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A Genetic Investigation of the Covariation Among Inspection Time, Choice Reaction Time, and IQ Subtest Scores

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Information processing speed, as measured by elementary cognitive tasks, is correlated with higher order cognitive ability so that increased speed relates to improved cognitive performance. The question of whether the genetic variation in Inspection Time (IT) and Choice Reaction Time (CRT) is associated with IQ through a unitary factor was addressed in this multivariate genetic study of IT, CRT, and IQ subtest scores. The sample included 184 MZ and 206 DZ twin pairs with a mean age of 16.2 years (range 15–18 years). They were administered a visual (π-figure) IT task, a two-choice RT task, five computerized subtests of the Multidimensional Aptitude Battery, and the digit symbol substitution subtest from the WAIS-R. The data supported a factor model comprising a general, three group (verbal ability, visuospatial ability, broad speediness), and specific genetic factor structure, a shared environmental factor influencing all tests but IT, plus unique environmental factors that were largely specific to individual measures. The general genetic factor displayed factor loadings ranging between 0.35 and 0.66 for the IQ subtests, with IT and CRT loadings of -0.47 and -0.24, respectively. Results indicate that a unitary factor is insufficient to describe the entire relationship between cognitive speed measures and all IQ subtests, with independent genetic effects explaining further covariation between processing speed (especially CRT) and Digit Symbol.

KEY WORDS: Inspection time; Choice RT; IQ subtests; processing speed; multivariate genetic modeling.

INTRODUCTION

Behavioral genetic studies (Luciano *et al.,* 2001a; Posthuma *et al.,* 2001) have recently confirmed that Inspection Time (IT), like other information processing speed measures, is genetically correlated with IQ. In these studies the relationship between IT and IQ was shown to be entirely mediated by genes. The next interesting question to ask is whether this genetic association reflects a unitary speed factor influencing diverse processing speed measures and IQ or whether this genetic factor is specific to IT and IQ. The present study has collected IT and Choice Reaction Time (CRT) measures of processing speed and investigates the genetic interrelationship among these measures with IQ subtest scores.

Phenotypic findings demonstrate that speed measures derived from diverse elementary cognitive tasks are moderately intercorrelated and their relationship with IQ is generally invariant across task type (Barrett *et al.,* 1982; Saccuzzo *et al.,* 1994; Vernon, 1983). One interpretation of this finding is that the relationship between different processing speed indices and IQ is due to a single factor, perhaps reflecting some aspect of central nervous system functioning (e.g., Jensen, 1993). This notion of a unitary speed factor has been supported by multiple regression analyses, which show that IT and CRT do not make independent contributions to the

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prediction of IQ (Larson and Saccuzzo, 1989; Vernon, 1983). However, other studies have shown that IT and RT measures/factors from a battery of elementary cognitive tasks do make independent contributions to the prediction of IQ (Kranzler and Jensen, 1991; Nettelbeck and Rabbitt, 1992). For instance, an RT factor (including CRT measures) explained 5.3% of variance in general ability (*g*), while an elementary task factor loading strongly on IT explained a further 9.6% of variance in *g* (Kranzler and Jensen, 1991). Detterman (1986) argues that the small size of the correlations between elementary cognitive tasks and IQ is indicative of a cognitive system composed of separate abilities and such a notion is consistent with the latter empirical results. Phenotypic analyses have yet to provide any definitive answers regarding the specificity vs. nonspecificity of the processing speed–IQ relationship.

Behavioral genetic studies (e.g., Vernon, 1989) have demonstrated differing strengths and patterns of genetic and environmental contributions to variance across diverse elementary cognitive tasks, indicating that there may not be a single processing mechanism influencing intelligence but rather different component processes (e.g., speed of perceptual apprehension, speed of short-term memory retrieval). The genes influencing these component processes may constitute the genes for intelligence. In terms of the present study it is possible that the genes affecting IT are different from those affecting CRT, despite the fact that both tasks index processing speed/ability of some kind. Different genes may correspond to the different cognitive processes that are tapped by each task rather than the predominance of a single genetic factor controlling some biological mechanism, such as neural transmission speed. By using IT and CRT as individual task measures rather than as a less informative composite index, a multivariate genetic analysis with the IQ subtest scores will establish whether the relationship is mediated by the same or separate genetic factors.

The notion that elementary tasks are related to a group factor of intelligence, such as perceptual speed, rather than the *g* factor (see Mackintosh, 1998) can also be addressed by including the IQ subtest scores rather than the scaled scores. Specific subtests might be shown to confer greater genetic relationships with either IT or CRT. In a phenotypic study (Crawford *et al.,* 1998) of IT and the WAIS-R subtests it was shown that IT was more strongly related to a perceptual-organization process than to *g* (IT and digit symbol loaded the least on *g*). Block design and object assembly also showed high loadings on the perceptual-organization factor, with the common features of these two tests being their requirement of spatial orientation and speed. These characteristics were thought to be related to IT by the brevity of stimulus presentation in the IT task. Based on these findings it may be expected that IT and CRT will show varying strengths of genetic associations with the different IQ subtests.

The aim of this study is to establish whether IT and CRT relate to IQ through the same genetic factor. Furthermore, we will address the question of whether there is a different pattern of genetic association between IT and CRT with the IQ subtest scores. A classical twin design is used in which measures of processing speed and IQ are collected in adolescent twins of similar age.

METHOD

Participants

Data from the first 390 twin pairs (97 MZ females, 87 MZ males, 52 DZ females, 48 DZ males, 106 DZ opposite-sex pairs) tested in the ongoing Brisbane Memory, Attention, and Problem-solving (MAPS) twin study (Wright *et al.,* 2001) are analyzed in the present study. Most twins had participated in a melanocytic naevi study 2 years earlier (Zhu *et al.,* 1999), and others were ascertained through mail-outs to secondary schools in the Brisbane region. Zygosity was determined by ABO, MN, and Rh blood groups and by nine independent polymorphic DNA markers; it could be assigned with a probability of error less than 10^{-3}. The twins were mostly in their penultimate year of secondary school and aged 15 to 18 years (mean = 16.2 years; SD = 0.3). At the time of testing, 75% of the sample were within 4 months of their 16th birthday, while 95% of the sample were younger than 16.9 years.

Experimental Protocol

Twin pairs were excluded if either cotwin had a history of significant head injury, neurological or psychiatric illness, or substance dependence or if they were currently taking long-term medications with central nervous system effects (25 twin pairs were excluded on this basis). All participants had normal or corrected-to-normal vision (better than 6/12 Snellen equivalent). Written informed consent was obtained from the participant, as well as from their parent/guardian, before testing.

Task Description

Inspection Time

Inspection Time was measured using a line discrimination task, presented as a pseudo-computer game of choosing the longer of two worms to go fishing (Luciano *et al.,* 2001a). The two lines of comparison were described as worms that would quickly burrow into the ground. The participant's task was to identify the longer worm in an effort to catch the most fish by pressing the corresponding left or right arrow key on the keyboard. The importance of accuracy and not RT was stressed verbally by the experimenter before initializing the task. Feedback on performance was provided.

The vertical lines measured 22 mm and 27 mm in length, were 9 mm apart, and joined at the top to a horizontal line 12 mm long (Fig. 1a). The probability of the longer line appearing on the left or right was equal. The stimulus duration was variable, ranging between 14.2 and 2000 ms. A flash mask, consisting of two vertical lines (37 mm) shaped as lightning bolts (Fig. 1b), immediately followed the stimulus and was presented for a period of 300 ms to limit further stimulus processing (Evans and Nettelbeck, 1993).

A Parameter Estimation by Sequential Testing (PEST) procedure was employed (Findlay, 1978; Pentland, 1980) to allow an efficient estimation from short to long ITs. The PEST estimated IT using a staircase method in which the stimulus duration was altered on the basis of the participant's previous responses. The PEST is a sensitive tracking procedure that is influenced by random responses and lapses in attention/interest. To minimize bias from these factors, IT was estimated by fitting post hoc a cumulative normal curve (mean = 0) to accuracy as a function of Stimulus Onset Asynchrony (SOA). The statistic of interest is the standard deviation of the curve, which is the SOA at which 84% accuracy is achieved. Multiplying this by the appropriate z-score will give the SOA at which any arbitrary accuracy is reached (e.g., 1.64 for 95%). A steeply rising psychometric function will have a lower standard deviation than a more gradually rising function. Participants with a high proportion of guesses could be identified by their poor fit ($R^2 < 0.95$) to the cumulative normal function. Twenty-one participants (2.7%) were excluded on this basis.

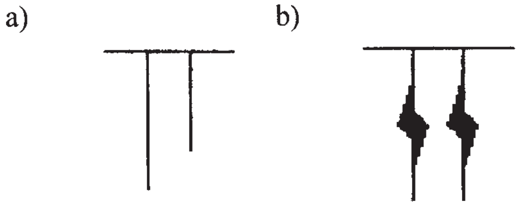

Fig. 1. The Inspection Time stimulus (a) is presented briefly; it is then hidden by a mask (b).

Choice Reaction Time

This task was presented to the participants in the visual form of dripping taps (see Luciano *et al.,* 2001b). The participant was instructed to quickly press the appropriate computer key (keyboard paradigm) to stop a tap from dripping. Two-choice reaction time was sampled through 96 trials, with the output measure being mean RT (in milliseconds) of correct responses only. RT trials less than 150 ms or greater than 2000 ms were excluded from the calculation of the mean. The correlation between mean RT and accuracy showed evidence of a slight speed-accuracy trade-off effect ($r = 0.10$). Mean RT was thus adjusted for percentage of correct responses in the means model of the genetic analysis.

Multidimensional Aptitude Battery

Three verbal subtests (Information, Arithmetic, Vocabulary) and two performance subtests (Spatial, Object Assembly) of the computerized Multidimensional Aptitude Battery (MAB; Jackson, 1998) were administered. These subtests were selected to obtain maximal differentiation between verbal and performance scales, as the Information, Arithmetic, and Vocabulary subtests correlated only moderately with Spatial and Object Assembly. All subtests complied with a multiple-choice format and were timed at 7 min each. Participants were not penalized for guessing and were verbally encouraged to answer every item within the time period, as advised in the administration instructions of the manual. Raw scores were analyzed.

A consequence of twins being tested close to their 16th birthday was the differential completion of months of schooling between pairs. As the MAB was primarily tapping crystallized ability the effects of months of schooling completed at time of study participation was included as a covariate in the analysis; age effects were not significant. Months of schooling was measured by calculating how many months had elapsed since the individual had initiated grade 10 (the lowest school grade in the sample).

Digit Symbol Substitution

This was a performance subtest of the Wechsler Adult Intelligence Scale–Revised (Wechsler, 1981) requiring the participant to pair random digits with their matching symbols. There were nine different digit-symbol pairs. The subject began by completing seven sample items, then they were allocated 90 s in which to complete the remaining 93 items. A score was derived from the total number of correct digit-symbol matches within the time constraint. Efficient performance demands the ability to rapidly produce distinctive verbal codes for each of the symbols in memory. The Digit Symbol test was introduced into the MAPS test battery 3 months after project commencement, and as a consequence the first 35 twin pairs in this study do not have Digit Symbol data.

Statistical Procedure

Using the statistical package, Mx 1.50 (Neale *et al.,* 1999), genetic and environmental models were fitted to raw data. The raw data option in Mx calculates the negative log likelihood function as: $-k.\log(2\pi) + \log|\Sigma| + (x_i - \mu_i)' \, \Sigma^{-1}(x_i - \mu_i)$, where $\boldsymbol{x}$ is the vector of observed twin data, k represents the number of observed variables in the analysis, $\boldsymbol{\Sigma}$ is the population covariance matrix, $\boldsymbol{\mu}_i$ is the vector of population means of the variables, $|\boldsymbol{\Sigma}|$ and $\boldsymbol{\Sigma}^{-1}$ are the respective determinant and inverse of the population covariance matrix (Neale *et al.,* 1999). Incorporating fixed effects in the means model (sex, schooling regression, etc.) removes the effects of these covariates so that the likelihood function is evaluated in terms of the residual scores. Doubling the negative log likelihood allows model comparisons as twice the difference in negative log likelihood between models is distributed asymptotically as χ^2—this is known as the likelihood ratio chi-square test.

Before genetic modeling, means and variances were tested for equality across birth order and zygosity. In this procedure, each of the twin groups (MZ female, MZ male, DZ female, DZ male, DZ opposite-sex first-born female, DZ opposite sex first-born male) has two means (one each for first- and second-born twin), two variances, and one covariance. A saturated model is initially fitted estimating all parameters for a single variable, then progressively simplified models are compared to the full model and assessed by the chi-square test. Birth order effects are tested by imposing equality constraints on the means of first-born and second-born twins within same-sex zygosity groups. Zygosity effects are tested by equating the means of MZ and DZ same-sex groups separately by sex. A test of whether the females and males in the DZ opposite-sex groups can be equated to the respective female and male mean of the other groups is then performed, before testing the equality of means between females and males. These series of hypotheses are then applied to the variances. The equality of cotwin correlations across male and female MZ pairs, and across DZ same-sex and opposite-sex pairs was tested to evaluate the presence of sex differences in genetic effects for the measures.

RESULTS

IQ measures were normally distributed, with a maximum of six outliers removed per subtest (Vocabulary) based on a criterion of scores exceeding three standard deviations from the mean. Inspection time was log transformed and eleven outlying scores removed. Mean CRT was slightly positively skewed so an outlier criterion of exceeding ±3.5 SD from the mean was used and eight outliers were excluded. In addition, one multivariate outlier was removed.

Assumptions concerning means, variances, and covariances across birth order and zygosity were generally met. Where inequalities were found they mostly pertained to a single group (e.g., higher mean for first-born than second-born females in DZ opposite-sex groups), rather than being a consistent effect of birth order or zygosity. A sex difference in the variance of IT was observed where the standard deviation of females (0.21) was lower than males (0.26). This effect was further investigated by applying more severe data transformations to the IT data to reduce skewness, but sex differences in the variance were still observed. Elimination of cases (10% of the sample) in the positive tail of the IT distribution resulted in an equality of variances between males and females, which raised the possibility that those with relatively long ITs (especially males) were not performing the task correctly, with their scores reflecting motivational and other extraneous influences. The effect of trimming IT data in this manner will be briefly explored in a genetic analysis, although in the main analysis, genetic models are specified in which the variance for females and males (for IT) is free to vary.

Various fixed effects were significant, these included sex for all IQ subtests except Vocabulary in the direction of a male superiority (Table I) and IT (males had a shorter IT by 3 ms), session order effects for CRT (those who completed CRT task in the first session showed faster RTs by an average of 14.8 ms), and months of schooling effects on all IQ subtests so that those participants who had completed more months of school tended to perform better. Each extra month of schooling conferred an increase in IQ ranging from

Table I. Maximum Likelihood Estimates (95% Confidence Intervals) of Phenotypic Correlations Between the IQ Subtests with Inspection Time and Choice RT for Females and Males

	Female (n = 357–401)			Male (n = 315–367)		
		Correlations			Correlations	
	Mean (SD)	Inspection time	Choice RT	Mean (SD)	Inspection time	Choice RT
Digit Symbol	63.50	−0.34	−0.38	55.22	−0.24	−0.41
	(9.59)	(−0.25 to −0.42)	(−0.29 to −0.46)	(10.16)	(−0.14 to −0.33)	(−0.32 to −0.48)
Spatial	28.43	−0.31	−0.20	31.74	−0.35	−0.26
	(9.32)	(−0.23 to −0.39)	(−0.11 to −0.29)	(8.83)	(−0.26 to −0.43)	(−0.17 to −0.34)
Object assembly	12.33	−0.26	−0.23	13.09	−0.34	−0.24
	(3.78)	(−0.17 to −0.34)	(−0.13 to −0.31)	(3.81)	(−0.26 to −0.42)	(−0.16 to −0.33)
Information	19.87	−0.22	−0.28	21.14	−0.18	−0.29
	(5.13)	(−0.13 to −0.31)	(−0.19 to −0.37)	(5.82)	(−0.10 to −0.27)	(−0.21 to −0.37)
Arithmetic	11.84	−0.24	−0.23	12.48	−0.28	−0.24
	(2.61)	(−0.15 to −0.33)	(−0.13 to −0.32)	(3.06)	(−0.19 to −0.36)	(−0.16 to −0.32)
Vocabulary	17.26	−0.14	−0.24	17.19	−0.24	−0.29
	(4.74)	(−0.05 to −0.23)	(−0.15 to −0.33)	(4.72)	(−0.14 to −0.32)	(−0.21 to −0.38)

Note: Means and standard deviation of IQ subtest scores are displayed separately for females and males.

0.015 of a standard deviation for Spatial to 0.037 of a standard deviation for Arithmetic; these regressions are consistent with changes in raw scores between ages 16 and 18 in the standardization of the MAB (Jackson, 1998). The means and standard deviations for IT and CRT were 95.07 ms ± 62.91 and 296.01 ms ± 30.43, respectively.

Maximum likelihood (ML) estimates of the phenotypic correlations between the IQ subtests with IT and CRT are shown in Table I, separately for females and males, although based on overlapping 95% confidence intervals (CI) no differences between sexes were observed. There was a trend for higher correlations of IT with the performance subtests than with the verbal subtests. Verbal and performance subtests showed roughly similar correlations with CRT, except for Digit Symbol, which tended toward a stronger correlation. The correlation between IT and CRT was 0.23 (95% CI: 0.13–0.32) for females and 0.19 (0.10–0.28) for males. Intercorrelations among the IQ subtest scores ranged from 0.29 (Vocabulary − Digit Symbol) to 0.68 (Vocabulary − Information). Because some of the correlations were lower than 0.30, a phenotypic hierarchical model was considered inappropriate as there would be a lack of hierarchical order (a weak general factor). Instead, modeling progressed from the approach of a Cholesky decomposition to which more restrictive submodels were compared. The genetic factor structure was of most interest, so two hypothesized models were formulated. The first genetic model included a general factor, a performance factor (Spatial, Object Assembly), a verbal factor, a speediness factor (IT, CRT, Digit Symbol), and specific genetic effects on each measure; the loadings from the performance factor to Spatial and Object Assembly subtests were constrained equal to ensure model identification. The second genetic submodel included three factors—a general factor, a performance-speed factor (Spatial, Object Assembly, Digit Symbol, CRT), and a verbal factor—plus specific genetic effects. Phenotypic correlations showed a heightened association between CRT and the performance IQ subtests, so IT was not hypothesized to be influenced by the performance-speed factor. Empirical tests of model identification were performed by initially fixing parameters in each hypothesized model to random values. From this model, MZ and DZ variance-covariance matrices are calculated, and the hypothesized models are then fitted to these matrices but starting optimization from parameter values that differ from the fixed parameter values. Models that recover the same fixed parameter values provide strong support for model identification.

Goodness of fit statistics for the various models fitted to the data are presented in Table II. All models are initially compared to a saturated phenotypic model in which means, variances, separate MZ and DZ covariances, and separate male and female intervariable correlations are parameterized. The saturated ACE Cholesky decomposition did not provide optimal fit to the data, perhaps indicating slight effects of sex limitation that are not investigated in this paper. Genetic and environmental submodels are further compared to the saturated ACE Cholesky decomposition. The standardized path coefficients of the saturated ACE

Table II. Goodness of Fit Statistics for the Multivariate Model of Inspection Time, Choice RT, and IQ Subtests: −2LL (& *df*) and Change in the −2LL (& *df*) of the Cholesky Decompositions and Hypothesized Models and Their Probability Level of Significance

	Fit relative to saturated model				Fit relative to specified model			
Model	χ^2	*df*	*p*	AIC	Model	χ^2	*df*	*p*
Saturated Model (−2LL = 32764.87, *df* = 5902)								
I. ACE Cholesky Decomposition	49.24	20	0.01	9.24				
i. 4 A factors + A specifics, C factor, E Cholesky Decomposition	66.60	62	0.32	−57.40	I	17.36	42	1.00
ii. 3 A factors + A specifics, C factor, E Cholesky Decomposition	67.62	62	0.29	−56.38	I	18.38	42	1.00
iii. 4 A factors + A specifics, C factor, reduced E Cholesky Decomposition	**94.77**	**88**	**0.29**	**−81.23**	**I(i)**	**28.17**	**26**	**0.35**
II. AE Cholesky Decomposition	67.59	56	0.14	−44.41	I	18.35	36	0.99
i. 4 A factors + A specifics, E Cholesky Decomposition	92.60	69	0.03	−45.40	II	25.01	13	0.02
ii. 3 A factors + A specifics, E Cholesky Decomposition	89.38	69	0.05	−48.62	II	21.79	13	0.06
III. CE Cholesky Decomposition	165.89	56	<0.01	53.89	I	116.65	36	<0.01

Note: Male and female variances for IT are free to vary in all models tested.
Akaike's information criterion (AIC) is calculated from the fully saturated phenotypic model. The best fitting model is highlighted in bold.

Cholesky are shown in Table III; they suggest the presence of a common environmental factor influencing all subtests but IT (the second Cholesky factor demonstrated path coefficients ranging from 0.20 to 0.48). Therefore submodels containing a common environmental factor influencing all subtests but IT are tested in addition to models only containing the hypothesized genetic factor structure and a unique environmental factor structure.

Compared to the saturated phenotypic model, the model encompassing four genetic factors and common and unique environmental effects (model I.i in Table II) provided the best fit to the data as judged by Akaike's Information Criterion (−57.40). This model was reduced further by dropping nonsignificant unique environmental path coefficients (model I.iii). In this model (Fig. 2), the general genetic factor explained between 6% and 44% of variance in the variables, with higher loadings on performance (Spatial, Object Assembly, Digit Symbol) and Arithmetic subtests than on Information and Vocabulary. The speed factor loaded strongly on CRT, moderately on Digit Symbol, and slightly on IT. The loadings from the performance genetic factor were moderate, with greater unique genetic variance observed for Object Assembly. The verbal genetic factor explained between 8% and 28% of variance in the verbal subtests. The percentage of variance explained by specific genetic factors ranged from 5% for Spatial to 31% for Digit Symbol; CRT and Information showed no unique genetic variance. The common environmental factor explained between 1% of variance for Digit Symbol and 31% of variance for Information. Unique environmental effects were generally specific, although there was some overlap between various combinations of IQ subtests.

Based on the skew of the IT distribution and the finding of inequality of variances between females and males, the Cholesky decomposition was repeated using an IT sample in which 77 cases (a further 10% of the sample) from the positive tail were removed—this included cases with IT values greater than 157.96 ms. If the IT of these participants reflected extraneous factors, such as motivation, rather than true IT, then it is likely that the genetic results would change, in particular the heritability of IT. Like the previous Cholesky analysis, an AE model did not show a significant change in fit ($\chi^2_{36} = 16.25$, $p > .05$) from the ACE model, whereas a CE model did. The genetic and unique environmental factor loadings of this model were compared with the AE Cholesky loadings of the previous analysis. The first Cholesky factor was of most interest because it was the only factor to influence IT. The heritability of IT showed no significant change, and the difference in the genetic loadings between the analyses for the other variables ranged between 0 and 0.08, while the difference in the environmental loadings

Table III. Standardized Parameter Estimates from Latent Factors to Inspection Time, Choice RT, and IQ Subtests for the Additive Genetic (A), Common Environment (C) and Unique Environment (E) Cholesky Decomposition (Model I)

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
IT	.63								.14								.76							
CRT	.35	.37							−.28	.43							.04	.69						
Digit Symbol	−.44	−.20	.61						.00	−.26	.16						−.03	−.08	.54					
Spatial	−.42	.12	.14	.55					−.08	−.24	.04	.04					−.07	−.06	.08	.63				
Object	−.40	.17	.08	.39	.38				−.10	−.33	.19	.03	.00				−.04	−.06	.06	.08	.58			
Information	−.33	.14	.00	.01	.18	.54			−.10	−.53	.01	.10	.00	.00			.04	−.04	.14	.06	−.01	.47		
Arithmetic	−.39	.19	.12	.15	−.01	.30	.38		−.05	−.37	.05	.04	.00	.00	.00		−.01	−.03	.07	.05	.04	.03	.62	
Vocabulary	−.36	.19	−.01	−.06	−.02	.39	−.06	.00	.00	−.47	.06	.06	.00	.00	.00	.00	.05	−.02	.10	.06	.03	.11	−.02	.64

ranged between 0 and 0.06. The results suggested that the original IT data selection was not biased by those participants with relatively long ITs, and hence this measure was considered to be tapping true IT processes rather than extraneous factors.

DISCUSSION

The covariation among Inspection Time, Choice RT, and IQ subtest scores was best explained by a model incorporating additive genetic and common environmental effects, whereas unique environmental effects were mostly specific to each measure. Inspection Time and CRT were associated with a genetic general cognitive ability factor, which appeared to be a fluid ability factor because its highest loadings were on the performance IQ subtest scores. Choice RT and IT were additionally related to Digit Symbol through a separate genetic factor, although this factor's influence on IT was minimal. These results indicate that the relationship between processing speed measures and varied IQ tests is primarily explained by a general cognitive function, but that independent relationships between specific speed and cognitive abilities measures may exist because of their mutual reliance on common processes mediated by a different (set of) gene(s). The genetic factor structure was similar to a phenotypic factor model reported in our sample for IQ subtests (i.e., correlated verbal and performance factors) and to other studies showing that elementary cognitive tasks have a more pronounced relationship with fluid ability tests (particularly Digit Symbol) than verbal tests (Deary, 1993; Luciano, in press; Vigil-Colet *et al.,* 1997).

The genetic general factor explained the greatest proportions of covariance between the speed and IQ measures, with the exception of the relationships between CRT with Information and Vocabulary, which was influenced to a greater extent by aspects of the common environment (because of their larger influence on Information and Vocabulary measures) and the relationship between CRT and Digit Symbol, which was predominantly mediated by the genetic speed factor. The presence of a strong genetic general factor emphasizes the centrality of common genes influencing the variation in diverse levels of cognitive processing. From a bottom-up perspective of speed determining variation in higher order cognitive abilities, it is possible that the common genetic variation relies in part on the biological speed of the brain. It may be that factors such as oscillation speed of neuronal excitatory potentials and myelination of neurons determine the speed of information processes (Jensen,

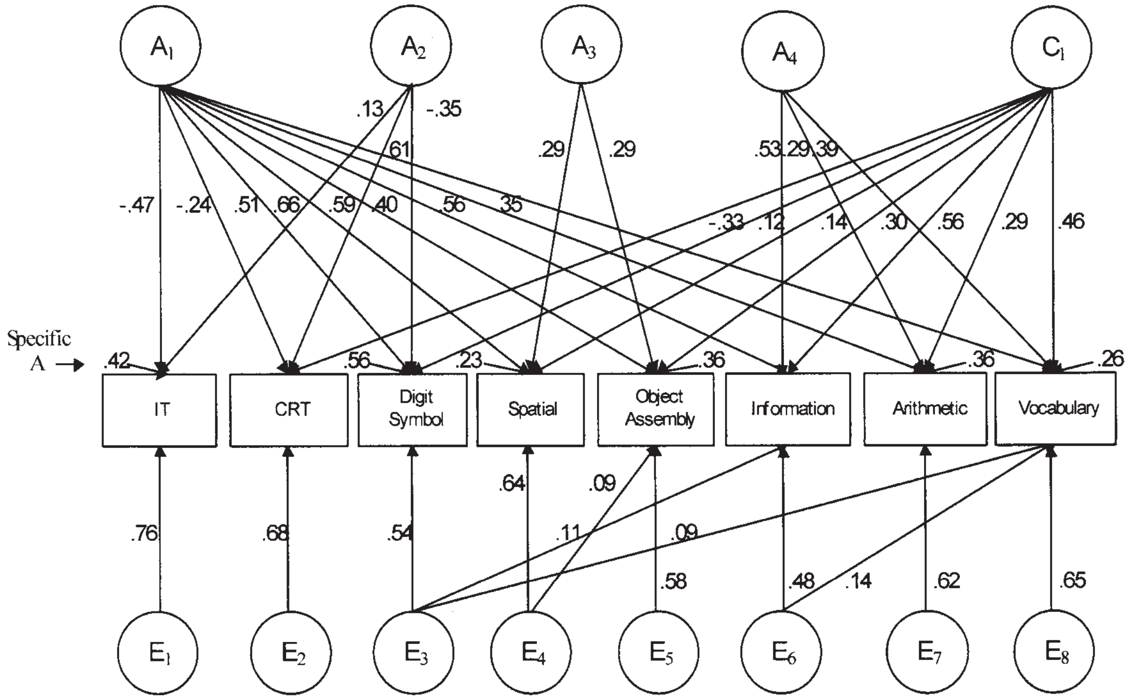

Fig. 2. Standardized path coefficients of the additive genetic, common environmental, and unique environmental model depicting the relationship between Inspection Time, Choice RT, and IQ subtests. The specific loadings on each variable represent the effects of additive genes.

1998). A faster oscillation frequency causes the action potential to be nearer to the threshold of excitation, resulting in a faster response. Increased myelination of neurons might also promote a faster speed and efficiency of information processing because myelinated fibers are responsible for transmitting neural information to differing regions of the brain and across the corpus callosum. A top-down interpretation of the general cognitive ability factor may be that smarter people are able to optimize their information processes and hence the association.

Three genetic group factors were further supported in this study. One factor clearly appeared to be a verbal group factor and another a MAB performance (or visuospatial ability) group factor, while the last factor influencing, IT, CRT, and Digit Symbol was perhaps a broad speediness fact. The last factor was not interpreted as a perceptual organization factor (e.g., Crawford *et al.,* 1998) because it showed no influence on Object Assembly. There has been some phenotypic support for an enhanced relationship between coding tasks with IT and CRT; for example, Burns and Nettelbeck (2003) showed a general speediness factor influencing such tests as Digit Symbol, IT, and movement time from the Odd Man Out paradigm. With the exception of IT, the defining feature of these tests was that under nontimed conditions perfect accuracy could be easily attained, but the relationship of IT to these tests was less clear. An alternative hypothesis for this genetic factor may relate to freedom from distraction, of which Digit Symbol is also a test. The IT and CRT tasks are likely to be especially sensitive to attentional processes because they are not cognitively demanding; in our study we aimed to exclude IT data consistent with a pattern of inattention by the participant, so this may explain the comparatively smaller factor loading on IT than on CRT. Although IT has been shown to demonstrate a particularly pronounced phenotypic relationship with Digit Symbol (Cooper *et al.,* 1986; Crawford *et al.,* 1998; Deary, 1993), in this study the larger correlation between IT and Digit Symbol was actually mediated by the general fluid ability factor rather than a factor characterizing perceptual speed/organization.

Common environmental effects were essentially generalized (no loading on IT), which agrees with the findings of Petrill *et al.* (1996), who studied the association of six elementary cognitive tasks and WISC-R subtests. They interpreted the shared common environmental relationship as a consequence of polyenvironmental influences. Eaves *et al.* (1984) give a different interpretation of generalized common environmental effects invoking an assortative mating hypothesis, in which the general common environmental factor is a linear combination of the additive genetic effects resulting from assortative mating of each specific cognitive ability. The results of our study do not provide much support for this hypothesis because the factor loadings from the general additive genetic factor do not even approximate a constant multiple of the general common environmental factor loadings (and there was no common environmental influence on IT). However, it appears that the verbal genetic factor loadings may be a scalar constant of the general common environmental factor loadings on the verbal subtests, which suggests that there may be assortative mating for verbal abilities so that the common environmental proportion of their variances are overestimated. However, this explanation does not account for the substantial common environmental factor loadings on CRT and Object Assembly.

In our study, the common environmental factor displayed a moderate loading on CRT (−0.33) and no loading on IT. Inspection Time has been touted as a better measure of the biological speed of the brain than other speed measures, and, if this is true, one might expect IT to be more resilient against these common environmental effects. Correlated unique environmental influences were only significant among the IQ subtests and may stem from shared measurement error or true nonshared environmental factors. For example, a unique environmental factor influencing the correlation between Information and Vocabulary may be differences between twins in extracurricular reading.

The present results may be compared with those of Rijsdijk *et al.* (1998), who analyzed the genetic covariation among simple RT, 2-choice RT, and WAIS subtests in a similar aged sample as ours. The phenotypic correlations between CRT and WAIS subtests in their study were generally of lower magnitude than those we obtained. The contribution of variance from the general genetic factor to the RT measures was also quite low (17% and 11%), and, further, they did not find any independent genetic association between RT and the Coding subtest. Their genetic correlations were actually stronger between CRT and verbal subtests (−0.33 to −0.40) than between CRT and performance subtests (−0.18 to −0.34), reflecting the fact that the genetic *g* factor had a larger influence on verbal than performance subtests. In the present study the reverse was found, and because the loadings from the genetic *g* factor to the speed measures were higher than theirs, this suggests that the speed factor is more strongly related to fluid than crystallized ability.

SUMMARY

The significant phenotypic relationships between IT and CRT with IQ were replicated; furthermore, it was demonstrated that these relationships were primarily genetically mediated. The correlation between CRT and IT was also within the range reported for these two measures. A pattern emerged whereby a single genetic factor influenced all the measures, but three genetic group factors (verbal, visuospatial, broad speediness) were also important. Although there was large overlap in the covariation between the elementary cognitive speed measures and IQ, there was an enhanced relationship between the speed measures (particularly CRT) with Digit Symbol, and this may reflect a speediness (or attention) factor that does affect general cognitive ability. Whereas IT and CRT were not shown to separately confer independent relationships with individual ability tests, other speed measures tapping such processes as short-term memory scanning or access to long-term memory retrieval may be able to predict specific cognitive abilities beyond IT and CRT capacities.

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