate the behavioral genetic contribution from the CAT memory group factor to the scholastic

Table V. Model-Fit Indices for Behavioral Genetic Models

Model	χ^2	df	CAT Submodel				
			χ^2 different from full model	Difference in df	NNFI	CFI	RMSEA
Full	392.648	279			0.883	0.889	0.057
	12,405.432	4690					
Reducing RST and IT group loadings	392.686	285	0.038	6			
	12,405.432	4696	0.000	6			
Reducing genetic residuals	396.395	288	3.747	6			
	12,410.668	4699	5.236	9			
Reducing common env. residuals	392.921	288	0.273	9			
	12,406.196	4699	0.767	9			
Reducing specific env. residuals	Incomputable						
	Incomputable						
Reducing genetic loadings of G	419.485	282	26.837**	3			
	12,435.192	4693	29.760**	3			
Reducing common env. loadings of G	409.892	282	17.244**	3			
	12,423.109	4693	17.677**	3			
Reducing specific env. loadings of G	393.634	282	0.986	3			
	12,413.729	4693	8.526*	3			
Reducing genetic loadings of M	403.685	280	11.037**	1			
	12,423.331	4691	17.899**	1			
Reducing common env. loadings of M	392.648	280	0.000	1			
	12,406.300	4691	0.868	1			
Reducing specific env. loadings of M	396.630	280	3.982*	1			
	12,409.757	4691	4.325*	1			
Simplified structure	394.309	294	1.661	15	0.902	0.906	0.052
	12,406.309	4705	1.106	15			
MAT Submodel							
			χ^2 different from full model	Difference in df	TLI	CFI	RMSEA
Full	26.659	24			0.998	0.999	0.023
	3118.785	1568					
Reducing genetic loadings	87.550	27	60.891**	3			
	3154.840	1571	36.055**	3			
Reducing common env. loadings	86.702	27	70.043**	3			
	3178.788	1571	60.003**	3			
Reducing specific env. loadings	69.435	27	42.776**	3			
	3162.618	1571	43.833**	3			
Reducing genetic residuals	27.919	27	1.260	3			
	3119.878	1571	1.093	3			
Reducing common env. residuals	35.466	27	8.807*	3			
	3127.432	1571	8.647*	3			
Reducing specific env. residuals	Incomputable						
	Incomputable						
Combined baseline models							
			TLI	CFI	RMSEA		
CAT G to Language	515.671	366	0.896	0.900	0.055		
	13,735.884	5227					
CAT G to Math	508.273	366	0.907	0.911	0.054		
	13,804.513	5227					
CAT G to Reading	519.121	366	0.904	0.908	0.056		
	13,828.049	5229					
CAT G to Scholastic	732.307	531	0.941	0.944	0.053		
	15,432.648	6270					

Note: In the simplified submodel of the CAT, the paths from the second-order RST and IT factors to their first-order counterparts, and the first-order common-environmental variances were all fixed to zero. Values in bold face were based on twice the negative log likelihood values through the raw data estimation procedure. * and ** indicate significant differences at $p < 0.05$ and $p < 0.01$ levels, respectively.

Table VI. Standardized Behavioral Genetic Parameter Estimates for the CAT and the MAT Variables

Genetic and environmental decomposition of CAT factor loadings						
	Genetic		Common env.		Specific env.	
	G	M	G	M	G	M
Genetic	0.286	0.315	0.347	0.000	0.040	0.216
	0.346	0.328	0.296	0.000	0.027	0.136
LRPC	0.447	0.493	0.140	0.000	0.067	0.357
	0.392	0.372	0.291	0.000	0.071	0.350
SPPC	0.370	0.407	0.315	0.000	0.024	0.126
	0.469	0.445	0.140	0.000	0.043	0.124
PRRT	−0.099		0.578		0.416	
	−0.013		0.652		0.413	
RT	0.201		0.495		0.600	
	0.192		0.602		0.611	
SD	0.321		0.633		0.091	
	0.365		0.580		0.114	
ITMT	0.314		0.096		0.063	
	0.295		0.094		0.065	
ITDT	0.250		0.035		0.107	
	0.192		0.069		0.107	
ITTH	0.535		0.227		−0.059	
	0.410		0.202		−0.082	
Genetic and environmental decomposition of scholastic factor loadings						
Variables	Genetic		Common env.		Specific env.	
LANG	0.471		0.782		0.383	
	0.487		0.779		0.242	
MATH	0.424		0.820		0.098	
	0.397		0.830		0.158	
READ	0.497		0.786		0.089	
	0.474		0.799		0.144	

Note: Values in bold face are based on estimates using the raw data minimization procedure.

variables. The baseline models consisted of the simplified CAT submodel and the relevant MAT variable(s), with genetic and environmental paths relating the CAT general factor to the MAT variable(s). For the baseline model using all three MAT variables, the CAT and the MAT behavioral genetic submodels were both incorporated into the combined model, and genetic and environmental paths were specified from the CAT general factor to the MAT scholastic factor. Model fit indexes for the baseline models (Table V) show that all the baseline behavioral genetic models fit reasonably well. Behavioral genetic contributions from the CAT memory group factor were evaluated through the chi-square differences between the extended models and the baseline models, with the extended behavioral ge-

netic models having additional paths from the memory group factor to the MAT variables. The identification problem for the extended phenotypic models was no longer a concern for the extended behavioral genetic models, since the simplified CAT submodel contained only the memory group factor, and path coefficients from the single group factor could be uniquely determined along with those from the general factor. Table VII depicts results related to the behavioral genetic contribution of the CAT memory group factor to the scholastic variables.

Chi-square differences between the baseline and extended models in Table VII show that all but one of the memory factor contributions are insignificant, suggesting trivial impacts of the path from the CAT mem-

Table VII. Behavioral Genetic Contributions of CAT Memory Group Factor to Scholastic Variables: Chi-Square Differences Between Baseline and Extended Models ($df = 3$)

Scholastic measures	χ^2 change
Language	3.913 3.837
Math	7.295* 7.200*
Reading	4.099 4.584
Scholastic	4.729 4.852

Note: *indicates significant difference at $p < 0.05$ level. Bold face values were based on the minimization procedure using raw data.

ory group factor on the scholastic variables. These results are commensurate with those from the phenotypic analysis, confirming that there are no substantial connections between the CAT group factors and the scholastic variables.

Given the substantial phenotypic contribution from the CAT general factor to the scholastic variables, the genetic and environmental mediation of such a contribution was analyzed. The additive genetic, common-environmental, and specific-environmental paths from the CAT general factor to the MAT variables in the baseline models each were fixed individually to assess the corresponding influences of the CAT general factor on scholastic performance.

Table VIII presents the results about the behavioral genetic mediation of the CAT general factor's contribution to the MAT variables. For both individual MAT measures and the scholastic factor, influences of the CAT general factor are mostly mediated through the genetic variance. Increments of the chi-square value induced by fixing either the genetic path or the common-environmental path from the CAT general factor to the MAT variables are all statistically significant, but the increments are considerably greater for models reducing the genetic paths. Chi-square increments caused by

Table VIII. Genetic and Environmental Contributions of CAT General Factor to Scholastic Variables

		Chi-square differences indicating genetic and environmental contributions of CAT general factor		
Scholastic variables	df	Genetic	Common env.	Specific env.
Language	1	-23.211**	-10.659**	-3.947
	1	-16.304**	-8.368**	-3.912
Math	1	-34.675**	-5.170*	-0.114
	1	-30.071**	-7.662**	-3.376
Reading	1	-33.380**	-11.779**	-7.926**
	1	-22.764**	-11.627**	-9.053**
Scholastic	1	-35.840**	-5.391*	-6.187*
	1	-34.009**	-6.252*	-5.844*
		Standardized genetic and environmental path coefficients relating CAT general factor to scholastic variables		
Scholastic measures		Genetic	Common env.	Specific env.
Language		0.320	0.281	0.053
		0.316	0.300	0.057
Math		0.372	0.221	-0.007
		0.355	0.263	-0.044
Reading		0.350	0.340	0.072
		0.347	0.358	0.076
Scholastic		0.382	0.247	0.068
		0.374	0.281	0.072

Note for top part: ** and * indicate significant differences at $p < 0.01$ and $p < 0.05$ levels, respectively. Bold face values were based on the raw data estimation procedure.

Note for bottom part: To attain the standardized estimates, path coefficient estimates were divided by the estimated standard deviation of the scholastic variable in the model. Values in bold face are estimates based on complete raw data set.

fixing the specific-environmental paths are generally small, indicating negligible specific-environmental mediation between the CAT general factor and the MAT measures. The standardized behavioral genetic path coefficients from the CAT general factor to the MAT measures are also shown in Table VIII. These coefficients are correlations estimates representing the mediation between the CAT general factor and the MAT variables via the respective genetic, common-environmental, and specific-environmental pathways. Magnitudes of these coefficients again underscore the importance of genetic mediation. Except for one path estimate related to READ, the genetic path coefficients are all greater than the environmental path coefficients.

DISCUSSION

At the beginning of the century, J. M. Cattell conducted his pioneering work relating elementary psychological tasks to school performance of Columbia students. In recent decades, contributions of elemental cognitive components to global intellectual abilities have again been an issue of interest, and studies in this direction have yielded encouraging results. However, researchers tackling this issue have focused mostly on traits of intelligence, particularly psychometric *g*, and the cognitive composition of scholastic performance has so far been ignored. The present study was an attempt to revitalize interest in such investigations. The results of the study indicated that an elemental cognitive component, chronometric in nature, makes a substantial contribution to individual scholastic domains as well as a general scholastic aptitude. This mental speed component was found to be salient in psychometric *g* in previous studies, and the fact it is also substantial in scholastic performance indicates that it may be the common cognitive mechanism that underlies both global intellectual capacities.

The behavioral genetic analysis of the present study revealed that mental speed as a pervasive element in complex intellectual capacities is determined by both genetic and environmental variances. The finding that environment played a crucial role in mental speed is somehow incongruent with those of the previous studies (Baker *et al.*, 1991; Ho *et al.*, 1988), which attribute individual differences in mental speed mainly to the genetic influence. The finding is curious also because mental speed is viewed by many as an unlearned cognitive property, and as such, it would not be expected to originate substantially from environment. Results of the present study seem to suggest that

mental speed is not as unlearned as it is often thought to be, and may to a certain degree reflect "acquired styles" of cognitive processing.

A cautionary note needs to be made about this finding, however. Although there is no evidence to show that assortive mating in terms of parents' mental speed exists in the current sample, it is not entirely inconceivable that this kind of assortive mating may have occurred. If it did occur, then the similarity between DZ twins in mental speed would be inflated, and so would the estimate of the common-environmental influence. The age of the sample could also be a factor for the substantial estimate of the common environmental influence. The sample consisted of only primary school students. It is therefore possible that the common environmental influence may diminish within an older and intellectually more mature sample. Further studies, e.g., studies of family data, are needed to clarify this uncertainty.

The behavioral genetic analysis of the study also indicated that, although both mental speed and scholastic performance are heavily influenced by the common family environment, what mediates the covariation between the two classes of measures is chiefly genetic. Earlier studies relating more global ability traits to scholastic performance suggest that, while common environment is important for both the ability traits and scholastic performance, mediation of the correlations between these traits and scholastic performance is basically genetic (Brooks *et al.*, 1990; Cardon *et al.*, 1990; Thompson *et al.*, 1991). Studies examining the association between mental speed and intelligence indicated that such an association is also mostly genetic (Baker *et al.*, 1991; Ho *et al.*, 1988). The results of the present study, taken in conjunction with the early findings, suggest that the genetic mediation relating global ability traits and scholastic performance may be rooted in a more fundamental origin, the speed of cognitive processing. In other words, mental speed is a common, genetic causal factor for both general intelligence and scholastic performance. The two complex constructs are correlated partly because of this factor. A more direct test is needed in future studies to investigate whether or not mental speed constitutes an important source of the genetic mediation between intelligence and scholastic performance. The test can be accomplished by employing elementary cognitive tasks, global ability tests, and scholastic measures in the same behavioral genetic model, and examining the genetic partial correlation between mental speed and scholastic performance above and beyond the mediation on the global level. The genetic partial correlation between

mental speed and scholastic performance, together with the zero-order genetic correlation between the same measures, can be used to determine the extent to which the association between global ability traits and scholastic performance originates from the heritability in the speed of cognitive processing.

The results of the study can aid in the understanding of the nature of scholastic aptitude, which has been a concept of enormous controversies. The notion that aptitude is a more universal potential than concrete knowledge of school subjects is partly supported by findings of the present study, as the active role of mental speed in scholastic performance evidently transcends concrete school knowledge, and its largely genetic contribution to scholastic performance clearly reflects a biological endowment of the aptitude. It also appears that, whereas intelligence and scholastic performance are complex mental constructs, what makes both constructs general and pervasive is probably a quite elemental cognitive ingredient, the component of mental speed.

APPENDIX 1

Model Identification for Paths from CAT Factors to MAT Measures

Loadings of the four orthogonal CAT factors can be represented as products of the first-order factor loadings and the second-order parameters as shown below:

$$\Lambda_{CAT} = \Lambda_{1st-order} * \Lambda_{2nd-order}$$

$$= \begin{bmatrix} \lambda_{PRPC} & 0 & 0 \\ 0 & \lambda_{PRRT} & 0 \\ 0 & \lambda_{RT} & 0 \\ \lambda_{LRPC} & 0 & 0 \\ \lambda_{SPPC} & 0 & 0 \\ 0 & \lambda_{SD} & 0 \\ 0 & 0 & \lambda_{ITMT} \\ 0 & 0 & \lambda_{ITDT} \\ 0 & 0 & \lambda_{ITTH} \end{bmatrix} * \begin{bmatrix} l_M & r_M & 0 & 0 \\ l_{RST} & 0 & r_{RST} & 0 \\ l_{IT} & 0 & 0 & r_{IT} \end{bmatrix}$$

$$= \begin{bmatrix} \lambda_{PRPC.g} & \lambda_{PRPC.group} & 0 & 0 \\ \lambda_{PRRT.g} & 0 & \lambda_{PRRT.group} & 0 \\ \lambda_{RT.g} & 0 & \lambda_{RT.group} & 0 \\ \lambda_{LRPC.g} & \lambda_{LRPC.group} & 0 & 0 \\ \lambda_{SPPC.g} & \lambda_{SPPC.group} & 0 & 0 \\ \lambda_{SD.g} & 0 & \lambda_{SD.group} & 0 \\ \lambda_{ITMT.g} & 0 & 0 & \lambda_{ITMT.group} \\ \lambda_{ITDT.g} & 0 & 0 & \lambda_{ITDT.group} \\ \lambda_{ITTH.g} & 0 & 0 & \lambda_{ITTH.group} \end{bmatrix}$$

where the second-order loading matrix $\Lambda_{2nd-order}$ comprises both the second-order general factor loadings and group factor loadings for the three first-order factors, Memory (M), Response Time (RST), and Inspection Time (IT). The transformed loading matrix has one column of general (g) loadings and three columns of group factor (group) loadings.

Apparently, the group factor loading of any observed variable is a linear function of its general loadings. Taking the RT group factor loading for an example:

$$\lambda_{RT.group} = \lambda_{RT.g} * r_{RST} = \lambda_{RT.g} * \frac{r_{RST}}{l_{RST}},$$

because

$$\lambda_{RT.g} = \lambda_{RT} * l_{RST}.$$

When one CAT factor is allowed to have a free path to the MAT variable(s), the expected covariances between the CAT variables defining the CAT factor and the MAT variable(s) are the products of the CAT factor loadings time the respective path coefficients time the MAT factor loading(s). For example, the expected covariance between RT of the CAT and MATH of the MAT via the path from the CAT general factor is:

$$\sigma_{RT.MATH} = \lambda_{RT.g} * p_g * \lambda_{MATH}$$

where p_g is the path coefficient from the CAT general factor to the scholastic factor, and λ_{MATH} is the factor loading of MATH on the scholastic factor. Alternatively

$$\begin{aligned} \sigma_{RT.MATH} &= \lambda_{RT.group} * p_{RST} * \lambda_{MATH} \\ &= \lambda_{RT.g} * \left(\frac{r_{RST}}{l_{RST}} \right) * p_{RST} * \lambda_{MATH} \end{aligned}$$

if the free path is specified from the CAT RST group factor with coefficient p_{RST} .

When both the CAT general and group factors are allowed to have free paths to the MAT variable(s) in question, the expected covariances between the CAT variables and the MAT variable(s) are the sum of such products, e.g.,

$$\sigma_{RT.MATH} = \lambda_{RT.g} * [p_g + \left(\frac{r_{RST}}{l_{RST}} \right) * p_{RST}] * \lambda_{MATH} \quad (1)$$

The two path coefficients in the parentheses, p_g and p_{RST} , may not be identified to the degree that, for any given value of either p_g or p_{RST} , the same expected covariance can be obtained by selecting a proper value for the other path coefficient. When some of the CAT group factors have fixed paths to the MAT variable(s), the path from the CAT general factor can be uniquely

identified, so can the rest of the free paths from the CAT group factors. Model under-identification will happen, however, if all the CAT general and group factors have free paths to the MAT variable(s). Under such a circumstance, for any given value of p_g , one can always select proper values for p_M , p_{RST} , and p_{IT} to obtain the same expected covariance. The path coefficients are thus not uniquely determined.

The above discussion on model identification also applies in general when the phenotypic models are expanded to behavioral genetic models. The linear constraints on the loadings of general and group factors do not permit a unique coefficient estimation for all the paths from these factors. For example, the genetic path from the CAT G to a MAT variable can not be uniquely identified unless one or more group factors are constrained to have no genetic path to the same MAT variable. When all the three behavioral genetic paths, i.e., the genetic, common environmental, and specific environmental paths from a CAT factor, say, the CAT G, are to be estimated, for each path from the CAT G, at least one of the group factors needs to be constrained not to have a path of the same kind to the MAT variable. The group factors to be constrained for the identification of the free paths from the CAT G do not need to be the same group factor, however, because the identification of the paths is dependent only on their relevant expected covariances, whether these expected covariances are genetic, common environmental, or specific environmental. For instance, the expected genetic covariance between RT of the CAT and MATH of the MAT can be denoted in the way analogous to Equation 1, and its observed counterpart is twice the difference between the MZ and DZ covariances. According to Equation 1, the path from the CAT G needs to be over-identified in order for the path from a group factor, e.g., RST, to be just identified, or vice versa. On the other hand, when Equation 1 is considered for the common environmental path involving a different CAT variable, e.g., ITTH, which is based on the observed counterpart of the between-DZ covariance minus half the genetic covariance, the path from the group factor in the equation can originate from a group factor other than RST, e.g., IT, and the path coefficient for the group factor is still identifiable as long as the path from the CAT G has been uniquely determined. In a similar vein, when the expected specific environmental covariance between PRPT of the CAT and MATH of the MAT, for example, is to be analyzed, the observed counterpart is the covariance between PRPT and MATH not attributable to either heritability or common environmentality, and the path from the group factor in Equation (1) can

come from a still different group factor, e.g., the CAT M. In other words, in the same behavioral genetic structural equation model, one could specify genetic paths from the CAT G and CAT RST, common environmental paths from the CAT G and CAT IT, and specific environmental paths from the CAT G and CAT M, respectively, to the endogenous scholastic variable, and the model would still be identified.

In the context of the present study, since some of the CAT group factors (RST and IT) were found to be trivial and were thereby fixed in the CAT behavioral genetic submodel for subsequent analysis, and in the extended models genetic and environmental paths originated only from some but not all of the CAT factors, the general and memory group factors, identification for structural relation parameters was no longer a concern for these models.

APPENDIX 2

Basic Behavioral Genetic Models and Example of MX Script

This appendix illustrates the baseline behavioral genetic model containing all the three MAT variables. The model consists of two submodels, the submodel of the CAT hierarchical factor structure and the submodel of the MAT variables. Paths representing the mediation of genetic, common-environmental, and specific-environmental influences are specified between the two submodels. Symbolically, the additive genetic part (A) of the CAT factor structure submodel can be written as:

$$\Lambda_{CAT/A} = \Lambda_{1st-order/A} * \Lambda_{2nd-order/A}$$

where the $\Lambda_{CAT/A}$ is a transformed structure in the fashion of Schmid-Leiman, i.e., a product of the first-order factor loading matrix, $\Lambda_{1st-order/A}$, and the second-order matrix, $\Lambda_{2nd-order/A}$. Similarly, the common-environmental and specific-environmental parts (C and E) of the CAT' submodel are written, respectively, as:

$$\Lambda_{CAT/C} = \Lambda_{1st-order/C} * \Lambda_{2nd-order/C}$$

and

$$\Lambda_{CAT/E} = \Lambda_{1st-order/E} * \Lambda_{2nd-order/E}$$

The additive genetic, common-environmental, and specific-environmental parts of the MAT submodel are denoted as $\Lambda_{MAT/A}$, $\Lambda_{MAT/C}$, and $\Lambda_{MAT/E}$, respectively. The matrixes representing paths from the CAT submodel to the MAT submodel are labeled as Γ_A , Γ_C , and Γ_E .

Orders of the matrixes are defined to facilitate modeling using MX. For example, the matrixes of the additive genetic part of the model are specified as follows:

$$\Lambda_{CATIA} = \Lambda_{1st-orderIA} * \Lambda_{2nd-orderIA}$$

$$= \begin{bmatrix} \lambda_{g.PRPC} & \lambda_{PRPC} & 0 & 0 \\ \lambda_{g.PRRT} & 0 & \lambda_{PRRT} & 0 \\ \lambda_{g.RT} & 0 & \lambda_{RT} & 0 \\ \lambda_{g.LRPC} & \lambda_{LR} & 0 & 0 \\ \lambda_{g.SPPC} & \lambda_{SP} & 0 & 0 \\ \lambda_{g.SD} & 0 & \lambda_{SD} & 0 \\ \lambda_{g.ITMT} & 0 & 0 & \lambda_{ITMT} \\ \lambda_{g.ITDT} & 0 & 0 & \lambda_{ITDT} \\ \lambda_{g.ITTH} & 0 & 0 & \lambda_{ITTH} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Gamma_A = |\gamma_{gIA} (\gamma_{MIA}) (\gamma_{RSTIA}) (\gamma_{ITIA})|$$

$$\Lambda_{MATIA} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \lambda_{langIA} \\ \lambda_{mathIA} \\ \lambda_{readIA} \end{bmatrix}$$

where the elements of Γ_A within parentheses may be freed one at a time to test the importance of the CAT group factors to the scholastic factor.

With the component matrixes so defined, the expected within-twin genetic covariance matrix is:

$$\Sigma_A = (\Lambda_{CATIA} + \Lambda_{MATIA} * \Gamma_A) * (\Lambda_{CATIA} + \Lambda_{MATIA} * \Gamma_A)' + (\Lambda_{MATIA} * Z_A) * (\Lambda_{MATIA} * Z_A)' + \Theta_A$$

where Z_A is a 1-by-1 matrix representing the variance of the scholastic factor not accounted for by the CAT factor(s), and Θ_A is a 12-by-12 diagonal residual matrix. The expected within-group common-environmental and specific-environmental covariance matrixes, Σ_C and Σ_E , are

formulated analogously. The expected within- and between-groups covariance matrix can be written in a partitioned form:

$$\Sigma = \begin{bmatrix} \Sigma_A + \Sigma_C + \Sigma_E & w \otimes \Sigma_A + \Sigma_C \\ w \otimes \Sigma_A + \Sigma_C & \Sigma_A + \Sigma_C + \Sigma_E \end{bmatrix}$$

where the scaler w for the Kronecker operator \otimes is either 1.0 or 0.5 depending on the zygosity of the twins.

The model described here can be quite readily accommodated by the MX Model statements. Following is the MX script for the described behavioral genetic model.

ACE HIERHICAL MODEL FOR DZ GROUP

DA NG=2 NI=24 NO=129

CM FU FI = dzcatmat.cov

se 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
21 22 23 24/

MAT

A FU 12 3

C FU 12 3

E FU 12 3

H FU 3 4

J FU 3 4

L FU 3 4

P FU 1 1

R DI 12 12

S DI 12 12

T DI 12 12

X FU 1 4

Y FU 1 4

Z FU 1 4

B FU 12 1

D FU 12 1

F FU 12 1

G FU 1 1

O FU 1 1

Q FU 1 1

MO

((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+R*R)
+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+S*S)
+((E*(L)+F*Z)*(E*(L)+F*Z)'+F*Q*(F*Q)'+T*T)|
(P@((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+
R*R)+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+
S*S))'-
(P@((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+
R*R)+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+
S*S))|
((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+R*R)
+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+S*S)
+((E*(L)+F*Z)*(E*(L)+F*Z)'+F*Q*(F*Q)'+T*T)/

SP A

1 0 0

0 2 0

0 3 0

4 0 0

5 0 0

0 6 0

0 0 7

0 0 8

0 0 9

0 0 0

0 0 0

0 0 0

SP C

21 0 0

0 22 0

0 23 0

24 0 0

25 0 0

0 0 0

0 26 27

0 0 28

0 0 29

0 0 0

0 0 0

0 0 0

SP E

41 0 0

0 42 0

0 43 0

44 0 0

45 0 0

0 46 0

0 0 47

0 0 48

0 0 49

0 0 0

0 0 0

0 0 0

SP H

60 63 0 0

61 0 64 0

62 0 0 65

SP J

70 73 0 0

71 0 74 0

72 0 0 75

SP L

80 83 0 0

81 0 84 0

82 0 0 85

SP R

91 92 93 94 95 96 97 98 99 100 101 102

SP S

111 112 113 114 115 116 117 118 119 120 121 122

SP T

131 132 133 134 135 136 137 138 139 140 141 142

SP X

10 0 0 0

SP Y

30 0 0 0

SP Z

50 0 0 0

SP B

0 0 0 0 0 0 0 0 0 0 302 303

SP D

0 0 0 0 0 0 0 0 0 0 312 313

SP F

0 0 0 0 0 0 0 0 0 0 322 323

SP G

304

SP O

314

SP Q

324

ST .4 all

MA P

0.5

ma a

0.6726 0.0000 0.0000

0.0000 0.0935 0.0000

0.0000 0.5338 0.0000

0.8485 0.0000 0.0000

0.7020 0.0000 0.0000

0.0000 0.7367 0.0000

0.0000 0.0000 0.5169

0.0000 0.0000 0.4811

0.0000 0.0000 0.7879

0.0000 0.0000 0.0000

0.0000 0.0000 0.0000

0.0000 0.0000 0.0000

ma c

0.3228 0.0000 0.0000

0.0000 0.9645 0.0000

0.0000 0.7112 0.0000

0.0272 0.0000 0.0000

0.2638 0.0000 0.0000

0.0000 0.9472 0.0000

0.0000 0.0000 0.0119

0.0000 0.0000 -0.0041

0.0000 0.0000 0.0420

0.0000 0.0000 0.0000

```

0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
ma e
-0.0038 0.0000 0.0000
0.0000 0.8051 0.0000
0.0000 1.8757 0.0000
0.0299 0.0000 0.0000
0.1936 0.0000 0.0000
0.0000 0.1409 0.0000
0.0000 0.0000 0.9408
0.0000 0.0000 -0.1000
0.0000 0.0000 0.1395
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000

```

```

ma h
0.6 .4 0 0
0.6 0 .4 0
0.6 0 0 .4
ma j
0.8 .4 0 0
0.6 0 .4 0
0.05 0 0 .2
ma l
0.6 .4 0 0
0.15 0 .4 0
0.2 0 0 .8

```

```

ma b
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000
1.1417
1.4010

```

```

ma d
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000

```

```

1.2076
1.2384
ma f
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000
0.7143
0.7618

```

```

BO -.10 3.0 ALL
OU ML IT=1500
ACE HIERACHICAL MODEL FOR MZ GROUP
DA NG=2 NI=24 NO=125
CM FU FI=mzcatmat.cov
se 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
21 22 23 24/
MAT
A FU 12 3
C FU 12 3
E FU 12 3
H FU 3 4
J FU 3 4
L FU 3 4
P FU 1 1
R DI 12 12
S DI 12 12
T DI 12 12
X FU 1 4
Y FU 1 4
Z FU 1 4
B FU 12 1
D FU 12 1
F FU 12 1
G FU 1 1
O FU 1 1
Q FU 1 1
MO
((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+R*
R)+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+
S*S)
+((E*(L)+F*Z)*(E*(L)+F*Z)'+F*Q*(F*Q)'+T*
T)|
(P@((A*(H)+B*X)*(A*(H)+B*X)'+B*G*(B*G)'+
R*R)+((C*(J)+D*Y)*(C*(J)+D*Y)'+D*O*(D*O)'+
S*S))'

```

$$(P@((A*(H)+B*X)*(A*(H)+B*X)' + B*G*(B*G)' + R*R) + ((C*(J)+D*Y)*(C*(J)+D*Y)' + D*O*(D*O)' + S*S))|$$

$$((A*(H)+B*X)*(A*(H)+B*X)' + B*G*(B*G)' + R*R) + ((C*(J)+D*Y)*(C*(J)+D*Y)' + D*O*(D*O)' + S*S) + ((E*(L)+F*Z)*(E*(L)+F*Z)' + F*Q*(F*Q)' + T*T)/$$

SP A

1 0 0

0 2 0

0 3 0

4 0 0

5 0 0

0 6 0

0 0 7

0 0 8

0 0 9

0 0 0

0 0 0

0 0 0

SP C

21 0 0

0 22 0

0 23 0

24 0 0

25 0 0

0 26 0

0 0 27

0 0 28

0 0 29

0 0 0

0 0 0

0 0 0

SP E

41 0 0

0 42 0

0 43 0

44 0 0

45 0 0

0 46 0

0 0 47

0 0 48

0 0 49

0 0 0

0 0 0

0 0 0

SP H

60 63 0 0

61 0 64 0

62 0 0 65

SP J

70 73 0 0

71 0 74 0

72 0 0 75

SP L

80 83 0 0

81 0 84 0

82 0 0 85

SP R

91 92 93 94 95 96 97 98 99 100 101 102

SP S

111 112 113 114 115 116 117 118 119 120 121 122

SP T

131 132 133 134 135 136 137 138 139 140 141 142

SP X

10 0 0 0

SP Y

30 0 0 0

SP Z

50 0 0 0

SP B

0 0 0 0 0 0 0 0 0 0 302 303

SP D

0 0 0 0 0 0 0 0 0 0 312 313

SP F

0 0 0 0 0 0 0 0 0 0 322 323

SP G

304

SP O

314

SP Q

324

ST .4 all

MA P

1.0

ma a

0.6726 0.0000 0.0000

0.0000 0.0935 0.0000

0.0000 0.5338 0.0000

0.8485 0.0000 0.0000

0.7020 0.0000 0.0000

0.0000 0.7367 0.0000

0.0000 0.0000 0.5169

0.0000 0.0000 0.4811

0.0000 0.0000 0.7879

0.0000 0.0000 0.0000

0.0000 0.0000 0.0000

ma c

0.3228 0.0000 0.0000

```

0.0000 0.9645 0.0000
0.0000 0.7112 0.0000
0.0272 0.0000 0.0000
0.2638 0.0000 0.0000
0.0000 0.9472 0.0000
0.0000 0.0000 0.0119
0.0000 0.0000 -0.0041
0.0000 0.0000 0.0420
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
ma e
-0.0038 0.0000 0.0000
0.0000 0.8051 0.0000
0.0000 1.8757 0.0000
0.0299 0.0000 0.0000
0.1936 0.0000 0.0000
0.0000 0.1409 0.0000
0.0000 0.0000 0.9408
0.0000 0.0000 -0.1000
0.0000 0.0000 0.1395
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
0.0000 0.0000 0.0000
ma h
0.6 .4 0 0
0.6 0 .4 0
0.6 0 0 .4
ma j
0.8 .4 0 0
0.6 0 .4 0
0.05 0 0 .2
ma l
0.6 .4 0 0
0.15 0 .4 0
0.2 0 0 .8
ma b
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000
1.1417
1.4010
ma d

```

```

0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000
1.2076
1.2384
ma f
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
1.0000
0.7143
0.7618
BO -.10 3.0 ALL
OU

```

Matrixes A, C, and E in the MX script above are the first-order genetic, common-environmental, and specific-environmental loading matrixes, respectively, for the CAT submodel. These second-order loadings and residuals were constrained in the fashion described by the MX manual (MX, 1999; p. 31) using constraint groups so that the group factors all have unit variances. Matrixes H, J, and L above in the CAT submodel are the second-order genetic, common-environmental, and specific-environmental factor matrixes. Matrixes R, S, and T are the first-order genetic, common-environmental, and specific environmental residual matrixes, respectively. For the simplified CAT submodel, the second-order residuals pertaining to the RST and IT group factors in matrixes H, J, L, and the first nine elements of the S matrix representing the first-order common environmental residuals for the CAT are all fixed to zero.

Matrixes B, D, and F above contain the genetic, common-environmental, and specific-environmental factor loadings for the MAT variables. One of the loadings in each of the three matrixes has a fixed value of 1.0 for the scale of the factorial variance. For models with one MAT variable only, component matrixes in the

model statements are specified in a similar fashion, but have reduced orders. For example, the additive genetic factor structure matrix for the CAT has an order of 10 by 4 in lieu of 12 by 4, and the loading matrix for the genetic scholastic submodel has an order of 10 by 1, i.e., nine zero elements and one fixed element of 1.0.

Matrixes X, Y, and Z are defined as path coefficient matrixes relating the CAT factors to the MAT scholastic factor, and G, O, and Q matrixes contain, respectively, the genetic, common-environmental, and specific environmental residuals of the scholastic factor unaccounted for by the CAT factors.

APPENDIX 3

Phenotypic and Behavioral Genetic Covariances Among the CAT and MAT Variables

Phenotypic covariances										
	PRPC	PRRT	RT	LRPC	SPPC	SD	ITMT	ITDT	ITTH	
PRPC	0.9958									
PRRT	0.3388	0.9930								
RT	0.4581	0.3982	0.9736							
LRPC	0.1181	0.2167	0.0469	0.9883						
SPPC	0.2705	0.2433	0.1999	0.4749	0.9654					
SD	0.3004	0.3148	0.2016	0.3599	0.4631	0.8981				
ITMT	0.0883	0.0805	0.1569	0.0410	0.1655	0.2028	0.9870			
ITDT	0.1396	0.1265	0.1293	0.0441	0.1737	0.1419	0.0363	1.0061		
ITTH	0.3221	0.2361	0.2749	0.0369	0.1831	0.3073	0.2252	0.1472	1.0296	
LANG	0.3196	0.2599	0.3207	0.1697	0.2762	0.2552	0.1552	0.1819	0.2431	
MATH	0.3528	0.3320	0.3999	0.1419	0.2806	0.2732	0.1749	0.1718	0.2993	
READ	0.4176	0.4013	0.4382	0.2721	0.3957	0.3563	0.2162	0.2754	0.3206	
LANG MATH READ										
LANG	1.3020									
MATH	1.3451	1.8196								
READ	1.4423	1.6685	2.0399							
Behavioral genetic covariances										
DZ twins										
	PRPC1	PRPT1	RT1	LRPC1	SPPC1	SD1	ITMT1	ITDT1	ITTH1	
PRPC1	1.2142									
PRPT1	0.1869	0.8411								
RT1	0.2472	0.2939	0.7819							
LRPC1	0.5306	0.1392	0.1985	1.1572						
SPPC1	0.3750	0.1611	0.2782	0.5115	0.9441					
SD1	0.3678	0.2828	0.4386	0.1995	0.3398	1.0661				
ITMT1	0.2113	0.1532	0.2404	0.1613	0.0804	0.2711	1.0355			
ITDT1	0.2380	0.0507	0.1096	0.1633	0.1737	0.2383	0.1113	0.9733		
ITTH1	0.3124	0.0612	0.2143	0.3287	0.3572	0.3754	0.3016	0.1604	1.1122	
LANG1	0.4353	0.2218	0.2905	0.4015	0.1614	0.2683	0.2441	0.2294	0.3495	
MATH1	0.5288	0.1357	0.3221	0.4718	0.1930	0.2444	0.2918	0.2966	0.3860	
READ1	0.6334	0.3242	0.4259	0.5169	0.2507	0.4546	0.3390	0.3736	0.4957	
PRPC2	0.2113	0.0849	0.2843	0.2942	0.2622	0.3874	0.0894	0.0230	0.3546	
PRRT2	-0.0639	0.3541	0.2856	0.0344	0.1694	0.2719	0.0067	0.0624	0.1118	
RT2	0.0873	0.3357	0.3828	0.0976	0.2678	0.3093	0.0231	-0.0319	0.1390	
LRPC2	0.1759	0.1188	0.2059	0.3436	0.2764	0.0837	0.2405	0.0788	0.2226	
SPPC2	0.3656	0.1681	0.2964	0.2996	0.3394	0.2967	0.1820	0.1638	0.2320	
SD2	0.0956	0.2383	0.2968	0.1311	0.2229	0.3153	0.0759	0.0245	0.1907	
ITMT2	0.0154	0.0060	0.1158	0.2244	0.0505	0.1082	0.0915	-0.0709	0.0806	
ITDT2	-0.0754	-0.0384	0.0904	-0.116	-0.0296	0.062	-0.0065	-0.1270	0.0515	

APPENDIX 3 *cont.*

ITTH2	0.1382	0.1155	0.2004	0.2289	0.1974	0.2266	0.1091	0.0663	0.4524
LANG2	0.3139	0.1321	0.1858	0.2942	0.1710	0.2163	0.2269	0.2288	0.3325
MATH2	0.3508	0.1715	0.2242	0.3910	0.1529	0.2534	0.1971	0.2249	0.3823
READ2	0.3266	0.2270	0.3046	0.3777	0.2016	0.3920	0.1966	0.2979	0.4263

	LANG1	MATH1	READ1	PRPC2	PRPT2	RT2	LRPC2	SPPC2	SD2
PRPC1									
PRRT1									
RT1									
LRPC1									
SPPC1									
SD1									
ITMT1									
ITDT1									
ITTH1									
LANG1	1.1619								
MATH	1.2678	1.7024							
READ1	1.3194	1.5773	1.8996						
PRPC2	0.2523	0.3270	0.3784	0.9854					
PRRT2	0.0769	0.0389	0.1390	0.1956	0.9919				
RT2	0.2130	0.1854	0.3038	0.2565	0.6157	1.0439			
LRPC2	0.1951	0.2184	0.2960	0.3561	-0.0255	0.1651	0.8283		
SPPC2	0.3599	0.4040	0.4931	0.4005	0.1131	0.2966	0.3288	0.9984	
SD2	0.1235	0.0894	0.1671	0.2623	0.3994	0.5084	0.1297	0.3243	0.7016
ITMT2	0.0448	0.0704	0.1161	0.0911	0.0652	0.1135	0.1178	0.0197	0.1283
ITDT2	0.1478	0.1246	0.1755	0.0711	0.0094	0.2575	0.1003	0.1389	0.1571
ITTH2	0.1371	0.2071	0.2034	0.2661	-0.0699	0.2383	0.2410	0.2923	0.2377
LANG2	0.8926	1.1124	1.1619	0.2558	0.0251	0.2534	0.2389	0.4369	0.2065
MATH2	1.0677	1.4364	1.4185	0.4284	0.0154	0.2848	0.3428	0.5308	0.2623
READ2	1.0731	1.3453	1.5229	0.4080	0.0951	0.3717	0.3257	0.5368	0.3128

	ITMT2	ITDT2	ITTH2	LANG2	MATH2	READ2
PRPC1						
PRRT1						
RT1						
LRPC1						
SPPC1						
SD1						
ITMT1						
ITDT1						
ITTH1						
LANG1						
MATH						
READ1						
PRPC2						
PRRT2						
RT2						
LRPC2						
SPPC2						
SD2						
ITMT2	1.0050					
ITDT2	0.0984	1.1334				
ITTH2	0.1838	0.1235	1.3222			
LANG2	0.1979	0.2883	0.2413	1.3365		
MATH2	0.1662	0.2382	0.3690	1.3488	1.8206	
READ2	0.2397	0.3372	0.3019	1.4140	1.6614	1.9394

APPENDIX 3 *cont.*

MZ twins									
	PRPC1	PRPT1	RT1	LRPC1	SPPC1	SD1	ITMT1	ITDT1	ITTH1
PRPC1	0.7605								
PRRT1	0.2331	0.9780							
RT1	0.1454	0.5787	1.1402						
LRPC1	0.3297	0.1451	0.2600	0.9910					
SPPC1	0.2914	0.2179	0.2345	0.4416	1.0106				
SD1	0.3608	0.3644	0.4269	0.2652	0.4111	1.1816			
ITMT1	0.0485	0.1303	0.1510	0.1468	0.1245	0.2142	0.9602		
ITDT1	0.0479	0.0038	0.1910	0.1115	0.1799	0.0748	−0.1184	0.9170	
ITTH1	0.1994	0.0940	0.1808	0.2029	0.2805	0.2714	0.142	0.1691	0.7905
LANG1	0.1583	0.4331	0.2795	0.2758	0.3631	0.3944	0.1095	0.1697	0.1782
MATH1	0.1410	0.4111	0.2317	0.3354	0.3359	0.4157	0.1792	0.1703	0.2326
READ1	0.2804	0.5368	0.3958	0.3933	0.4827	0.6123	0.1285	0.2903	0.2579
PRPC2	0.2878	0.2477	0.2242	0.4627	0.3545	0.4063	0.0593	0.1023	0.1925
PRRT2	0.2326	0.6194	0.3310	0.0113	0.1456	0.4908	−0.156	0.0056	0.0664
RT2	0.0614	0.2696	0.4492	0.1695	0.1418	0.5406	0.1621	0.0659	0.2461
LRPC2	0.2206	0.1302	0.2424	0.4226	0.4003	0.2249	0.0633	0.2831	0.2403
SPPC2	0.1136	0.1626	0.1665	0.4266	0.4389	0.1507	0.1291	0.1024	0.2900
SD2	0.3468	0.4363	0.2943	0.2432	0.4347	0.7479	0.2375	0.1898	0.4335
ITMT2	0.1072	0.0591	0.0784	0.1719	0.3732	0.1262	0.0369	0.1246	0.0986
ITDT2	0.0383	−0.0168	0.0382	0.0140	0.0795	0.0121	0.0235	0.1849	0.0846
ITTH2	0.2071	0.1214	0.1076	0.1824	0.2149	0.1470	0.0548	0.1467	0.1867
LANG2	0.0759	0.3339	0.2101	0.2676	0.2778	0.3169	0.1992	0.1680	0.1499
MATH2	0.1000	0.3543	0.1589	0.3158	0.3069	0.3060	0.1729	0.2215	0.2283
READ2	0.2118	0.4165	0.3272	0.3750	0.4731	0.6523	0.1198	0.2571	0.2029
	LANG1	MATH1	READ1	PRPC2	PRPT2	RT2	LRPC2	SPPC2	SD2
PRPC1									
PRRT1									
RT1									
LRPC1									
SPPC1									
SD1									
ITMT1									
ITDT1									
ITTH1									
LANG1	1.4412								
MATH	1.5047	2.0174							
READ1	1.6314	1.8387	2.3157						
PRPC2	0.1540	0.1612	0.2741	1.0282					
PRRT2	0.3321	0.3517	0.3684	0.2878	1.3213				
RT2	0.2471	0.2508	0.3200	0.3244	0.6511	1.1739			
LRPC2	0.2701	0.3399	0.4217	0.4100	0.0621	0.1441	0.8887		
SPPC2	0.3474	0.3906	0.4045	0.3481	0.0980	0.2527	0.5251	0.9889	
SD2	0.4389	0.5358	0.5484	0.3859	0.4775	0.4072	0.2601	0.2745	1.1590
ITMT2	0.0251	0.0614	0.1030	0.0682	−0.0538	0.0388	0.2275	0.1953	0.2560
ITDT2	0.0618	−0.0260	0.1534	0.0236	−0.0077	0.0357	0.0011	0.0055	−0.0169
ITTH2	0.0693	0.0598	0.1202	0.2575	0.1014	0.1029	0.3061	0.2801	0.3772
LANG2	1.2165	1.4251	1.5030	0.1051	0.1768	0.2921	0.2428	0.3472	0.4441
MATH	1.4084	1.8097	1.7892	0.1812	0.2707	0.2821	0.3400	0.4331	0.5320
READ2	1.6321	1.8745	2.2275	0.2858	0.3365	0.3956	0.3813	0.4546	0.5681
	ITMT2	ITDT2	ITTH2	LANG2	MATH2	READ2			
PRPC1									
PRRT1									
RT1									

APPENDIX 3 *cont.*

LRPC1							
SPPC1							
SD1							
ITMT1							
ITDT1							
ITTH1							
LANG1							
MATH							
READ1							
PRPC2							
PRRT2							
RT2							
LRPC2							
SPPC2							
SD2							
ITMT2	0.9586						
ITDT2	-0.0036	0.9634					
ITTH2	0.3049	0.0739	0.9078				
LANG2	0.0815	0.0795	0.1514	1.4009			
MATH2	0.0714	-0.0282	0.1605	1.4419	1.9738		
READ2	0.1920	0.1033	0.1769	1.6201	1.9064	2.4523	

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