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What Needs to Be Explained to Account for Age-Related Effects on Multiple Cognitive Variables?

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Structural equation methodology was used to investigate age-related influences across a number of cognitive variables in 204 adults ranging from 18 to 91 years of age with a hierarchical structure that contained 4 1st-order factors and 1 2nd-order common factor. Direct age relations were found to the common factor as well as to 1st-order speed and memory factors. Replicability of the findings was explored by investigating the same structure of age relations, using 2 different data sets, and a similar pattern was found in each. These results suggest that at least 3 statistically distinct types of age-related influences are operating on a wide variety of cognitive variables and presumably require separate explanatory mechanisms.

It has been recognized from the earliest studies of aging and cognition that increased age is associated with lower performance on an assortment of different cognitive tasks (e.g., Foster & Taylor, 1920; Jones & Conrad, 1933). Over the past 20 years a variety of multivariate analytical procedures have been used to attempt to characterize the nature of age-related effects on different cognitive variables. Because it can be argued that researchers who have focused on a single variable have implicitly assumed that the age-related effects on that variable are independent of age-related effects on other variables, one analytical model that has been investigated is a complete independence model in which each variable has a separate and distinct age-related influence. Models of this type have invariably been found to provide very poor fits to the data (e.g., Salthouse, 1998, 2001; Salthouse & Czaja, 2000), and thus there is little support for the view that each cognitive variable has an independent age-related influence. Moreover, to the extent that the number of distinct age-related influences is less than the number of variables exhibiting age-related differences, it seems likely that this will also be the case for the number of independent explanatory mechanisms needed to account for these effects. However, the question remains as to how many distinct explanatory mechanisms are required to account for the age-related declines in different cognitive variables, and more complex types of multivariate analytical models have been used to attempt to answer this question.

Among the first analytical models used to investigate age-related effects on cognitive variables were mediational models. These models typically examined the effect of partialling or otherwise controlling one or more variables on the relations of age to another variable. Some of the earliest analyses were based on partial or semipartial correlations (e.g., Horn, Donaldson, & Engstrom, 1981; Salthouse, 1985), but later analyses have been based on hierarchical regression, path analyses, or structural equation models. A very large number of reports has now been published of mediational models with speed, working memory, inhibition, or some other construct serving as the hypothesized mediator of at least some of the effects of aging on cognitive variables (e.g., Anstey, Lusczc, & Sanchez, 2001; Hambrick, Salthouse, & Meinz, 1999; Persad, Abeles, Zacks, & Denberg, 2002; Salthouse, Fristoe, McGuthry, & Hambrick, 1998; Verhaeghen & Salthouse, 1997).

Motivated in part by the discovery that certain noncognitive variables (e.g., measures of visual acuity, auditory sensitivity, grip strength, and lower limb strength) shared age-related variance with cognitive variables, common cause or shared influence models were proposed in which age was assumed to have broad effects on whatever is common to many different types of variables (e.g., Anstey & Smith, 1999; Christensen, Mackinnon, Korten, & Jorm, 2001; Deary, 2000; Kliegl & Mayr, 1992; Lindenberger & Baltes, 1994; Lindenberger, Mayr, & Kliegl, 1993; McArdle & Prescott, 1992; Salthouse, 1994, 1996; Salthouse, Fristoe, & Rhee, 1996; Salthouse, Fristoe, et al., 1998; Salthouse, Toth, Hancock, & Woodard, 1997; Verhaeghen & Salthouse, 1997).

Mediational and shared influence models are based on somewhat different analytical procedures and assumptions, but both can provide quantitative estimates of shared and unique age-related influences on cognitive variables or constructs. That is, the models do not simply indicate whether a particular type of age-related effect exists, but they also indicate its relative magnitude. Mediational models assume that the target construct is a mediator of at least some of the age-related influences on other variables, and consequently they yield estimates of mediated (or shared) and direct (or unique) age-related effects on the target variables. Common cause or shared influence models do not assume that any particular variable or construct has a privileged status as a mediator, but instead they postulate that the age-related effects on many variables are at least partially a reflection of age-related effects on

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whatever is common to them all. Models of this type yield estimates of shared (through the common factor) and unique (direct) age-related effects on the target variables, although the direct effects are sometimes merely inferred on the basis of the difference between the observed age effect and the effect estimated through the indirect paths. Quantitative estimates of the magnitude of shared age-related effects have varied across studies, but they have almost always been found to be greater than zero, and frequently were substantially larger than the unique effects of age on the variables. A conclusion from mediational and shared influence models has therefore been that at least some of the age-related effects on many cognitive variables are shared, and hence that mechanisms are needed to account for broad, as well as specific, age-related influences.

However, a limitation of mediational and shared influence models is that they ignore most of the relations among variables that do not involve age. That is, although they are useful for obtaining estimates of the degree to which age-related influences on different variables are independent, these models neglect a vast amount of psychometric research establishing that cognitive variables are typically positively related to one another. Indeed, Deary (2000) has characterized this positive manifold phenomenon as “arguably the most replicated result in all psychology” (p. 6).

There is little dispute about the existence of multiple first-order ability factors (e.g., Carroll, 1993), but a number of alternative organizations of first-order factors can be postulated. For example, four different models with various cognitive abilities are portrayed in Figure 1. Model A is the simplest possible structure with first-order ability factors because the factors are assumed to be completely independent of one another. Model B differs from Model A in that the factors are assumed to be correlated with one another rather than completely independent. Because correlations in structural equation models represent causes of covariation that are not explicit in the model, Model B can be interpreted as acknowledging the existence of relations among the factors without attempting to explain them.

Model C is a hierarchical model in which the correlations among the first-order factors are accounted for by a higher order factor. That is, instead of leaving the relations among factors unexplained as in Model B, the hierarchical model postulates that the relations are attributable to a common higher order influence. There is currently some consensus on a hierarchical structure of cognitive abilities in which one or more second-order and possibly even third-order factors are postulated to exist at a level above the first-order factors (e.g., Brody, 1992; Carroll, 1993; Deary, 2000; Gustafson, 1984; Jensen, 1998).

Models B and C are similar in that both attempt to partition the variance in the first-order factors into shared and unique aspects. However, it is important to note that when age-related influences are considered in the models, there is no possibility in Model B of examining relations of age to variance that is shared among the first-order factors (because age cannot be related to correlations), whereas in Model C it is possible to examine the relations of age to the second-order factor that represents variance common to the first-order factors.

Model D represents an alternative partitioning of the variance with common and ability-specific factors both operating at the level of observed variables. That is, two sets of orthogonal first-order factors are specified by simultaneously estimating a factor common to all variables in addition to factors specific to particular groups of variables (e.g., Schmiedek & Li, 2002). Because the common factor in this type of analysis is extracted at the level of observed variables rather than at the level of first-order factors, the common factors in Models C and D may not be equivalent, and it is an empirical question whether the pattern of age-related influences on the common and first-order factors in the two models would be similar.

Methodological Concerns in Multivariate Analyses of Aging and Cognition

A major goal of the current article was to examine age-related effects on a set of cognitive variables using the multivariate models just described. However, several concerns have recently been raised about multivariate analyses in aging and cognition. A certain number of reservations should probably be expected with respect to any analytical procedure, but they can vary with respect to the severity or pervasiveness of the problem. In the following paragraphs, we discuss some of these issues and suggest that the concerns may not be as serious, and the analytical methods not as flawed, as sometimes implied.

One issue is that because most of the analyses have relied on cross-sectional data, they are severely limited with respect to possible inferences about processes of aging. There is little dispute that the strongest conclusions about aging at the level of individuals requires longitudinal data with sufficiently long intervals between observations to detect any age-related effects that might be occurring, and that it is desirable to include a broad variety of variables, to document reliability of the changes, and to rely on analytical methods that can distinguish practice effects and time-of-measurement effects from age changes. Few data sets approach this ideal, but it is noteworthy that evidence of shared age-related effects across different types of cognitive variables has been reported in several recent longitudinal studies (e.g., Hertzog, Dixon, Hultsch, & MacDonald, 2002; Hultsch, Hertzog, Dixon, & Small, 1998; Lindenberger & Ghisletta, 2002; Wilson et al., 2002; Zelinski & Kennison, 2002; Zimprich, Martin, & Rott, 2002).

Although for many purposes longitudinal data would be preferred, it is nevertheless important to recognize that large cross-sectional age differences have been reported on many different cognitive variables, and consequently it is meaningful to attempt to characterize the nature of these effects. In this respect it is productive to consider an analogy with sex-related cognitive differences. A researcher might have little interest in speculating about how sex differences in cognitive functioning originated, or how they might evolve over time, but he or she might nevertheless be very interested in determining the level at which sex-related influences operate in a structure of cognitive abilities. We argue that the same is true for cross-sectional age differences in cognition, regardless of what might eventually be found with longitudinal data.

A second concern is that models in which age is represented as a causal factor may be misleading. That is, age is best conceptualized as a continuum along which influences occur rather than as a causal influence itself, and because it cannot be experimentally manipulated or randomly assigned, research involving age (longitudinal as well as cross-sectional) is only correlational and not causal. Although we agree with both of these points, we believe that it is still meaningful to examine models in which age is treated

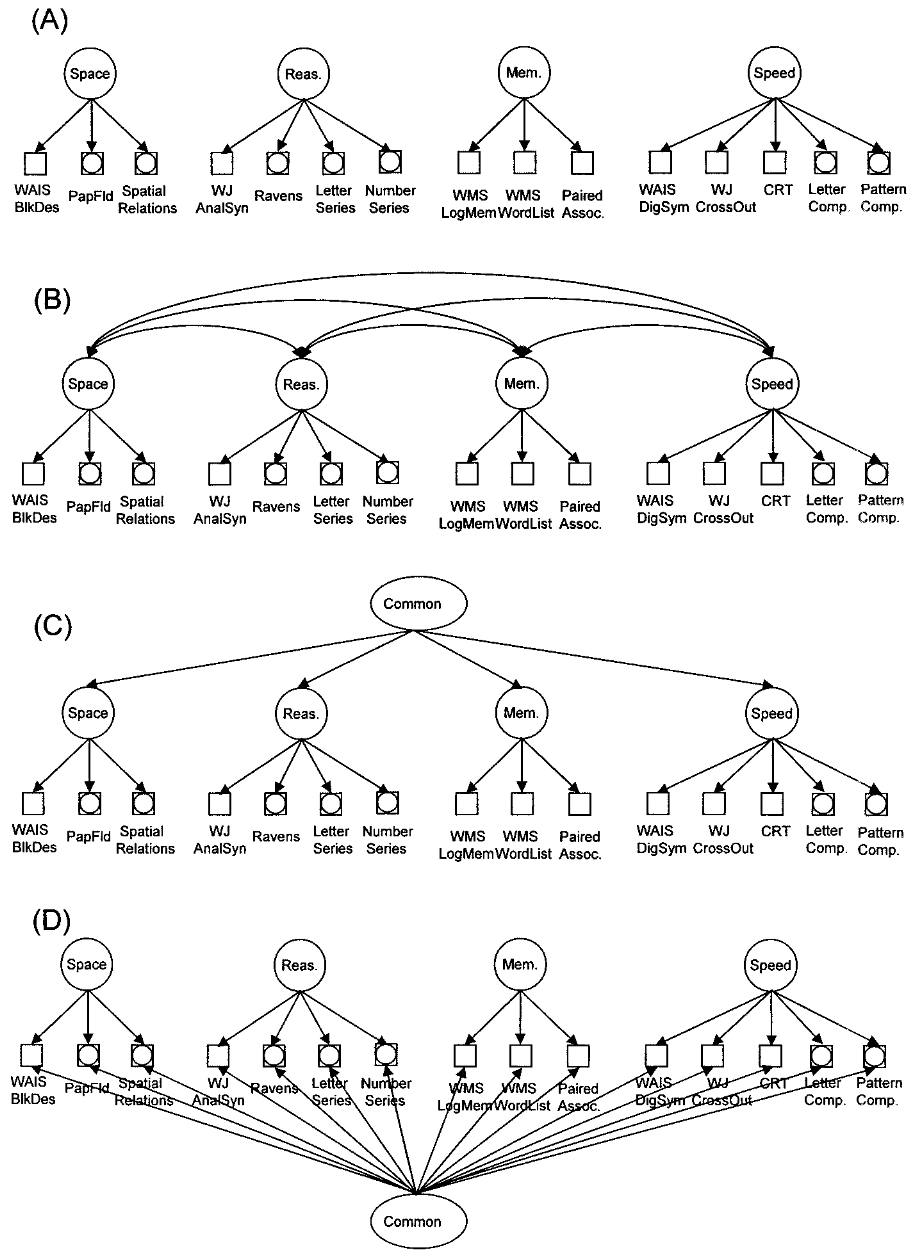

Figure 1. Four alternative structures with four first-order ability factors. See text for complete details about the variables.

as a potentially causal variable. One reason is that even though age does not cause the observed effects, it is a convenient index of the cumulative impact of the causal influences and thus it is useful as a proxy for the as-yet-unknown true causes. A second reason is that although correlation does not imply causation, causation does imply correlation. Therefore, whereas one cannot infer causation from a pattern of correlational results, patterns of correlations are relevant to the plausibility of causal hypotheses. Analytical models that include age as an exogenous, potentially causal, variable are thus useful in evaluating the plausibility of different causal hypotheses.

A third concern about prior multivariate analyses of age–cognition relations is that most of the analyses have focused exclusively on variables with negative age correlations, and, consequently, a potentially misleading impression of adult cognition may have been reached when aspects that improve or remain stable with age were ignored. Of course, it is eventually desirable to obtain a complete portrayal of cognitive effects by including as many different types of variables as possible and exploring interrelations between variables with both negative and positive age relations. However, it should be recognized that the goal of many of the prior analyses has been to investigate the nature of age-related cognitive decline; thus, variables that do not exhibit decline are not directly relevant to the phenomenon under investigation. Furthermore, models with both negative and positive age relations are likely to be relatively complex, and, at least initially, faster progress might be expected by focusing on simpler models.

A fourth issue with respect to multivariate analyses of age-heterogeneous data is that some of the covariation among variables may be induced by the relation of each variable to age. This spurious correlation problem is well recognized in correlational research, and it has been discussed many times in the context of research in aging (e.g., Hofer & Sliwinski, 2001; Lindenberger & Potter, 1998; Salthouse, 1985, pp. 127–128, p. 312; Salthouse, Fristoe, et al., 1998). Two different methods have been used to investigate the possibility of spurious correlations in aging research. One involves partialling the variation associated with age when examining the relation between two or more other variables (e.g., Salthouse, 1998; Salthouse, Hambrick, & McGuthry, 1998). This method controls the influence of age at the average level of age in the sample, but the possibility that the relations among variables vary as a function of age can be investigated by examining interactions of age and one variable in the prediction of the other variable (cf. Salthouse & Nesselroade, 2002). A second method that can be used to investigate the possibility that correlations are spuriously induced by the relations of the variables to age involves examining the relations among variables in a sample with a narrow age range. There is necessarily a tradeoff between sample size and narrowness of the age range unless the samples are very large, but several studies have reported similar relations in adults at different age ranges, such as under and over the age of 50 (e.g., Salthouse, 2001; Salthouse, Hambrick, et al., 1998; Verhaeghen & Salthouse, 1997) and in comparisons with a group within a very narrow age range (Salthouse, 1998).

Another issue concerning multivariate analyses is that under certain circumstances the relations among variables can become quite complicated. Specifically, it has recently been shown that the effects of controlling one variable (*Z*) on the relations between two other variables (*X* and *Y*) depend on the relation between *Y* and *Z* that is independent of *X* (Lindenberger & Potter, 1998). Although in their report the authors emphasized a scenario based on hierarchical regression analytical procedures with *X* as age and *Y* and *Z* as cognitive variables, the phenomenon they described does not appear to be restricted to certain types of variables or to particular analytical procedures. That is, the dependence could presumably occur whenever relations among three or more variables are examined, whether this is in the context of cross-sectional, longitudinal, or nondevelopmental research, and regardless of the specific type of multivariate analysis in which statistical control procedures are used (e.g., analysis of covariance, multiple regression, commonality analysis, path analysis, structural equation modeling, etc.). Virtually all multivariate analytical procedures therefore appear to be vulnerable to this problem, and not simply analyses based on cross-sectional comparisons of cognitive variables.

Although the analyses described by Lindenberger and Potter (1998) are elegant and convincing, the practical implications of the problem, and precautions that might be taken to avoid it, are not yet obvious. Many other conditions have been identified that could lead to distorted estimates in multivariate analyses, such as unreliability, restriction of range, use of groups from the extremes of a distribution instead of sampling throughout the entire distribution, nonlinear relations between variables, and so on. With each of these other problems, methods are available for their detection, and in some cases corrections can be applied to minimize their consequences. However, this does not appear to be the case for the problem identified by Lindenberger and Potter (1998), as there is currently little information about the prevalence or the severity of the problem, nor is it obvious what can be done if one is concerned about it. The authors did mention three implications of their analyses: (a) Interpretations should be based on theoretical considerations, and not exclusively on the results of a particular analysis; (b) convergence should be sought with additional analytical or experimental methods that are not based on examining relations among two or more variables after controlling the effects of other variables; and (c) researchers should be careful in stating the conclusions of their analysis. With respect to this last point, Lindenberger and Potter suggested that instead of claiming that the effects of *X* on *Y* are partially attributable to effects of *X* on *Z*, a more accurate characterization would be that the effects of *X* on *Y* are partially attributable to variation in *Z* (i.e., not simply on the relation between *X* and *Z*). Although these recommendations are all reasonable, unfortunately they do not help either in the detection of the problem or in its remedy, should it be suspected to be serious.

A final consideration that has been mentioned with respect to multivariate analyses in research on aging and cognition is that it is important to consider, and evaluate, alternative models of the structural relations (e.g., Allen et al., 2001). This is a familiar principle in the literature on structural equation modeling because it is widely recognized that almost all data are consistent with many potential models, and thus it is often more informative to learn which models are not consistent with the data rather than which are consistent with it (MacCallum, Wegener, Uchino, & Fabrigar, 1993; McDonald & Ho, 2002). However, several issues should be recognized when comparing the fit of alternative structural equation models.

First, both absolute and relative fit of the models should be considered. Absolute fit is informative because if the absolute fit is low, then a finding that one model fits better than another is not very interesting because neither is very accurate at reproducing the interrelations among the variables. On the other hand, if the absolute fit is high and both models can reproduce the interrelations among the variables fairly accurately, then the differences between them may be rather minor. That is, what the models have in common may be more important in accounting for the interrelations among the variables than what distinguishes them.

Relative fit is clearly important because it indicates which of the models more accurately reproduces the relations among the variables. However, not all alternative models are equally plausible or meaningful, and thus a strong rationale should be provided for the alternative models that are to be compared. To illustrate, it is usually not informative to discover that a model with no relations among the variables does not provide a good fit to the data. Furthermore, because the fit of a model can often be improved for theoretically irrelevant reasons, it may not be reasonable to treat such alternatives as meaningful unless they have a clear theoretical justification (McDonald & Ho, 2002). Statistical power also needs to be considered when evaluating relative fit because some theoretical models may not be distinguishable with the data sets typically available in aging studies (e.g., samples of less than 400 individuals and moderate correlations among most variables).

Another issue with respect to model comparisons is that the fit of the measurement model, which in this context we refer to as the representation of the relations among variables ignoring age, should be considered when evaluating the fit of the corresponding structural model that incorporates relations of age to the components of the measurement model. That is, one structural model may provide a better fit than another not because it is necessarily more accurate at representing the age-related influences, but because it is more accurate at representing interrelations among the other variables. Unfortunately, there do not appear to be any statistical tests to compare the change in fit from a measurement specification (neglecting age) to a structural specification (including age) across different sets of models, because addition of another variable results in a qualitative change in the model. Nevertheless failure to consider differences in the fits of the respective measurement models when evaluating differences in the fits of structural models can result in potentially misleading conclusions.

To summarize, a major goal of the current study was to examine the plausibility of four alternative structures of age-related influences on a broad set of cognitive variables. A second goal was to investigate the robustness of a hierarchical structure in different age groups and in data after partialling effects of age from all variables. The third goal was to examine the applicability of the hierarchical structure to variables not used in the creation of the structure. These extension analyses are informative because they indicate the degree to which age-related influences on new variables can be interpreted in terms of influences on the structure. A final goal was to compare age-related effects on the hierarchical structure with effects associated with another individual difference variable, namely, sex differences.

The primary analyses to be reported are based on a new cross-sectional data set involving 19 variables from 204 adults between 20 and 91 years of age. However, in order to examine the generalizability of the results, parallel analyses are reported on two earlier data sets, and results are also reported from an aggregate analysis based on the data combined across the three data sets.

Method

Participants

Participants were recruited from advertisements and referrals from other participants, and they received $100 for completing three sessions of approximately 2 hr each. Characteristics of the sample, arbitrarily divided into three age groups, are summarized in Table 1. It can be seen that the sample was highly educated and generally healthy, although increased age was associated with somewhat poorer ratings of self-reported health. (Partialling the health variable from the correlations between age and the cognitive variables only slightly reduced the magnitude of the correlations, from a median of −.47 to a median of −.41; thus, the health variable was ignored in subsequent analyses.) The representativeness of the sample can be determined by converting the scores from the standardized Wechsler tests into age-adjusted scaled scores (cf. Salthouse, 2000; Salthouse & Czaja, 2000). These age-adjusted scores, also reported in Table 1, indicate that the sample performed between 0.5 and 1.0 *SD*s above the nationally representative normative sample and that there was little relation between age and the age-adjusted scaled scores.

Only partial data are available from the first 54 participants because several new tasks were added to the research protocol for the remaining participants. However, the two subsamples were very similar on the variables common to both and thus they were treated together.

Variables

The variables included in the analyses are summarized in Table 2. Also included in this table are the source of the variable, the sample size for the variable, and an estimate of its reliability. It can be seen that the reliability estimates were generally in the acceptable range, with a median of .82 and only one value below .68. The first 15 variables in the table were used in

Table 1
Descriptive Characteristics of the Sample

	Age group						
	20–39		40–59		60–91		
Characteristic	*M*	*SD*	*M*	*SD*	*M*	*SD*	Age *r*
N	52		84		68		
Age (years)	27.9	5.7	49.5	5.9	70.0	7.4	
Self-rated health	1.9	0.8	1.9	0.9	2.5	0.8	.27*
Years of education	15.5	2.7	16.2	2.3	16.1	2.5	.09
% women	75		70		53		−.19*
Age-adjusted scores							
Vocabulary	13.0	4.0	13.6	2.8	13.3	2.9	.01
Block Design	13.1	2.9	11.9	2.8	11.8	2.7	−.02
Digit Symbol	11.5	4.0	11.8	3.2	11.6	3.3	−.14*
Letter Number	12.1	3.3	12.1	3.1	11.9	2.8	−.10
Logical Memory	13.7	3.0	13.0	3.0	12.5	2.7	−.03
Word List	12.9	3.3	12.4	3.1	12.1	2.7	−.13

Note. Health was rated on a 5-point scale (1 = *excellent*, 5 = *poor*). Vocabulary, Block Design, Digit Symbol and Letter Number are from the Wechsler Adult Intelligence Scale—Third Edition (Wechsler, 1997a), and Logical Memory and Word List are from the Wechsler Memory Scale—Third Edition (Wechsler, 1997b). The values for these variables are age-adjusted scaled scores, which have a mean of 10 and a standard deviation of 3.
* $p < .01$.

Table 2
Characteristics of Variables

Label	Description	*N*	*M*	*SD*	Est. rel.
1 - BlkDes	WAIS–III Block Design (Wechsler, 1997a)	204	40.8	13.9	.83
2 - PapFld	Paper Folding (Ekstrom et al., 1976)	150	6.7	3.1	.83
3 - SpaRel	Spatial Relations (Bennett et al., 1997)	150	9.8	5.3	.90
4 - AnalSyn	WJ–R Analysis Synthesis (Woodcock & Johnson, 1989)	204	26.0	5.0	.91
5 - Ravens	Odd-numbered items from Raven's (1962)	150	7.6	3.4	.80
6 - LetSer	Letter Series Completion (Noll & Horn, 1998)	150	9.7	3.2	.80
7 - NumSer	Number Series Completion (Salthouse & Prill, 1987)	150	3.1	1.2	.78
8 - LogMem	WMS–III Logical Memory (sum idea units recalled across 3 stories)	204	45.1	11.4	.80
9 - Recall	Sum of score across 4 trials in WMS–III (Wechsler, 1997b) Word List	204	36.5	5.7	.91
10 - PairAs	Average number of correct pairs across 2 trials	204	2.7	1.6	.68
11 - DigSym	WAIS–III Digit Symbol (Wechsler, 1997a)	204	76.8	19.3	.84
12 - CrossOut	WJ-R Cross Out (Woodcock & Johnson, 1989)	204	119.3	23.8	.78
13 - CRT	Four-alternative choice reaction time	204	601	230	.95
14 - LetCom	Letter Comparison (Salthouse & Babcock, 1991)	150	11.0	2.6	.88
15 - PatCom	Pattern Comparison (Salthouse & Babcock, 1991)	150	18.0	3.6	.88
16 - Recall B	WAIS–III Recall of new list after 4 trials of old list (Wechsler, 1997b)	204	6.6	2.0	.44
17 - Directions	Report final direction after a series of turns (Craik & Dirkx, 1992)	150	3.5	1.5	.82
18 - LetNum	WAIS–III Letter Number Sequencing (Wechsler, 1997a)	204	11.8	3.2	.82
19 - ConnDif	Difference between connecting items in alternation versus connecting them in sequence (Salthouse et al., 2000)	150	13.0	5.7	.76

Note. For most variables the coefficient alpha index of internal consistency was used as the estimate of reliability (Est. rel.). The correlation among parts boosted by the Spearman–Brown formula was used for the NumSer, LogMem, Recall, PairAs, CRT, LetCom, and PatCom variables, and the test–retest values from the manuals were used for DigSym and CrossOut. WAIS–III = Wechsler Adult Intelligence Scale—Third Edition; WJ–R = Woodcock–Johnson Tests of Cognitive Ability—Revised; WMS–III = Wechsler Memory Scale—Third Edition.

the primary analyses, and the remaining four were used in a separate set of extension analyses to explore the applicability of the structural model to new variables. The correlation matrix for these variables as well as the age and sex variables, with the latter coded 0 for male and 1 for female, is presented in Table 3.

Four vocabulary tests (Wechsler Adult Intelligence Scale—Third Edition [WAIS–III] Vocabulary Scale; Wechsler, 1997a; Woodcock–Johnson Revised Picture Vocabulary; Woodcock & Johnson, 1989; and Antonym and Synonym Vocabulary tests from Salthouse, 2001) were also administered. Because these variables had positive correlations with age (i.e., .06, .27, .12, and .22, respectively), they were not included in the current analyses, which were designed to investigate the dimensionality of age-related declines in cognitive functioning.

Data Analytic Strategy

The analytical strategy in the current project involved the following steps. First, the fit of the four models portrayed in Figure 1 with four first-order ability factors was examined without consideration of age. These models were termed measurement models because the primary variable of age was not explicitly included in the models. Next, age was introduced into the four models, which were then termed structural models. In Models A and B age was only related to the first-order factors, but in Models C and D relations of age were examined to the first-order factors and to the common factor. Models B and C are similar in that both attempt to partition the variance in the first-order factors into shared and unique aspects. Furthermore, to the extent that the correlations among first-order factors in Model B represent the same shared variance as the second-order common factor in Model C, the relations of age to the first-order factors would be expected to be similar in the two models when there is no relation specified between age and the second-order factor. In Models C and D age-related effects were also examined at the level of individual variables in addition to the first-order and second-order factors. Age-related influences in Model C were examined following the logic described by Carroll (1993, p. 623), in which influences are evaluated starting from the highest level in the hierarchy and proceeding to successively lower levels because it is not meaningful to examine (or even to identify) unique effects until shared effects have first been extracted. However, it is important to realize that the same end result will be obtained when proceeding from either the top-down or bottom-up direction as long as the parameters are not fixed after any particular step.

The degree to which the hierarchical structure (Model C) was invariant across age was then examined by partialling age and by comparing models for samples under and over the age of 50. Finally, age-related effects were examined on new variables to determine whether they could be interpreted in terms of age-related influences on the existing structure.

Results and Discussion

In order to illustrate the age trends in the data, composite scores were formed by averaging the *z* scores from the variables identified in the measurement models (described later) as representing distinct factors. These scores are plotted as a function of age in Figure 2. It can be seen that there were sizable age relations on each composite score, with a cumulative difference of approximately 2 *SD*s across the range from 25 to 75 years of age. Correlations between age and the composite scores were −.73 for speed, −.55 for memory, −.50 for reasoning, and −.43 for space.

Structural Equation Analyses

The structural equation analyses were conducted with the AMOS 4.0 (Arbuckle & Wothke, 1999) program using the Full Information Maximum Likelihood (FIML) algorithm for missing data (because the first 54 participants were not administered all of the tasks). The advantages of this algorithm for estimating missing data are described in Arbuckle and Wothke (1999, pp. 332–333), among the most important of which is that it has been found to

Table 3
Correlation Matrix for Variables Included in Analyses of Data Set A

Variable	1	2	3	4	5	6	7	8	9	10	11
1	—										
2	.76	—									
3	.80	.80	—								
4	.60	.58	.57	—							
5	.69	.75	.72	.63	—						
6	.74	.71	.67	.72	.75	—					
7	.56	.60	.53	.54	.65	.74	—				
8	.46	.52	.51	.43	.54	.60	.56	—			
9	.47	.49	.44	.51	.60	.58	.49	.59	—		
10	.54	.57	.53	.48	.55	.54	.43	.54	.66	—	
11	.44	.47	.41	.50	.61	.60	.54	.41	.61	.52	—

	12	13	14	15	16	17	18	19	Age	Sex
1	.51	.52	.29	.45	.44	.59	.40	.26	−.37	−.21
2	.49	.52	.29	.49	.40	.61	.46	.21	−.43	−.10
3	.49	.45	.24	.47	.41	.61	.43	.14	−.38	−.12
4	.46	.50	.29	.35	.42	.57	.46	.19	−.36	−.10
5	.63	.56	.47	.56	.45	.61	.52	.34	−.56	−.03
6	.60	.57	.43	.52	.45	.69	.56	.32	−.47	−.09
7	.47	.46	.43	.44	.33	.59	.58	.22	−.37	−.07
8	.39	.38	.25	.43	.51	.47	.41	.08	−.32	.04
9	.54	.47	.41	.56	.68	.52	.46	.36	−.57	.18
10	.50	.54	.30	.43	.62	.54	.42	.26	−.51	.08

	11	12	13	14	15	16	17	18	19	Age	Sex
11	—									−.68	.17
12	.75	—								−.71	−.01
13	.59	.55	—							−.51	.06
14	.64	.63	.36	—						−.53	.11
15	.63	.71	.49	.59	—					−.63	.04
16	.46	.44	.44	.32	.41	—				−.44	−.03
17	.53	.49	.44	.34	.39	.48	—			−.40	−.09
18	.44	.44	.50	.39	.50	.43	.41	—		−.40	.04
19	.52	.54	.38	.39	.47	.21	.19	.28	—	−.60	.10

Note. Correlations with an absolute magnitude greater than .18 are significantly different from zero ($p < .01$). Variable identifiers are presented in Table 2.

yield efficient and robust estimates. Although the primary analyses were conducted with the FIML algorithm, it is important to note that analyses based on only the 150 participants with complete data yielded an identical pattern of results with very similar parameter estimates. A number of fit statistics were considered when evaluating model fit, including the chi-square test, which evaluates discrepancy between the model and the data, and the nonnormed fit index (NNFI), comparative fit index (CFI), and root-mean-square error of approximation (RMSEA; Kline, 1998). The NNFI and the CFI statistics represent improvement compared to an alternative model; therefore, values closer to 1:0 correspond to better fit. The RMSEA is a measure of the discrepancy between the predicted and observed values; therefore, values closer to 0 correspond to better fit.

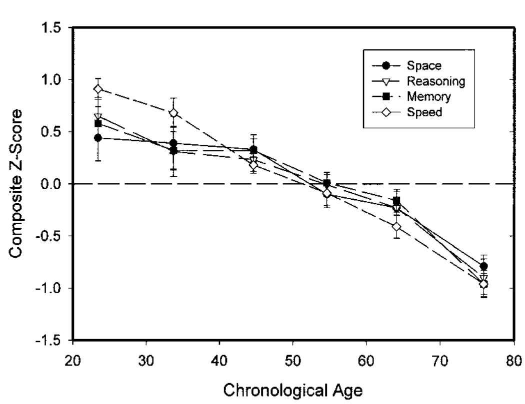

Figure 2. Mean (and standard error) of composite scores for space, reasoning, memory, and speed as a function of age.

Measurement Models

Fit statistics for the four measurement models portrayed in Figure 1 are summarized in the top part of Table 4. It is apparent that the model with independent first-order factors (Model MA) provided a poor fit to the data, but that the other three models had good fits. This pattern of results implies that the variables are related to each other beyond the grouping into first-order ability factors because the model with only that grouping was not very accurate at reproducing the relations among the variables. The fits of Models B (MB), C (MC), and D (MD) were slightly different,

Table 4
Structural Equation Model Fit Statistics

Model	χ^2	*df*	NNFI	CFI	RMSEA (90% CI)	$\Delta\chi^2/\Delta df$
Measurement model						
MA: Four independent 1st-order factors	709.49	91	.905	.928	.183 (.171, .196)	
MB: Correlated 1st-order factors	163.07	84	.987	.991	.068 (.052, .084)	546.42/7, $p < .01$
MC: Hierarchical model	187.04	87[a]	.984	.988	.075 (.060, .090)	23.97/3, $p < .01$
MD: Orthogonal common and 1st-order ability factors	130.05	76	.990	.994	.059 (.041, .076)	
Structural models including age relations						
SA1: Age to independent 1st-order factors	553.40	102	.935	.951	.148 (.136, .160)	
SB1: Age to correlated 1st-order factors	179.30	95	.987	.991	.066 (.051, .081)	
SC0: Age to 1st-order factors but not to common	193.33	98	.986	.990	.069 (.055, .084)	
SC1: Age to common	277.24	101	.974	.981	.093 (.080, .106)	
SC2: Age to common and speed	209.96	100	.984	.988	.074 (.060, .088)	62.71/1, $p < .01$
SC3: Age to common, speed, and memory	195.38	99	.986	.990	.069 (.055, .083)	14.58/1, $p < .01$
SC4: Age to common, speed, memory, and space	193.33	98	.986	.990	.069 (.055, .084)	2.05/1, $p > .15$
SC5: Age to common, speed, memory, and reason	193.33	98	.986	.990	.069 (.055, .084)	2.05/1, $p > .15$ (vs. SC3)
SC6: Model SC3 plus age to Ravens, and age to Logical Memory	166.42	97	.989	.993	.059 (.044, .074)	28.96/2, $p < .01$ (vs. SC3)
SD0: Age to 1st-order factors but not to common	198.15	87	.981	.988	.079 (.065, .094)	
SD1: Age to common	226.61	90	.978	.985	.096 (.073, .101)	
SD2: Age to common and speed	154.11	89	.989	.993	.060 (.044, .076)	72.50/1, $p < .01$
SD3: Age to common, speed, and memory	135.15	88	.992	.995	.051 (.033, .068)	18.96/1, $p < .01$
SD4: Age to common, speed, memory, and space	132.28	87	.992	.995	.051 (.032, .067)	2.87/1, $p > .05$
SD5: Age to common, speed, memory, and reason	133.24	87	.992	.995	.051 (.032, .067)	1.91/1, $p > .15$ (vs. SD3)
SD6: Model SD3 plus age to Ravens, and age to Logical Memory	115.75	86	.995	.997	.041 (.018, .060)	19.40/2, $p < .01$ (vs. SD3)
Hierarchical model (Model C) with age-partialled residuals						
AP	161.37	87	.917	.940	.065 (.049, .080)	
Age equivalence of hierarchical (Model C) model						
E1: No constraints	266.94	174	.985	.989	.051 (.039, .063)	—
E2: Equal 1st-order loadings	282.51	185	.985	.989	.051 (.039, .063)	15.58/11, $p > .15$
E3: Equal 1st-order and 2nd-order loadings	291.13	189	.985	.988	.052 (.040, .063)	8.61/4, $p > .07$
E4: Equal 1st-order and 2nd-order loadings and equal factor variances	293.12	192	.985	.988	.051 (.039, .062)	1.99/3, $p > .57$

Note. NNFI = nonnormed fit index; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval.
[a] One degree of freedom was lost because the variance of the reasoning factor was fixed to 1.0. This was done because in the original analysis the variance was negative, but not significantly different from zero, (i.e., critical ratio = −0.51) and, thus, it was fixed to 1.0 to achieve an admissible solution.

and this may be attributable to the degree to which the models captured shared variance. That is, Model C represented the shared variance only in terms of a single second-order factor, Model B represented the shared variance more completely in terms of correlations between each pair of first-order factors, and Model D represented variance shared among the observed variables instead of among the first-order ability factors.

The strongest relations to the second-order common factor in Model C were with the space (standardized coefficient of .89) and reasoning (standardized coefficient of .95) factors. This pattern is consistent with previous psychometric research indicating that reasoning and spatial visualization variables tend to have the highest loadings on a higher order factor corresponding to fluid intelligence or general intelligence (e.g., Carroll, 1993; Gustafson, 1984; Jensen, 1998).

Structural Models

The second part of Table 4 contains the fit statistics for the series of models in which age was added to the structure.[1] As was the case with the measurement models, the model with separate age-related influences on the four independent first-order factors (i.e., Model SA1) had the poorest fit. The model that differed only by allowing correlations among the first-order factors (i.e., Model SB1) had a much better fit, but inspection of the top and middle parts of Table 4 reveals that the superiority over the independent factors structural model was actually slightly smaller than that for the corresponding measurement models (i.e., Models MA and MB). This suggests that the differences between Models SA1 and SB1 are largely attributable to differences in the representation of the covariation among the first-order ability factors, and not to differences in the accuracy of representing the age-related influences on the factors or variables. The standardized regression coefficients relating age to the first-order factors are also consistent with this interpretation, as the values were identical in the two models (i.e., age–space = −.45, age–reasoning = −.55, age–memory = −.63, and age–speed = −.79). Furthermore, the coefficients were nearly the same (i.e., age–space = −.45, age–reasoning = −.53, age–memory = −.63, and age–speed = −.79) in the version of the hierarchical model in which age was related only to the first-order factors and not to the second-order common factor (i.e., Model SC0). The coefficients were slightly different in the variant of Model D in which common variance was extracted at the level of observed variables (i.e., Model SD0), as they were age–space = −.07, age–reasoning = −.17, age–memory = −.54, and age–speed = −.79. A very similar pattern of age-related influences is therefore obtained when the variance shared among the first-order factors is omitted from the model (SA1), when the shared variance is orthogonal to the first-order factors because of the presence of correlations among the factors (SB1), and when the shared variance is orthogonal to the first-order factors because of the existence of a second-order factor that is not related to age (SC0). Only when the shared variance is extracted at the level of observed variables (SD0) does the pattern differ, and even then only for the relations of age to the first-order space and reasoning factors.

Although under certain conditions Models A, B, and C may be functionally equivalent, only with Models C and D is it possible to determine if there is an age-related effect on the variance shared across either the first-order factors (Model C) or across the observed variables (Model D). An initial version of each of these latter models was therefore specified in which age was related to all first-order factors but not to the common factor representing shared variance. Subsequent tests of each model were based on the following sequence. In the first model (S_1) all of the age-related effects were postulated to occur on the common factor (i.e., at the highest, second-order, level in the hierarchical structure for Model SC1 or at the orthogonal first-order common factor for Model SD1). The next model (S_2) allowed an additional direct path from age to the first-order speed factor, the third model (S_3) allowed an additional direct path from age to the first-order memory factor, the fourth model (S_4) allowed an additional direct path from age to the first-order space factor, and the fifth model (S_5) allowed a direct path from age to the first-order reasoning factor in addition to paths from age to the common factor and to the speed and memory first-order factors. Inspection of the fit statistics in Table 4 indicates that with both sets of models the fit improved significantly when direct paths were allowed from age to the first-order speed and memory factors, but that there was not a significant improvement in fit when a path was added from age to either the first-order space factor or the first-order reasoning factor.

The possibility of unique age-related effects on individual variables was also investigated by determining whether the direct path from age to each variable was significantly different from zero. Two variables were found to have significant direct relations from age after considering the age relations through the common factor and the first-order factors. One variable was Raven's (1962) Advanced Progressive Matrices, Set II, and the other was WMS–III Logical Memory. Fit statistics for this final model (S_6) are presented in Table 4, and the hierarchical model (Model SC6) with standardized regression coefficients is portrayed in Figure 3.

Because Models C and D each involved a common factor, it is instructive to compare the pattern of results with these models. In both cases the version of the model in which age was related to all first-order factors (S_0) had a better fit than the version in which age was only related to the common factor (S_1), but the fit with an influence of age only on the common factor was either the same or worse than the version in which age was related to the speed and memory factors in addition to the common factor (S_3). In neither model was there a significant relation of age to either the reasoning or space factors when age was related to the common factor, which suggests that the effects of age on these factors are captured by the effects on the common factor even when that factor was defined at the level of observed variables as in Model D. Furthermore, in both Models C and D age also was significantly related (in the same direction) to two individual variables, Raven's (negative) and

[1] Structural models incorporating age were examined for all of the corresponding measurement models. The results with the measurement models indicated that they differed with respect to their fits to the data, and some researchers would argue that only the best-fitting model should be examined in the structural analyses. However, the models differ in the manner in which variance in the variables is partitioned, and restriction to one type of model would preclude examination of how age was related to each component of variance. Furthermore, comparison of several different measurement and structural models is likely to be more informative about the nature of the age-related influences operating in these data than a focus on only one model.

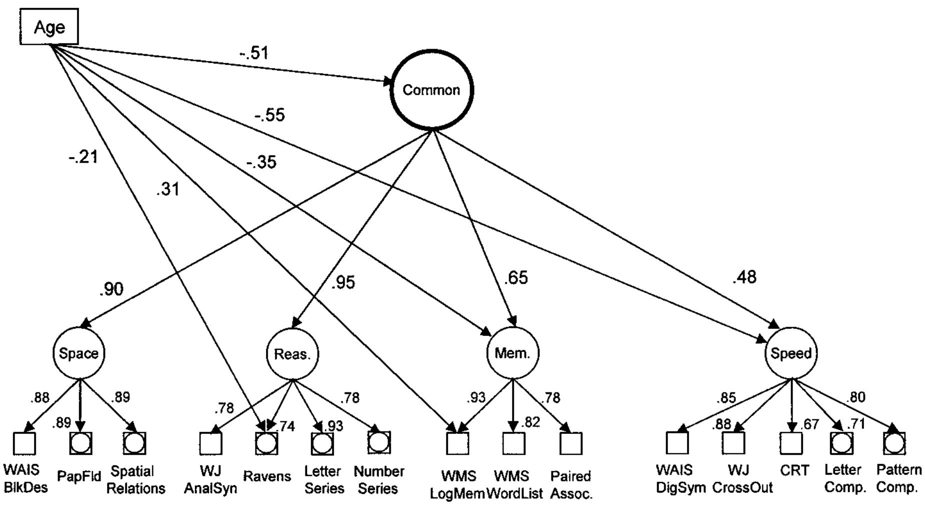

Figure 3. Standardized regression coefficients for the best-fitting model (SC6 in Table 4) to the new data, Data Set A. Variables with incomplete data are portrayed as circles within boxes following the notation of McArdle (1994). See text for complete details about the variables.

Logical Memory (positive). Finally, comparison of the standardized regression coefficients for Model S_3 indicated that the age–common relations were very similar (i.e., −.53 for Model C and −.55 for Model D), but that there were larger paths from age to the speed (i.e., −.75 vs. −.53) and memory (i.e., −.44 vs. −.26) factors in Model D than in Model C. These differences in the magnitude of the unique age-related influences on the first-order factors may be attributable to the manner in which the common factor is defined in the two models. That is, in Model C the common factor is extracted from variance shared among the first-order factors, and thus there may be relatively little residual factor-specific variance that can be uniquely related to age. In contrast, in Model D the common factor is extracted from variance shared among the observed variables, and thus the first-order factors could have more variance available to be associated with age (or any other variable), than in Model C. The overall patterns of age-related influences were therefore similar with Models C and D, but because Model C is more familiar in the psychometric literature and can be fit under a broader range of conditions (e.g., when only two indicators of the factors are available), it was used in all subsequent analyses.

Two sets of analyses were conducted to examine the possibility that at least some of the relations among the variables were attributable to the effects of age on each variable. The first analysis repeated the hierarchical measurement model (MC) on the residuals created by partialling age from every variable. The fit of this model is presented in the bottom part of Table 4, and the standardized coefficients are presented in Table 5. It can be seen that the fit with the age-partialled data (i.e., Model AP) was somewhat better than with the original data (i.e., Model MC), and although the standardized coefficients were somewhat smaller in magnitude with the age-partialled data (cf. Table 5), the pattern was similar in both models.

The next set of models, E1 through E4, investigated the equivalence of the hierarchical structure among adults under (N = 102) and over (N = 102) the age of 50. This is a relatively crude grouping of age, but any finer differentiation of the age variable would have resulted in small samples with undesirably low statistical power. Progressively more restrictive models examined the effects of allowing the two groups to have separate loadings of the variables on the first-order factors and separate loadings of the first-order factors on the second-order factor (E1), constraining the loadings on the first-order factors to be equivalent in the two groups (E2), constraining both the first-order and second-order factor loadings to be equivalent (E3), and constraining all factor loadings as well as the factor variances to be equal (E4). Comparison of the model fit statistics in the bottom of Table 4 indicates that imposing these successive constraints on the model did not result in a statistically significant loss of fit compared to the model with no constraints. The factor structure in the two age groups can therefore be inferred to be configurally invariant (because the same variables were related to the factors) and metrically invariant (because the loadings of the variables on the factors did not significantly differ across groups). In addition, there was no evidence of differences in the variances of the factors, which indicates that although the groups may differ with respect to the mean levels of the factors, they were similar in the variability around their respective means. Standardized coefficients for the two age groups (derived from Model E1) are presented in Table 5, where it can be seen that they are similar to each other and to the coefficients from the complete sample and from the age-partialled data.

Figure 3 can be considered to represent the number of unique age-related influences operating in this data set, as well as the relative strength of each influence. Estimates of the shared and unique age-related influences on each variable can be derived from this model by applying conventional path analysis tracing procedures. Two types of shared or indirect influences were estimated, one through the second-order common factor (i.e., the product of age–common, common–first-order, and first-order-variable coefficients), and one only through the first-order factor with direct relations from age (i.e., the product of the age–first-order and first-order-variable coefficients). The unique influence was esti-

Table 5
Standardized Path Coefficients for Hierarchical Measurement Model With Original Variables, Age-Partialled Variables, and Samples Under and Over the Age of 50

Variable	Original (MC)	Age-partialled (AP)	Age	
			<51	>50
Space–SpaRel	.89	.87	.90	.84
Space–PapFld	.89	.85	.88	.86
Space–BlkDes	.88	.87	.89	.83
Reas–LetSer	.92	.91	.91	.92
Reas–Ravens	.87	.79	.80	.84
Reas–AnalSyn	.77	.74	.74	.80
Reas–NumSer	.78	.74	.75	.73
Mem–PairAS	.79	.69	.77	.66
Mem–Recall	.82	.72	.79	.77
Mem–LogMem	.71	.72	.77	.68
Speed–CRT	.67	.52	.62	.56
Speed–CrossOut	.88	.73	.79	.82
Speed–DigSym	.86	.71	.75	.79
Speed–LetCom	.71	.54	.40	.80
Speed–PatCom	.80	.62	.73	.76
Common–Space	.89	.88	.89	.87
Common–Reas	.95	.93	.93	.94
Common–Mem	.86	.76	.84	.76
Common–Speed	.81	.69	.72	.78

Note. Variable identifiers are presented in Table 2.

mated from the direct relation of age to the variable. The resulting estimates for the 15 variables included in the structural analyses are presented in Table 6. Notice that with every variable, a sizable proportion of the total age-related effect on the variable was indirect and shared with the second-order common factor. Several of the variables also had a substantial indirect effect through the first-order speed and memory factors, but only two variables had significant direct effects that were independent of the age-related effects on other variables.

The data presented in Figure 3 and Table 6 imply the following interpretation of the age-related effects on the 15 variables in these analyses. First, although there were large negative age relations on the three spatial ability variables and on the four reasoning variables, only one of those variables had a statistically significant independent, or unique, age-related influence. With this variable, Raven's Advanced Progressive Matrices, Set II, the age relations were underestimated by the effects through the second-order and first-order factors. This pattern may reflect age-related influences on strategies or processes that are specific to the Raven's task and that are not involved in the other three reasoning tasks.

Second, the model suggests that the speed and memory variables were influenced by age-related effects through the second-order

Table 6
Estimates of Shared (Indirect) and Unique (Direct) Age-Related Influences on the Variables

Variable	Indirect		Direct
	Through 2nd-order	Through 1st-order	
BlkDes	−.41	0	0
PapFld	−.41	0	0
SpaRel	−.41	0	0
AnalSyn	−.38	0	0
Ravens	−.36	0	−.21
LetSer	−.45	0	0
NumSer	−.38	0	0
LogMem	−.31	−.32	.31
Recall	−.27	−.27	0
PairAs	−.26	−.27	0
DigSym	−.21	−.47	0
CrossOut	−.22	−.48	0
CRT	−.17	−.37	0
LetCom	−.17	−.39	0
PatCom	−.20	−.44	0

Note. Variable identifiers are presented in Table 2.

common factor and also by age-related effects on their respective first-order factors. The first-order factors resemble established psychometric ability factors (e.g., Carroll, 1993), but it is not obvious what strategies or processes might be involved in memory for stories, lists of unrelated words, and pairs of unrelated words on the one hand, or in visual–motor reaction time or the speed of substitution, cancellation, and comparison of letters and patterns on the other hand. In other words, although these results imply that there are unique age-related influences on the speed and memory variables independent of the influences on what all the variables have in common, the exact nature of these unique influences cannot be determined from the current analyses.

Third, the unique age-related influence on the logical memory variable is in the opposite direction of the other age-related influences on that variable and implies an age-related increase in some aspect of story memory performance. One possible interpretation of this effect is that it reflects a relative advantage associated with increasing age in the ability to integrate and remember meaningful and organized information. Three distinct age-related influences of nearly equal magnitude may therefore be operating on the logical memory variable: a negative influence through what many different cognitive variables have in common, a negative influence through the first-order factor representing episodic memory, and a positive influence specific to that variable.

Extension Analyses

The results reported thus far suggest that the interpretation of age-related effects on many different cognitive variables may be facilitated by consideration of the structure among the variables and where in that structure the age-related influences operate. In order to explore the generalizability of this analytical strategy, the structure represented in Figure 3 was used to examine age-related influences on variables available in the data set but not included in the original analyses. Four different variables were examined. The Recall B variable represented the number of words recalled on a new list of words after four study–test trials with the same old list of words. The Directions variable represented the accuracy of reporting the correct spatial orientation after a sequence of four repositioning directions (e.g., "turn left," "turn backwards"). The LetNum variable is used in the latest Wechsler Adult Intelligence Scale (Wechsler, 1997a) and Wechsler Memory Scale (Wechsler, 1997b) test batteries to represent the construct of working memory. It is based on the accuracy of immediately recalling progressively longer series of intermixed letters and numbers with letters reported first in alphabetical order followed by numbers reported in numerical order. The ConnDif variable is derived from a variant of the Trail Making Test (Salthouse et al., 2000) and represents the additional time needed to complete a sequence that alternates between numbers and letters compared to a sequence with only numbers or only letters.

The first step in these analyses involved specifying relations of the new variable to each of the first-order factors (M1 in Table 7). The nonsignificant relations were then deleted, and the remaining relations were estimated again (M2). Finally, a direct path from age to the variable was added to determine whether the unique age relation on the variable was significant in addition to the age-related influences operating through the second-order common factor and the first-order factors to which the variable was related (M3). Results of the analyses are summarized in Table 7. As might have been expected, the primary loading of the Recall B variable was on the memory factor, and the primary loading of the ConnDif variable was on the speed factor. Somewhat surprisingly, both the LetNum and Directions variables had their primary loadings on the reasoning factor. This may reflect the requirement to deal with sequentially presented information instead of any more abstract aspect of reasoning. Most important, only with the LetNum and ConnDif variables was the unique age relation on the variable significantly different from zero. In both cases, the age relations on the variables were underestimated from the effects operating through the hierarchical structure; thus, one can infer the existence of unique age-related influences on aspects of working memory (LetNum) and sequence switching efficiency (ConnDif).

Table 7
Standardized Regression Coefficients for Variables Not in Original Analysis

Variable	Space	Reasoning	Memory	Speed	Age
Recall B					
M1	.01	−.24	1.03*	−.10	—
M2	—	—	.75*	—	—
M3	—	—	.83*	—	.11
Directions					
M1	.15	.48*	.17	−.00	—
M2	—	.76*	—	—	—
M3	—	.73*	—	—	−.06
LetNum					
M1	−.27	.69*	.17	.15	—
M2	—	.62*	—	—	—
M3	—	.54*	—	—	−.14*
Connections difference					
M1	−.18	−.17	−.07	.94*	—
M2	—	—	—	.62*	—
M3	—	—	—	.30*	−.37*

Note. Variable identifiers are presented in Table 2.
* $p < .01$.

The implications of the results in Table 7 are similar to those described earlier, but these results serve to extend the earlier conclusions. That is, not only does it appear meaningful to attempt to interpret age-related influences in the context of a hierarchical ability structure, but that same structure can also be applied to new variables not used to determine the structure. There are obviously limitations on the number and range of variables that can be incorporated into a structure as simple as that portrayed in Figure 3, but, at least in principle, the analytical procedure seems applicable to almost any type of cognitive variable.

Other Data Sets

The generalizability of the results summarized above was examined by applying the same analytical procedures in two additional data sets, which are designated Data Sets B and C, as they are discussed after the primary data set, which can be designated Data Set A. The samples and variables in these data sets have been described elsewhere and, hence, this information is not repeated here. Data Set B was originally reported in Salthouse et al. (1996) and re-analyzed in Salthouse and Czaja (2000), and involved 259 adults between 18 and 94 years of age with a mean age of 51.4 years. Data Set C was originally reported in Salthouse (2001) and involved 206 adults between 18 and 84 years of age, with a mean age of 53.3 years. Both data sets included two or more variables representing each of four distinct abilities: reasoning, spatial visualization, episodic memory, and perceptual speed. Six of the 11 variables in Data Set B were the same as those in Data Set A, and 7 of the 12 variables in Data Set C overlapped with those in Data Set A. Each data set also had one or two vocabulary or general knowledge variables, but they were not included in the analyses because of the focus on examining interrelations of variables with negative age relations.

Data Set B

Composite scores representing the four distinct abilities were created by averaging *z* scores from the relevant variables (see Figure 4A). Correlations of these composite scores with age were −.67 for speed, −.55 for memory, −.50 for reasoning, and −.49 for space. These values are very similar to those reported in Data Set A (i.e., −.73, −.55, −.50, and −.43, respectively).

The sequence of structural models examined with this data set was identical to that described earlier, and the fit statistics for successive models are reported in Table 8. It can be seen that the model fit improved significantly with additions of paths from age to the first-order speed and memory factors, but that there was no significant improvement of fit with the addition of a path from age to either the space or reasoning factors. Examination of direct relations from age to individual variables revealed that four variables had significant age relations. Two were reasoning variables (i.e., Wisconsin Card Sorting Test Number of Categories [WCST-NumCat], standardized regression coefficient = −.16; and Abstraction, standardized regression coefficient = .21), and two were speed variables (i.e., letter comparison [LetCom]; standardized regression coefficient = .27; and pattern comparison [PatCom]; standardized regression coefficient = −.19). Only the latter two speed variables had significant direct relations from age when all of these variables were examined simultaneously. The standardized regression coefficients for the final model, S6, are portrayed in Figure 4A.

Estimates of the unique and shared age-related influences on each variable are presented in the bottom of Table 8. As in Data Set A, all variables had sizable indirect effects through the second-order factor, and the speed and memory variables also had indirect effects through their respective first-order factors. All of the age-related effects on the reasoning and space variables were mediated through the second-order common factor.

Data Set C

As in the other two data sets, composites representing the four first-order abilities were computed by averaging relevant *z* scores. The correlations between age and the composite scores were similar to those in Data Sets A and B, as they were −.57 for speed, −.53 for memory, −.66 for reasoning, and −.52 for space. Fit statistics for the structural models examined in the same sequence as in the other data sets are presented in Table 9. Note that the pattern was very similar to that for Data Sets A and B. In particular, the fit to the data improved significantly when direct paths were allowed from age to the first-order speed and memory factors in addition to the path from age to the second-order common factor, but there was little improvement of fit when direct paths were allowed from age to either the space or reasoning factors.

Examination of unique age relations on individual variables revealed two variables with direct effects, and both were reasoning variables. One was analytical reasoning ([AnalReas]; standardized regression coefficient = −.19), and the other was conditions ([Cond]; standardized regression coefficient = .21). When examined simultaneously, only the relation of age to the AnalReas variable was significant. Standardized regression coefficients for the final model, S6, are portrayed in Figure 4B, and estimates of the unique and shared age-related influences derived from this model are presented in the bottom of Table 9.

Sex Differences

In order to explore the applicability of the current analytical strategy with a different individual difference variable, the same analytical procedure described above was applied with the age variable replaced by a variable representing sex (coded 0 for male and 1 for female). In Data Set A there was no sex effect on the second-order common factor, but there were significant effects (reported in standardized coefficients) on the first-order speed (.17), memory (.24), and space (−.11) factors. The same pattern was apparent in Data Set B with a significant sex effect on the speed (.09), memory (.12), and space (−.17) first-order factors, but not on the second-order factor. In Data Set C, the sex effect was significant on the second-order common factor (−.22) and also on the first-order memory (.32) and space (−.16) factors. The analyses therefore revealed a consistent advantage of females on episodic memory abilities and of males on spatial abilities, with some variation across data sets in whether there were also effects on the second-order common factor or on the first-order speed factor. It is noteworthy that this is a different pattern than that reported with the age variable, but it is broadly consistent with reviews of sex differences in cognitive abilities (e.g., Halpern, 2000).

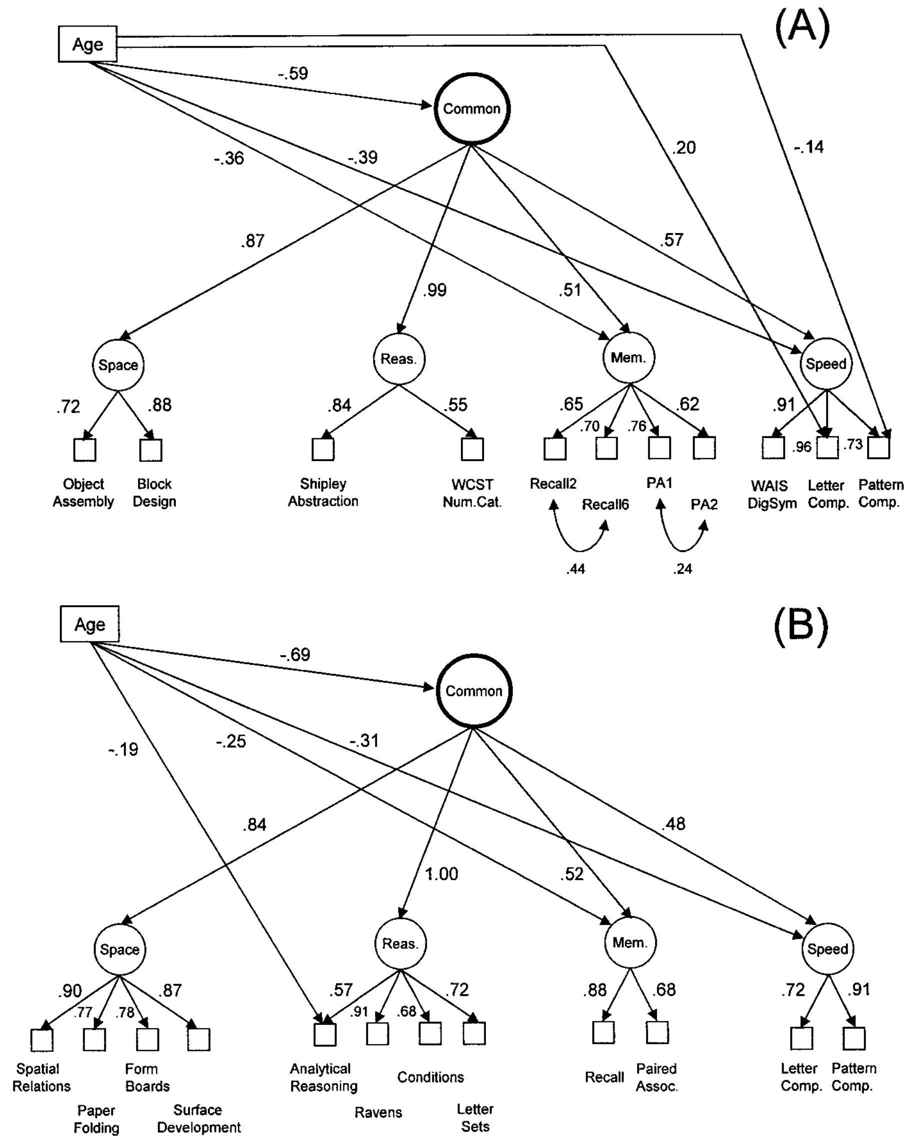

Figure 4. Standardized regression coefficients for the best-fitting models to Data Set B (A) and Data Set C (B). See text for complete details about the variables.

Aggregrate Analyses

The results described above (and summarized in Tables 4, 8, and 9 and portrayed in Figures 3, 4A, and 4B) suggest a similar pattern of relations across data sets, but because each sample involved a different combination of variables it was not possible to make direct comparisons across the complete data sets. However, a direct comparison is possible if one is willing to assume that composites of the variables associated with each first-order factor represent comparable constructs across the data sets. This is a strong assumption, which cannot be tested with the present data, but it does allow examination of the equivalence of the structural pattern of results in the different data sets by means of multiple-group analyses.

Two sets of multiple-group structural models were therefore examined with the four composite variables (created by averaging the relevant *z* scores) serving as manifest variables and a single common factor. In the first set of models, age was ignored and comparisons were made when there were no constraints on the loadings of the composite variables on the common factor (A1 in Table 10) and when there were constraints across the three data sets on the loadings of the composite variables on the common factor (A2). Because the fit of the model was not significantly reduced by imposing this restriction, it can be inferred that the three data sets were similar in common factor loadings. This model, suggesting an invariant metric structure, served as the starting point for subsequent analyses.

The next set of models investigated the effects of imposing successive constraints on the age relations. The first model (B1) reproduced the structure in A2 and added a path from age to the common factor that could vary in magnitude across the three data

Table 8
Structural Equation Model Fit Statistics for Data Set B (Salthouse et al., 1996)

Model	χ^2	*df*	NNFI	CFI	RMSEA (90% CI)	$\Delta\chi^2/\Delta df$
S1: Age to common	113.10	49	.947	.961	.071 (.054, .088)	—
S2: Age to common and speed	93.29	48	.962	.972	.060 (.042, .079)	19.81/1, $p < .01$
S3: Age to common, speed, and memory	73.56	47	.977	.984	.047 (.024, .067)	19.73/1, $p < .01$
S4: Age to common, speed, memory, and space	72.48	46	.977	.984	.047 (.025, .067)	1.08/1, $p > .29$
S5: Age to common, speed, memory, and reason	72.48	46	.977	.984	.047 (.025, .067)	1.08/1, $p > .29$ (vs. S3)
S6: Age to common, speed, memory, LetCom, and PatCom	56.11	45	.990	.993	.031 (.000, .054)	7.45/2, $p < .01$ (vs. S3)

Variable	Indirect: Through 2nd-order	Indirect: Through 1st-order	Direct
ObjAssm	−.37	0	0
BlkDes	−.45	0	0
Abstr	−.49	0	0
WCST NumCat	−.32	0	0
Recall2	−.20	−.23	0
Recall6	−.21	−.25	0
PA1	−.23	−.27	0
PA2	−.18	−.22	0
DigSym	−.30	−.35	0
LetCom	−.32	−.37	.20
PatCom	−.24	−.28	−.14

Note. Variable identifiers are presented in Table 2. See text for further details. NNFI = nonnormed fit index; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval.

sets. The next model (B2) constrained the age–common relation to be equal across data sets. The following models added the age–speed and age–memory relations (B3), and then constrained those relations to be equal across data sets (B4). A final model (B5) added an age–space relation that could vary across data sets, but it did not lead to a significant improvement in fit and therefore was not considered further.

Results of these analyses are summarized in the middle of Table 10. Notice that there was a substantial improvement in fit when paths were allowed from age to speed and to memory in

Table 9
Structural Equation Model Fit Statistics for Data Set C (Salthouse, 2001)

Model	χ^2	*df*	NNFI	CFI	RMSEA (90% CI)	$\Delta\chi^2/\Delta df$
S1: Age to common	122.65	61	.951	.962	.070 (.052, .088)	—
S2: Age to common and speed	113.91	60	.956	.966	.066 (.047, .085)	8.74/1, $p < .01$
S3: Age to common, speed, and memory	108.25	59	.959	.969	.064 (.044, .083)	5.67/1, $p < .05$
S4: Age to common, speed, memory, and space	104.34	58	.961	.971	.062 (.043, .081)	3.90/1, $p < .05$
S5: Age to common, speed, memory, and reason	104.34	58	.961	.971	.062 (.043, .081)	3.90/1, $p < .05$ (vs. S3)
S6: Age to common, speed, memory, and AnalReas	101.84	58	.963	.973	.061 (.041, .080)	6.41/1, $p < .01$ (vs. S3)

Variable	Indirect: Through 2nd-order	Indirect: Through 1st-order	Direct
SpaRel	−.53	0	0
PapFld	−.45	0	0
FrmBrd	−.46	0	0
SurDev	−.51	0	0
AnalReas	−.40	0	−.19
Ravens	−.63	0	0
Cond	−.47	0	0
LetSet	−.50	0	0
Recall	−.32	−.22	0
PairAs	−.25	−.17	0
LetCom	−.24	−.22	0
PatCom	−.30	−.28	0

Note. Variable identifiers are presented in Table 2. See text for further details. NNFI = nonnormed fit index; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval.

Table 10
Structural Equation Model Fit Statistics for Aggregate Analyses Across Data Sets

Model	χ^2	*df*	NNFI	CFI	RMSEA (90% CI)	$\Delta\chi^2/\Delta df$
Without age						
A1: No constraints	13.77	6	.964	.993	.044 (.012, .075)	—
A2: Equal loadings on common factor	29.16	14	.970	.986	.040 (.019, .061)	15.39/8, $p > .05$
Adding age						
B1: Equal loadings of composites to common factor, unequal age-common	127.77	23	.933	.966	.083 (.069, .097)	—
B2: Equal common factor loadings, equal age-common	131.84	25	.937	.965	.080 (.067, .094)	4.07/2, $p > .13$
B3: Equal common factor loadings, equal age-common, unequal age-speed, and unequal age-memory	39.34	19	.984	.993	.040 (.022, .058)	92.50/6, $p < .01$
B4: Equal common factor loadings, age-common, age-speed, and age-memory	41.95	23	.988	.994	.035 (.017, .052)	2.61/4, $p > .62$
B5: Add unconstrained age-space to B4	41.16	20	.985	.993	.040 (.022, .057)	0.79/3, $p > .85$

	Standardized coefficients for Model B4		
	Data Set A	Data Set B	Data Set C
Age → common	−.62	−.65	−.58
Age → speed	−.41	−.39	−.32
Age → memory	−.21	−.21	−.18
Common → reason	.94	.84	.93
Common → space	.81	.78	.79
Common → memory	.57	.56	.51
Common → speed	.52	.48	.44

Note. NNFI = nonnormed fit index; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; CI = confidence interval.

addition to that from age to the common factor, but that there was no significant loss of fit when all of the paths were constrained to be equal across the three data sets. These results therefore indicate that there is no evidence of differences across the three data sets in the structural relations among age and the composite variables. The standardized coefficients in the three data sets for Model B4, in which the unstandardized coefficients were constrained to be equal, are presented in the bottom of Table 10. Comparison of these values with those in Figures 3, 4A, and 4B based on the structural models conducted on the complete data reveals that the general pattern was very similar across the different types of analyses. In all cases there is evidence of age-related influences that are shared across what the variables have in common, and there are also age-related influences that are unique to the speed and memory first-order factors or composites.

General Discussion

In this report we examined the four models portrayed in Figure 1, both with respect to how well they represented the interrelations among variables ignoring age and with respect to how well they also represented relations of age to the variables. Although the models represent theoretically distinct conceptualizations of the relations among variables, it is not possible to investigate age-related effects that might be shared beyond first-order factors with Models A and B because variance shared among factors is either ignored (Model A), or it is captured in a way not amenable to investigation of age effects (Model B). Shared age effects could be examined in Models C and D, and the pattern of age-related effects was found to be similar in both models. However, Model D is not identifiable with only two indicators per construct unless further constraints are imposed, and it is less established in the psychometric literature than hierarchical model (Model C), and, hence, only the hierarchical model was examined in the remaining analyses.

Alternative organizations of the data, such as mediational or shared influence models, are based on different theoretical assumptions, but results of the current and earlier analyses indicate that there is substantial convergence across different analytical methods and models on the conclusion that at least some age-related effects are shared across different types of cognitive variables. The consistency of this pattern over many such studies led Deary (2000) to conclude that "the data showing that there are shared age-related influences on diverse cognitive abilities are monumental and diverse" (p. 260). However, the specific nature of the shared and unique age-related effects needs to be explored to determine precisely what needs to be explained to account for age-related declines in cognitive functioning.

Additional analyses revealed that the hierarchical structure was not induced by the relations of all variables to age, because a similar structure was obtained when age was partialled from all variables and when groups under and over the age of 50 were compared. Relations among the variables could have been distorted due to the influence of age on the variables, because there are cases in which the relations among variables have been attenuated when the variation in age was statistically controlled. For example, Salthouse, Hambrick, et al., (1998) found a weaker relation between noncognitive variables and cognitive variables; Nilsson et al. (1997) found weaker relations between health and memory variables; and Head, Raz, Gunning-Dixon, Williamson, and Acker, (1999) and Raz, Briggs, Marks, and Acker (1999) found reductions in some correlations between cognitive performance and volume of particular brain regions. However, this was not true in these data, nor in earlier analyses where age-partialled or multiple-group analyses were conducted (e.g., Salthouse, 1998, 2001; Salthouse, Hambrick, et al., 1998; Verhaeghen & Salthouse, 1997).

The results described above imply that at least three distinct categories of explanations are needed to account for age-related effects at the level of first-order factors or ability constructs: (a) one to account for common age-related effects across reasoning, memory, spatial, and speed abilities; (b) one to account for additional age-related effects on speed; and (c) another to account for additional age-related effects on memory. A similar pattern was apparent with models in which the common factor was defined at the level of first-order abilities and at the level of observed variables, across three independent data sets involving different combinations of variables, and in a multiple-group analysis based on composite scores, thus providing evidence of the robustness of the findings.

In addition to the effects on the second-order and first-order factors, some direct age-related effects were evident on individual variables that were not accounted for by the influences through the second-order and first-order factors. These effects are potentially quite interesting because they represent unique influences that presumably require separate task- or variable-specific explanations, such as differential use of a particular strategy or variation in the efficiency of a component limited to certain types of tasks. However, these unique variable-specific effects should be replicated before they can be considered to be sufficiently well-established to warrant an explanation because the pattern of direct effects on individual variables varied across the three data sets. To illustrate, there was a direct age-related influence on the Raven's variable in Data Set A but not in Data Set B, and the LetCom and PatCom variables had direct age-related influences in Data Set B but not in Data Sets A or C. At least some of the variation in the variable-specific age-related effects is likely attributable to the other variables used to represent the relevant first-order factor and to the other variables included in the analysis. Unfortunately, it is not yet clear why certain combinations of variables are associated with unique age-related influences on individual variables whereas other combinations are not. Exploration of the reasons for this variation should be a high priority for future research in order to understand how and why a variable is unique with respect to age-related influences. At the current time, however, there appears to be less consistency with respect to age-related influences at the level of individual variables than age-related influences at the level of first-order abilities or composite scores.

It is tempting to speculate about the cognitive processes or neural substrates responsible for the unique and shared age-related influences identified from the current analyses. However, one should be cautious about treating factors as real entities and assuming that they necessarily correspond to a specific theoretical process or have a discrete neuroanatomical locus or neurochemical substrate. For example, it is conceivable that the first-order and second-order factors have no more meaning than the mere presence of covariation of individual differences among sets of cognitive variables. Nevertheless, even if the interpretation of the factors is unclear, the discovery of a coherent, and consistent, organization or structure to the pattern of age-related effects on different types of cognitive variables is still informative, because it indicates which combinations of variables are likely to require separate explanations of age-related influences.

Of course, a much more interesting possibility is that the factors identified in these analyses correspond to particular theoretical processes, to functioning in different regions of the brain, or to selected neurobiological or neurochemical changes. For example, the age-related influences on the second-order common factor may reflect effects on (a) processes such as goal maintenance (Duncan, Emslie, Williams, Johnson, & Freer, 1996), control and allocation of attention (Hunt, 1980), or assorted executive processes (Smith & Jonides, 1999); (b) the quantity or allocation of mental energy (Spearman, 1927) or attentional resources (Kahneman, 1973); (c) the functioning of a specific neuroanatomical region, such as the prefrontal cortex (e.g., Cabeza, 2001; Esposito, Kirkby, Van Horn, Ellmore, & Berman, 1999; Raz, 2000); or (d) the quantity of neurotransmitters such as dopamine (e.g., Braver et al., 2001; Li, 2002; Prull, Gabrieli, & Bunge, 2000), or intactness of myelin (e.g., Greenwood, 2000; Peters et al., 1996). Unique age-related influences on the first-order memory factor may reflect effects on memory-specific processes such as encoding, rehearsal, or retrieval, or effects on a neuroanatomical region important for memory functioning, such as the medial-temporal lobe and hippocampal complex (e.g., Eustache et al., 1995; Golumb et al., 1994). Because the variables comprising the speed factors involved different types of stimuli, decisions, and responses, the unique age-related influences on the first-order speed factor are presumably not very localized. They could reflect effects on a neural structure responsible for either general arousal (e.g., reticular activating system) or coordination of different cognitive processes (e.g., dorsal lateral prefrontal cortex; Madden et al., 1999; Rypma & D'Esposito, 2000), effects on a neurotransmitter system (e.g., the dopaminergic system; Backman et al., 2000; McRae, Spirduso, & Wilcox, 1988; Volkow et al., 1998), or more diffuse effects related to degree of myelination (e.g., Greenwood, 2000; Peters et al., 1996), level of cerebral connectivity (e.g., Esposito et al., 1999), and so on.

Although speculations such as these are intriguing, it is unlikely that they can be distinguished on the basis of the current data. That is, correlational results such as those in the current report are best viewed as implying a classification of age-related effects on different cognitive variables, and not as an explanation of those effects. Other types of research will therefore be necessary to interpret and explain the classifications that have been identified from these analyses. For example, a process-oriented theorist might attempt to identify processes common to remembering stories, remembering lists of unrelated words, or remembering associations between words, but not involved in any of the other variables. To the extent that such processes could be specified, and the categorization verified with a new combination of variables, then one might claim an understanding of the nature of the unique age-related effects on the first-order memory factor in terms of theoretical processes. Alternatively, a researcher interested in the neural regions associated with each type of unique age-related influence might rely on patterns of brain activations observed when different types of tasks are being performed. If the factors correspond to functioning in different neuroanatomical regions, then the same regions should be active for all tasks associated with a given factor even if superficially the tasks appear quite different. The strategy of searching for patterns of brain activation that are common across different cognitive tasks is similar to what Price and Friston (1997) termed *cognitive conjunction analysis*, and it appears to be a particularly promising direction for the investigation of neuroanatomical substrates of shared age-related influences on cognitive functioning.

Regardless of the eventual interpretation of the factors and of the shared and unique age-related influences, however, the results reported above demonstrate the feasibility of the current analytical approach to investigating the existence, and relative magnitude, of statistically distinct age-related influences on a variety of cognitive variables. Moreover, the consistency of the outcomes across three independent data sets involving different combinations of variables suggests that the methods are reasonably robust.

Four directions, or recommendations, for future research can be suggested on the basis of the results in this article. First, it is desirable that the organizational structure of cognitive variables be taken into account when investigating, and attempting to interpret, the effects of individual difference variables such as age. A hierarchical structure is not the only possible organization of cognitive variables, but its extensive use in the psychometric literature indicates that it is applicable to a variety of influences, such as individual differences associated with sex, personality type, socioeconomic status, and so on, and potentially to effects of interventions such as physical or mental exercise. Furthermore, the results of the extension analyses examining effects of age on variables not used in establishing the original structure revealed that a substantial proportion of the age-related influences on these variables could be interpreted in terms of influences operating through the structure.

Second, whenever possible, the generalizability of the findings should be examined by repeating the analyses in data from different samples, and ideally with different operationalizations of the relevant theoretical constructs. In some cases this may only be feasible in meta-analyses that combine the results across many separate studies (e.g., Verhaeghen & Salthouse, 1997), whereas in other cases it may be possible to assemble the data in a single aggregate data set as was done here. Regardless of the manner in which replication and generalization is accomplished, however, strong conclusions should generally not be based on results from a single study. Although this recommendation may seem obvious, we suspect that effects of chance are frequently underestimated in aging research. Even in the moderately large samples in the current data sets there was variability in the pattern of unique age-related influences at the level of individual variables, and even more fluctuation would be expected in studies based on smaller samples.

Third, specificity or uniqueness of age-related influences should not merely be assumed, but instead should be subjected to empirical test. The analytical methods used in this article represent only a small subset of the possible methods of investigation, and alternative methods for estimating unique and shared age-related influences should continue to be explored. All analytical procedures are based on assumptions that may not be valid, and confidence will be greatest when results from different procedures, and involving different sets of assumptions, converge on the same conclusion. Nevertheless, it should be recognized that if a researcher is interested in establishing that at least some of the age-related effects on a particular variable are specific to that variable, possibly because they are attributable to task-specific processes or strategies, a variety of different types of cognitive variables will have to be examined to allow shared and unique age-related influences to be distinguished. It is difficult to imagine how estimates of unique and shared age-related influences can be obtained with any analytical procedure when only a single variable is examined.

Finally, we encourage reliance on standardized tests to assess the representativeness and comparability of different age groups in the sample (cf. Salthouse, 2000). In Data Set A there were only slight relations between age and age-adjusted scores based on the nationally representative normative sample, but that need not always be the case. For example, the older adults in Data Set 2 in the article by Salthouse and Czaja (2000) were found to be functioning at a higher level relative to their age peers than were the young adults; thus, the estimates of the magnitude of the age relations in that sample were somewhat misleading because of a confounding of age with representativeness of the individuals for their age group. As illustrated here, one means of detecting confounds of this type involves obtaining estimates of the cognitive performance of each participant in the research project relative to his or her age peers in a nationally representative sample.

In summary, analyses of three separate data sets with different samples of participants and combinations of variables suggest that relatively few unique, or statistically independent, age-related influences may be operating across a wide variety of cognitive variables. One influence operates on what is common to all variables, another on a first-order speed factor, and another on a first-order memory factor. This pattern of results was consistent across data sets and was found to be equivalent when the data were pooled in a simultaneous multiple-group test. Although many issues concerning multivariate analytical methods for investigating age differences in cognition still need to be resolved, the available results suggest that explanations of age-related declines in cognitive functioning will need to incorporate mechanisms to account for effects unique to individual variables and particular cognitive abilities and for effects that are common to different types of cognitive abilities.

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