Evaluating Competing Models of the Relationship Between Inspection Time and Psychometric Intelligence

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Confirmatory factor analysis (CFA) was used to test models of the relationship between inspection time (IT) and psychometric measures of intelligence (the eleven subtests of the Wechsler Adult Intelligence Scale-Revised). The sample consisted of 134 healthy adults and was broadly representative of the adult United Kingdom population in terms of the distributions of age and social class. A Nested Factors parameterization consisting of *g* plus three orthogonal group factors with IT loading on all factors provided a reasonably good fit to the data. Variants on this model that incorporated theoretical and empirically derived constraints were tested; constraining IT to have zero loadings on all factors produced a significant deterioration in fit. Constraining IT to load only on General Intelligence (*g*) and Perceptual Organization did not produce a significant deterioration; nested variants on this latter model in which IT was constrained to load on either of these two factors alone produced a significant deterioration in fit.

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INTRODUCTION

An individual's inspection time (IT) is an estimate of the stimulus presentation time required by a participant in order to make a given discrimination to a predetermined criterion of accuracy. The original and commonest form of the task involves presentingtwo parallel vertical lines of markedly different lengths to participants who are then asked to indicate, in their own time, which of the lines is longer (Vickers, Nettelbeck, & Willson, 1972). Stimulus duration is manipulated by the experimenter to obtain an estimate of the minimum exposure time required by the participant to reach a given accuracy criterion. The principal focus of interest in IT arises from claims that it is an indicator of the general factor and/or group factors underlying performance on psychometric measures of intelligence (e.g. Brand & Deary, 1982; Deary & Stough, 1996).

The present paper will focus on the association between IT and different general and group factors obtained in the Wechsler Adult Intelligence Scale-Revised. However, it should also be noted that there are other active areas of research into inspection time as reviewed by Deary (1996) and Deary and Stough (1996). Among these areas of research activity is a detailed re-evaluation of the mental processes indexed by the commonly-used forms of the IT task, and the wider theory of perception and decision-making from which IT as a measure was derived. For example, White (1993) has suggested that the theory of backward masking might provide a better theoretical account of IT than that offered by Vickers, Nettelbeck and Willson (1972). In a later paper White (1996) has explored the consequences of such a theoretical shift.

The prototypical approach to investigating the relationship between IT and psychometric intelligence has been to gather data from samples of convenience (normally undergraduates) and to compute the correlation between the manifest variables. Because such samples will have a restricted range of talent, the correlations between the manifest variables are usually corrected for this source of attenuation. Two reviews of studies using this approach have concluded that the averaged *attenuation corrected* correlation between IT and psychometric intelligence is around –0.5 (Kranzler & Jensen, 1989; Nettelbeck, 1987).

An alternative but complimentary approach adopted in the present study was (1) to recruit a sample which was broadly representative of the general adult population in terms of demographic characteristics and (2) to examine the relationship between IT and the latent variables underlying performance on measures of psychometric intelligence. This approach has the advantage that statistical corrections for restricted range are unnecessary. Such corrections assume that the relationship observed in the samples' range of ability holds across the general populations; this assumption may be incorrect (Detterman & Daniel, 1989).

Deary (1993) used confirmatory factor analysis (CFA) to examine the relationship between IT and psychometric intelligence in a sample of people with insulin dependent diabetes ($N = 87$). A short-form of the Wechsler Adult Intelligence Scale Revised, (WAIS-R; Wechsler, 1981) consisting of nine of the eleven subtests, was employed as the measure of psychometric intelligence. Two models were examined. The first was a single, general factor model in which all WAIS-R subtests and IT loaded on the general factor. Although this was a poor fitting model, IT was found to have a significant loading.

A different model of the relationship between intelligence and inspection time was suggested by the reviews of Nettelbeck (1987) and Kranzler and Jensen (1989) in which IT was found to correlate more strongly with performance IQ than verbal IQ. Deary (1993) argued that this suggested that the association between fluid intelligence (g_f) and IT was stronger than the link between crystallized intelligence (g_c) and IT. The empirical confirmation of this differential association has theoretical and empirical importance. If IT is more strongly associated with g_f then it is, arguably, reflecting some of the variance of the here-and-now mechanics of intelligence and thereby offering some information about the participant's present efficiency. This is corroborated by the finding that IT-like measures are strongly related to memory and performance IQ scores in elderly participants whose cognitive performance is deteriorating (Rabbitt, 1992).

To test this alternative model, Deary (1993) constructed a correlated factors model of WAIS-R subtests in which all Verbal subtests were constrained to load only on the verbal factor (which was equated with crystallized ability) and all Performance subtests were constrained to load only on the performance factor (which was equated with fluid ability). The fit indices for this model were good and it was demonstrated that constraining IT to load only on the performance factor did not produce a significant decrease in fit over that which would have been achieved by allowing IT to load on both factors.

In common with Deary's (1993) report, the present study employed the WAIS-R (full-length administration) as the measure of psychometric intelligence. Although some reservations have been expressed about the WAIS-R (see Carroll, 1993), it was selected because it has been standardized relatively recently on a large, representative sample of the adult population, has good psychometric characteristics and is widely regarded as the principal measure of psychometric intelligence. Kaufman (1985) for example has stated that the WAIS-R is "*the* criterion of adult intelligence" (p. 1702).

The present approach differs from that of Deary (1993) in the parameterization of the models used to study IT's relationship with intelligence. Exploratory and confirmatory factor analytic studies have commonly identified three, as opposed to two, latent variables underlying WAIS-R performance (e.g. O'Grady, 1983; Crawford, Allan, Stephen, Parker & Besson, 1989; see Leckliter, Matarazzo & Silverstein, 1986 for a review). The first of these three factors has been labelled the Verbal factor (V) and is indexed by the Vocabulary, Information, Comprehension and Similarities subtests; the second factor has been termed Perceptual Organization (PO) and is indexed primarily by Block Design and Object Assembly, although other Performance subtests also load on this factor; and the third factor has been termed Attention/Concentration or Freedom-From-Distractibility (A/C) and is indexed by Arithmetic and Digit Span (e.g. O'Grady, 1983). The basic model used in the present study incorporates these three factors. Given that IT involves a fast perceptual discrimination, and given the interest in attentional processes as contributors to individual differences in IT (Caryl, 1994; Nettelbeck, Hirons, & Wilson, 1984), it is of particular interest to model IT with respect to PO and A/C.

A second difference in parameterization arises from the desirability of comparing IT's loading on the general factor with IT's loading on the Performance/Perceptual Organization factor. As noted, in Deary (1993) this issue was examined by using two separate models, viz. the general factor and the two-factor models. This approach may not be optimal as the general factor model had poor fit and the method does not permit investigation of IT's loading on one of these two factors when IT is simultaneously allowed to load on

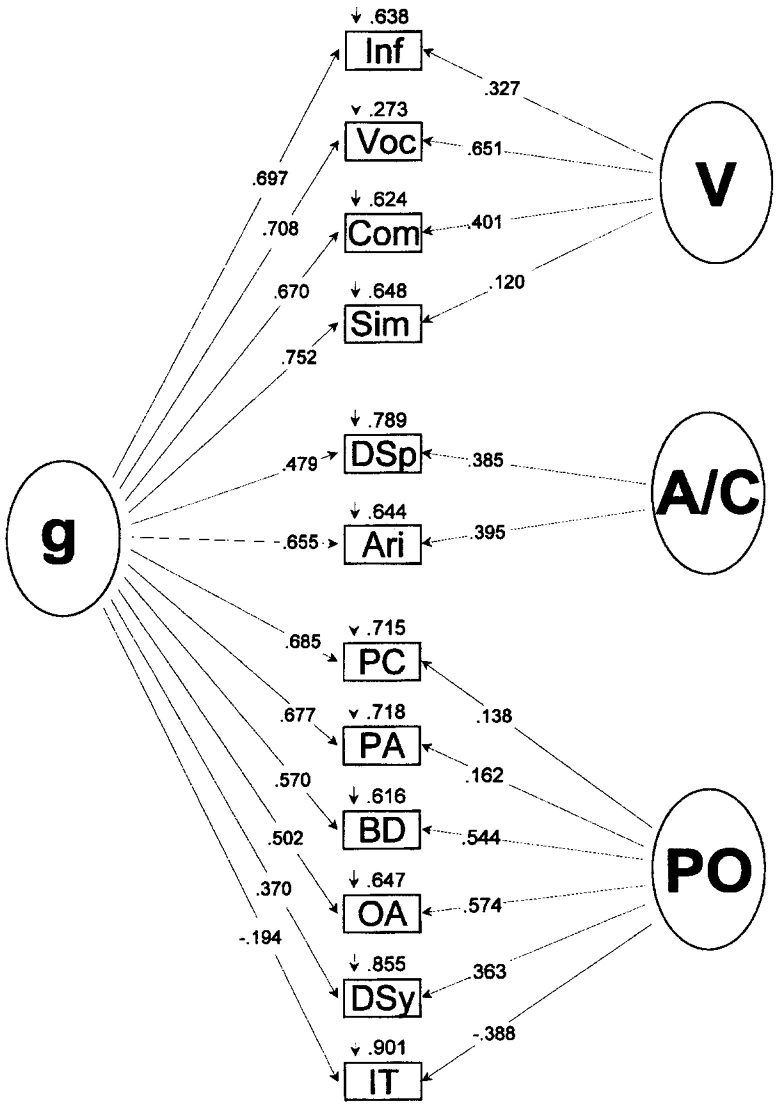

Figure 1. Graphical representation of a (nested factors) confirmatory factor analytic model in which inspection time is an indicator of general intelligence and an (orthogonal) specific perceptual organizational factor. The latent variables are represented as circles; g= general, V = verbal, A/C = attention/concentration, PO = perceptual organization. The manifest variables are represented as rectangles; Inf = Information, Voc = Vocabulary, Com = Comprehension, Sim = Similarities, DSp = Digit Span, Ari = Arithmetic, PC = Picture Completion, PA = Picture Arrangement, BD = Block Design, OA = Object Assembly, DSy = Digit Symbol, IT = Inspection Time. The numbers above each arrow pointing from the latent variables to manifest variables represent the standardized loading s of each manifest variable on its respective latent variables. Each manifest variable also has an error component; these are presented alongside the arrows which appear above each manifest variable.

the other. In the present study the basic model was parameterized to allow simultaneous identification of a general factor and the three specific factors. This method of parameterization has been used successfully by Gustafsson & Balke (1993) to examine the relationship between general and specific ability measures and academic achievement. The basic model, which, following Gustafsson & Balke (1993) we have termed the nested factors model, consists of a general factor indexed by all manifest variables and specific factors which are orthogonal to both the general factor and each other (see Figure 1 for a graphical representation). Each manifest variable is constrained to load on only one specific factor (Gustafsson & Balke, 1993).

METHOD

Participants

The sample consisted of 134 participants (62 females and 72 males) screened by interview to exclude individuals with a history of neurological, psychiatric, or systemic disorders. Participants were recruited from a variety of sources including recreational clubs, community centers, the public service and commercial organizations. Participants received a small honorarium for their participation. The mean age of the sample was 42.7 (17.75) and mean years of full-time education or equivalent was 13.1 (2.99).

The UK system of coding social class is based on occupation and consists of five categories in which 1 = professional, 2 = intermediate, 3 = skilled, 4 = semi-skilled, and 5 = unskilled. Each participant's social class was coded on the basis of their current occupation (or last occupation where a participant was not in employment) using the Office of Population Censuses and Surveys (OPCS) Classification of Occupations (OPCS, 1980).

Recruitment was aimed at obtaining a sample which was broadly representative of the adult U.K. population in terms of age, sex and social class. To examine if this aim was achieved the social class distribution of the sample was compared to the social class distribution of the adult U.K. population using U.K. census figures. The observed and expected numbers are presented in Table 1. A goodness-of-fit test revealed that the observed and expected numbers did not differ significantly ($\chi^2 = 9.24$, df = 4, ns); however, it can be seen that social class 1 occupations were overepresented. A similar procedure was adopted to examine the representativeness of the sample in terms of age. Three age bands were formed on the basis of ready availability of summary figures from the UK census. The sample numbers in each band compared to the census-derived expected numbers (Table 2).

Table 1. Social Class Distribution in the WAIS-R Sample and in the Adult U.K. Population (Entries are Percentages)

	Social Class				
	1	*2*	*3*	*4*	*5*
Sample	10.4	24.6	44.5	14.9	5.2
Adult U.K. population	5	23	48	18	6

Table 2. Age Distribution in the WAIS-R Sample and in the Adult U.K. Population (Entries are Percentages)

	Age Band		
	16-35	*36-60*	*61-80*
Sample	41	37	22
Adult U.K. population	39	38	23

A goodness-of-fit test revealed that the observed and expected numbers did not differ significantly ($\chi^2 = 0.27$, df = 2, ns).

Procedure

All participants were administered a full-length WAIS-R according to standard procedures (Wechsler, 1981; Lea, 1986). Inspection Time (IT) was estimated using the same device and procedure as that described in Petrie and Deary (1989) and Deary (1993). Briefly, participants were required to state which of two lines of markedly different lengths was longer. As is usual for this test, there was no requirement for speeded responses. Participants indicated whether the right- or left-hand line was longer. The critical variable was the duration of presentation prior to backward mask onset (stimulus onset asynchrony). The IT estimate obtained was the minimum presentation duration at which the participant was 85% correct. Stimulus lines and the backward mask were composed of light-emitting diodes and the program was controlled using a BBC Master microcomputer. Untimed responses were made using the appropriate thumb press. Individual ITs were estimated using the PEST adaptive staircase algorithm (Taylor & Creelman, 1967). This, in essence, uses a reliability criterion to stop participants in the task and then assigns them an IT score. Initial stimulus presentation time was 200 ms and the initial step size in the adaptive staircase was 75 ms, which halved with each reversal. The stopping criterion was the point at which the staircase attempted to move from a step size of 2 ms to 1 ms.

Statistical Analysis

As expected, IT scores were positively skewed. Therefore a log transformation was applied to IT scores prior to performing CFA. A Kolmogorov-Smirnov test revealed that the transformed scores did not deviate significantly from a normal distribution. All CFAs were performed using WAIS-R subtest scaled scores. Confirmatory factor analysis was performed using the EQS for Windows program (Bentler, 1995) on a 486DX microcomputer. Model fit was assessed using Chi Square, the average of the off-diagonal standardized residuals, and the Comparative Fit Index (Bentler, 1995). Off-diagonal standardized residuals reflect the extent to which covariance between measured variables has not been accounted for by the models under consideration. Values for the Comparative Fit Index (CFI) can range from zero to unity; the CFI essentially expresses the fit of a model relative to what is termed the null model (the null model posits no relationship between any of the measured variables). There is general agreement that a model with a

Table 3. Descriptive Statistics for WAIS-R IQs and Inspection Time (IT)

Measure	*Mean*	*SD*	*Range*
FSIQ	105.8	12.3	71-140
VIQ	105.7	11.8	76-133
PIQ	104.9	12.9	67-139
IT (msec)	45.6	19.3	21-123

CFI of less than 0.9 should not be viewed as providing a satisfactory fit to the data (e.g. Bentler, 1989).

RESULTS AND DISCUSSION

Summary Statistics

Summary statistics (means, *SD*s and ranges) for IT and the WAIS-R Full, Verbal and Performance IQ scales are presented in Table 3. The mean Full Scale IQ of 106 indicates that the sample was of essentially average intellectual ability. Although the sample mean was above 100, inflation of the population mean is also to be expected since standardization of the WAIS-R because of the phenomenon of IQ gains (e.g. Flynn, 1987). The covariance matrix for the twelve manifest variables is presented below the diagonal of Table 4; correlations are shown above the diagonal. IT has higher correlations with Object Assembly and Digit Symbol (> .3) than with other WAIS-R subtests. Correlations between IT and summed WAIS-R scaled scores were as follows: Full Scale = –.28 ($p < .001$), Verbal = –.18 ($p = .04$), Performance = –.35 ($p < .001$).

Deriving the Basic Model

The fit of the nested factors model, consisting of *g* plus three orthogonal group factors (V, PO and A/C) was evaluated prior to imposing substantive constraints on IT's loadings on these factors. Thus in this basic model IT was free to load on all four factors. The A/C factor in variants of this model (see below) has only two indicators, Digit Span and Arithmetic. Therefore, to avoid model underidentification, the loadings for these variables were constrained to be equal. Indices of fit for this model (Model 1) are presented in Table 5. Although this model had a significant Chi Square, the comparative fit index was high (0.968) and the average of the off-diagonal standardized residuals was low (0.038). This suggests that the model had reasonable practical fit. Obtaining a significant Chi Square value for a model of ability measures is a common occurrence. Loehlin (1987) and others such as Gustaffson & Balke (1993) have suggested that a reasonable practical level of fit can be assumed if the Chi Square value for the model does not exceed twice the number of degrees of freedom. It can be seen from Table 5 that the model meets this criterion. For comparison purposes the fit of a single general factor model was also examined (Model 2). This CFI for this model was low (.826) and the average of the off-diagonal standardized residuals was high (0.07), indicating poor fit. As the single factor model is a nested variant

Table 4. Covariance Matrix (Below Diagonal), Variances (Diagonal) and Correlation Matrix (Above Diagonal) for the Eleven WAIS-R Subtests and Inspection Time (IT)

	Inf	*DSp*	*Voc*	*Ari*	*Com*	*Sim*	*PC*	*PA*	*BD*	*OA*	*DSy*	*IT*
Inf	8.297	.247	.708	.477	.589	.559	.526	.473	.397	.322	.129	-.179
DSp	2.094	8.669	.405	.466	.335	.411	.259	.385	.248	.126	.269	-.135
Voc	4.533	2.650	4.943	.459	.736	.607	.503	.493	.330	.283	.214	-.124
Ari	3.942	3.939	2.932	8.247	.426	.486	.369	.486	.417	.411	.291	-.105
Com	4.525	2.631	4.361	3.267	7.121	.583	.502	.418	.298	.270	.312	-.089
Sim	3.641	2.736	3.052	3.151	3.517	5.108	.510	.462	.462	.415	.309	-.162
PC	4.063	2.046	3.001	2.840	3.589	3.091	7.188	.511	.494	.410	.281	-.144
PA	4.171	3.471	3.351	4.273	3.415	3.196	4.190	9.354	.440	.456	.308	-.217
BD	3.386	2.164	2.176	3.553	2.357	3.093	3.924	3.986	8.787	.609	.418	-.285
OA	2.527	1.014	1.717	3.218	1.964	2.561	2.997	3.802	4.925	7.441	.351	-.324
DSy	1.024	2.184	1.316	2.306	2.298	1.928	2.084	2.603	3.427	2.644	7.632	-.318
IT	0.188	0.145	0.100	0.110	0.086	0.133	0.140	0.241	0.307	0.321	0.319	0.132

Table 5. Fit Indices for WAIS-R/Inspection Time (IT) Confirmatory Factor Analysis Models

Model	*Chi Square*	*df*	*CFI**	*AODSR*
(1) (g + 3) (orthogonal group factors, IT loading on all)	61.57	41	.968	.038
(2) g only	167.01	54	.826	.070
(3) (g + 3) (IT constrained to have zero loading on all factors)	80.24	45	.946	.062
(4) (g + 3) (IT constrained to load only on g)	72.57	44	.956	.044
(5) (g + 3) (IT constrained to load only on PO)	65.78	44	.967	0.05
(6) (g + 3) (IT constrained to load only on g and PO)	61.73	43	.971	.037

Note: CFI = Comparative Fit Index; AODSR = average off-diagonal standardized residual.

of Model 1 the relative fit of these models can be compared statistically by performing a Chi Square test on the difference in Chi Squares for the two models. The results of this procedure are presented in Table 6. Removing the group factors produced a highly significant deterioration in fit (p <.0001).

Imposing Constraints on the Factor Loadings for IT

The foregoing analysis suggested that the nested factors model constituted a good starting point from which to impose theoretically and empirically derived constraints on the loadings for IT. A series of nested variants on this basic model were therefore evaluated for fit; a significant deterioration in fit for these nested models when compared with the basic model would indicate that the hypothesis represented by the imposed constraint is not supported. The first of this series of models (Model 3) constrained IT to

Table 6. Comparisons of Model Fit for Nested Models

Comparison	*Chi Square**	*df*	*p*
Model 1 vs Model 2	105.44	13	<.0001
Model 1 vs Model 3	18.67	4	<.0001
Model 1 vs Model 4	11.00	3	<.05
Model 1 vs Model 5	4.21	3	ns
Model 1 vs Model 6	0.16	2	ns
Model 6 vs Model 5	4.05	1	<.05

Note: Value for Chi Square is derived by subtracting the Chi Square value for the less constrained model from the Chi Square value for the more constrained model. df = df for the more constrained model minus df for the less constrained model.

Table 7. Standardized Solution for the Nested Factors Model with IT Constrained to Load Only on *g* and Perceptual Organization Factors

		*Group Factors**		
Measured Variable	*g*	*v*	*po*	*a/c*
IT	-.194	0	-.388	0
Information	.697	.327	0	0
Vocabulary	.708	.651	0	0
Comprehension	.670	.401	0	0
Similarities	.752	.120	0	0
Digit Span	.479	0	0	.385
Arithmetic	.655	0	0	.395
Picture Completion	.685	0	.138	0
Picture Arrangement	.677	0	.162	0
Block Design	.570	0	.544	0
Object Assembly	.502	0	.574	0
Digit Symbol	.370	0	.363	0

Note: All zero loadings on each of the group factors were imposed. Loadings of Arithmetic and Digit Symbol were constrained to equality to avoid model underidentification.

have zero loadings on all factors; testing the "null" hypothesis that IT is unrelated to psychometric intelligence. The fit indices for this model are presented in Table 5. Comparison of this model with the basic model (Table 6) revealed that it produced a highly significant deterioration in fit ($p < .0001$). Model 4 tested the hypothesis that IT is related only to g and not the group factors by constraining it to load only on *g* (see Table 5 for fit indices). Comparison of this model with the basic model revealed that it also produced a significant deterioration in fit ($p < .05$). Model 5 tested the hypothesis that IT is related only to the PO or Performance factor by constraining IT to have zero loadings on g and the remaining two group factors. Comparison of this model with the basic model revealed that it did not produce a significant deterioration in fit ($p > .05$). Thus constraining IT to load only on PO is not significantly poorer in terms of fit than the basic model in which IT was free to load on all four factors. However, this comparison does not address whether, when IT is permitted to load on PO, a loading on *g* is unnecessary. To examine this a further model (Model 6) was specified in which IT was constrained to load on only PO and *g*. Fit indices for this model are presented in Table 5. The fit of this model did not differ significantly from the basic model (Table 6). The crucial comparison, however, is with Model 5. As can be seen from Table 6, Model 5 has a significantly poorer fit than Model 6. Model 6 is therefore to be preferred and, on the basis of the fit indices presented in Table 5, is a good fitting model: the CFI is high (.971), the average of the off-diagonal standardized residuals is low (.037) and the Chi Square value, although significant, does not exceed twice the degrees of freedom. The standardized solution for this model is presented in Table 7. It can be seen that the estimated correlation of IT with *g* is modest (-.194) but the correlation with the PO factor is substantial (-.388) and exceeds that of the majority of the WAIS-R Performance subtests. A graphical representation of Model 6 is provided in Figure 1.

CONCLUSION

One of the present authors has stated elsewhere that there is little need further to replicate the IT-IQ correlation (Deary & Stough, 1996). However, it is over 15 years since Mackintosh (1981) identified the testing of both IT and cognitive ability in a normal population sample as a priority. To our knowledge the present report is the first such attempt. It has the further advantages of using the WAIS-R and a LED-based IT device that can deliver precise durations. The main advance made here is the modelling of IT in terms of factor-referenced abilities. The study by Deary (1993) suggested that, though IT was related to *g*, its strongest association was with the performance factor of the WAIS-R. Using a more representative sample and a complete WAIS-R battery we have extended this result, employing a nested structural equation modelling approach, to show that IT is most strongly associated with the Perceptual-Organizational factor of the WAIS-R, but is only modestly related to *g*. Alternative approaches to higher-order modelling of these data are considered in Appendix.

The optimal model of IT and WAIS-R subtests fitted here (Figure 1) shows that *g* accounts for the largest portion of variance for most subtests, but that IT and Digit Symbol have the lowest *g* loadings, and the largest residual variances. IT's strongest loading is on the PO factor, which has especially high loadings for Block Design and Object Assembly. These two tests are characterized by: (a) their spatial content, (b) the need to combine fragments of a stimulus in the correct spatial orientation, and (c) the need to work at speed. Therefore, perhaps it is understandable that IT—testing the ability to make correct decisions when stimuli are presented briefly—contributes to these abilities in particular. With regard to discriminant validity, it is notable that IT did not load significantly on the A/C factor. Intuitive theories of IT performance have frequently appealed to the notion of attention (Mackintosh, 1986; Howe, 1988; Irwin, 1984) but these have not been supported here.

In conclusion, these results can be viewed as disappointing for a view which posits that basic information processing speed partly determines individual differences in *g*. Firstly, at the level of the manifest variables, the correlations between IQ and IT were modest. Secondly, confirmatory factor analysis suggests that the modest correlations may arise from shared group factor variance rather than *g* variance. In the nested factors model fitted here *g* and PO are *orthogonal.* Thus the PO factor represents variance unrelated to *g* and should not be viewed as representing fluid intelligence. One note of caution in this regard is that the *g* factor obtained from the WAIS-R is rather biased toward verbal tasks, and that a *g* factor from another test battery might be somewhat more rotated toward IT.

We believe it is time to move beyond stating broadly that IT correlates significantly with IQ. Approaches which are more specific—even than the present study—should examine IT in association with the tertiary, secondary and primary level factors of, say, Carroll's (1993) grand synthesis. This will add to the current multifaceted research effort (see Deary & Stough, 1996) that is attempting to divine the reasons for the IT-cognitive ability association and the true nature of the psychological construct(s) that contribute variance to IT performance.

APPENDIX

Alternative Hierarchical Models for Relations Between Cognitive Abilities and Inspection Time

Several alternative hierarchical models may be specified to estimate relations between latent abilities and a single observed measure of IT. One possible approach is to treat the IT measure as an indicator of ability along with the cognitive tests, and fit a higher-order model (see, e. g., Gustafsson, 1988; Gustafsson & Balke, 1993). Such a model is shown in Figure A.1.

The model is a standard higher-order model with three first-order factors (V, PO and AC) and one general factor (*g*). In the path-diagram residuals in manifest and latent variables are enclosed in circles, and are, according to the conventions of the MB meta-language for structural equation models (Gustafsson & Stahl, 1997) assigned a label which is formed through appending an "&" to the label of the corresponding dependent variable. This model can easily be estimated with any structural equation modeling program, and here the ML estimator of the LISREL 8 program (Joreskog & Sorbom, 1996) has been used. The standardized parameter estimates are presented in Figure A.1. PO has a standardized loading of .84 on *g*, and IT has a loading of .34 on PO. This implies that the relation between *g* and IT is .84 × .34 = .29. To obtain the relation between IT and the part of PO which remains after *g* has been partialed out, the loading of IT on PO should be multiplied with the relation between PO& and PO, which is .54. This product is .18, which thus is the estimate of the relationship between the first-order PO-factor and IT.

One problem, however, with this model is that it is quite constrained. The relations between abilities at different levels and a manifest variable thus are multiplicative functions of the parameters of the model. To get an unconstrained determination of the amount of relationship between IT and the ability factors, a model is needed which does not impose any restrictions, except empirical ones. To specify such a model within the higher-order modeling framework, the IT variable may be moved from the measurement model, and instead be regressed as a dependent variable on the ability factors. Such a model is shown in Figure A.2.

In this model *g* and PO are used as the independent variables. It should be observed that PO must not be used as an independent variable, because that would cause an indirect relation involving *g* and PO, in addition to the direct relation with PO. According to this model the standardized estimate of the relation between IT and *g* is .19, and the relation with PO& is .41. Another possibility is to specify the model as a nested-factor model (Gustafsson & Balke, 1993), as is done in the present paper. This model yields essentially the same estimates as does the higher-order model.

The estimates of the relative importance of *g* and PO thus are quite different when obtained from a model in which the relation between the second-order factor and the IT measure goes through a first-order factor (Figure A.1), compared to when the IT-measure is regressed directly upon the ability factors (Figure A.2). Because the constraints in Figure A.1 are essentially arbitrary, there is reason to put more reliance on the less constrained estimates obtained with the model in Figure A.2, or with the nested-factor model employed in the paper.

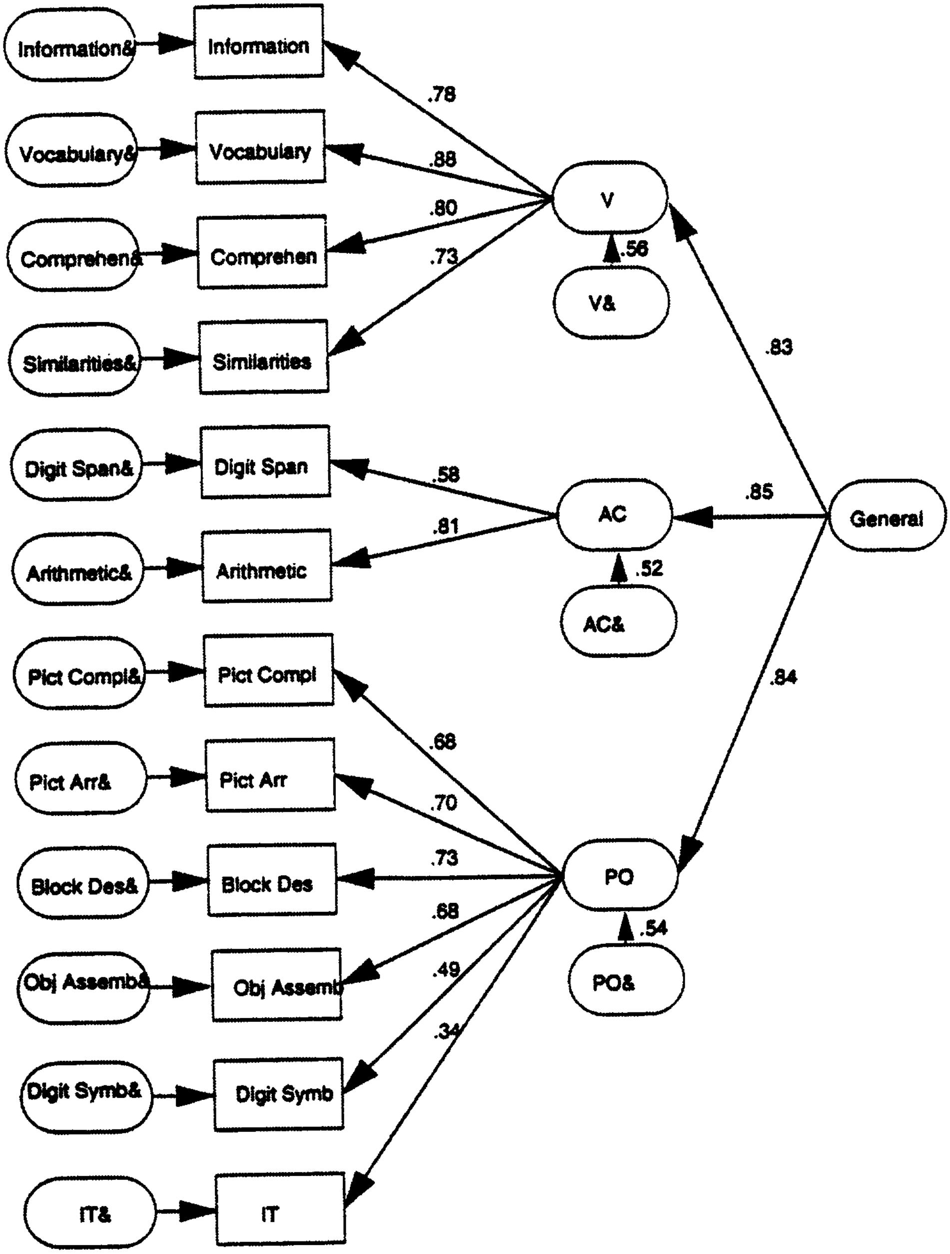

Figure A.1. Higher-order model which treats the IT measure as an indicator of ability along with the cognitive tests. For explanation of terms see text of Appendix.

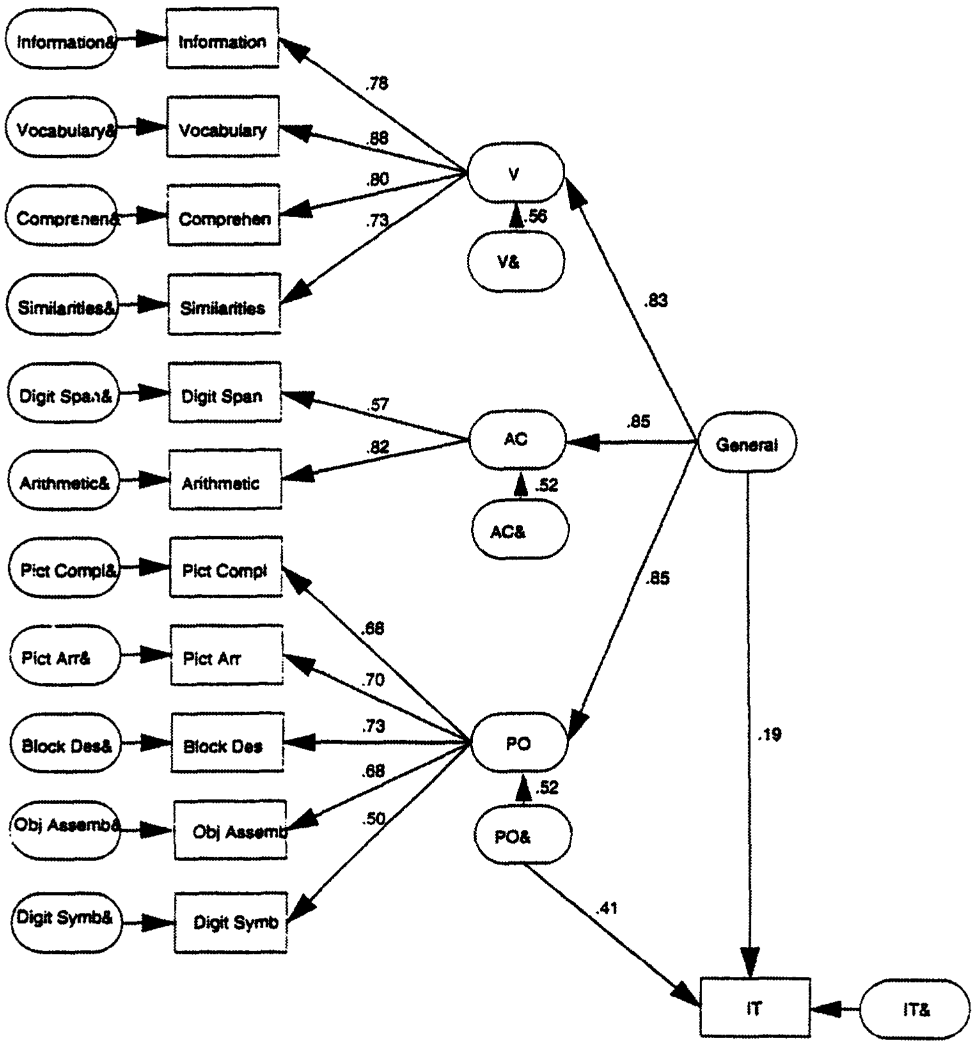

Figure A.2. Higher-order model which moves the IT variable from the measurement model and regresses IT as a dependent variable on the ability factors. For explanation of terms see text.

NOTE

1. Following a referee's comments we evaluated the fit of the basic nested factors model for the WAIS-R alone (i.e. excluding IT from the analysis). The CFI for this model was .97 and the average of the off-diagonal standardized residuals was .037. Chi Square for this model was 51.52 with 34 degrees of freedom. Thus the model of the latent structure of the WAIS-R, ignoring IT, fulfills all the criteria noted above. It can therefore be regarded as having good fit.

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