Localizing age-related individual differences in a hierarchical structure

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Abstract

Data from 33 separate studies were combined to create an aggregate data set consisting of 16 cognitive variables and 6832 different individuals who ranged between 18 and 95 years of age. Analyses were conducted to determine where in a hierarchical structure of cognitive abilities individual differences associated with age, gender, education, and self-reported health could be localized. The results indicated that each type of individual difference characteristic exhibited a different pattern of influences within the hierarchical structure, and that aging was associated with four statistically distinct influences; negative influences on a second-order common factor and on first-order speed and memory factors, and a positive influence on a first-order vocabulary factor.

Keywords

Individual differences; First-/second-order factors; Hierarchical structure

1. Introduction

Research spanning nearly a century has clearly established that most cognitive variables are positively related to one another. Because the correlations vary in magnitude, the variables can be organized into factors hypothesized to represent distinct cognitive abilities. However, no consensus has yet been reached regarding the precise number of separate cognitive abilities, as the number of hypothesized cognitive abilities has ranged from 5 to 40 or more (e.g., Carroll, 1993; Ekstrom, French, Harman, & Dermen 1976; Horn, 1982, 1988; Horn & Hofer, 1992). There is also controversy about the nature and existence of factors at higher levels of abstraction. Higher-order factors are often invoked to account for correlations among first-order factors, but theoretical considerations sometimes dictate which correlations are explained in this fashion. For example, higher-order constructs corresponding to fluid and crystallized abilities are correlated with each other in moderately large samples of adults[1], but some theorists prefer not to interpret the correlations as reflecting the influence of a common higher-order factor because these constructs have different developmental trends (e.g., Horn, 1982, 1988; McArdle, Ferrer-Caja, Hamagani, & Woodcock, 2002; Stankov, 2002). However, it is important to note that the issue of organizational structure is distinct from the issue of the number of statistically independent age-related influences operating on that structure. That is, different cognitive abilities might all have variance in common with the same higher-order factor, but they could still have

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[1]To illustrate, correlations between latent constructs or composite scores corresponding to fluid and crystallized abilities in the data used to establish norms in standardized test batteries were .72 for the KAIT (Kaufman & Kaufman, 1993), and depending on the ages of the participants, ranged between .68 and .80 in the WAIS III (Wechsler, 1997a), between .56 and .65 in the WASI (WASI, 1999), and between .66 and .69 in the Woodcock Johnson III (Woodcock, McGrew, & Mather, 2001).

different developmental trajectories if one or more of them also have a unique age-related influence.

Despite the disputes over the details, there is a broad agreement for a hierarchical structure in which the first-order factors are related to higher-order factors at one or more levels of abstraction (e.g., Carroll, 1993; Deary, 2000; Gustafsson, 1984, 1988; Horn, 1982, 1988; Jensen, 1998; Mackintosh, 1998). An important implication of the organization of variables into a hierarchical structure is that individual differences, such as those associated with age in adulthood, on what is unique to a particular variable cannot be meaningfully investigated unless effects on higher-order factors are taken into consideration. This point was eloquently expressed in the following quotations:

> Carroll (1993, p. 623)—Performance on a series of tasks that are loaded on abilities at three levels of analysis must be explained, first, in terms of individual differences on the factor at the highest level of analysis. These differences must be controlled for or partialled out in studying variation at the second level of analysis-variation that will depend upon the particular aspects of ability represented in tasks at the second level of analysis. A similar process of control or partialling occurs in the transition to the explanation of differences at the first level of analysis.

> Gustafsson (2002, p. 86)—…if our intention is to measure one or more narrow abilities, it is necessary to partial out, or in some other way control for, the influence of the general factor and of other broad factors that may be related to performance, but which we are not interested in measuring.

Salthouse and Ferrer-Caja (2003) recently employed this broad-to-narrow strategy to investigate where in a hierarchical structure influences associated with adult age operate. They reported analyses of data from a new study, and of data from two earlier studies, and found a similar pattern in all three data sets. In each case, three statistically distinct negative age-related influences were found to be operating, one on a first-order construct corresponding to episodic memory, a second on a first-order construct corresponding to perceptual speed, and a third on a second-order construct representing variance that the first-order constructs had in common. The Salthouse and Ferrer-Caja findings are potentially quite important because if the pattern is generalizable, it would likely focus the search for explanations of age-related differences in cognitive functioning. That is, a very large number of cognitive variables has been found to be negatively related to increased age, and it is reasonable to assume that progress in identifying causal mechanisms may be more rapid if the variables could be organized into a smaller number of groups with shared age-related influences.

Although some researchers have inferred the existence of different age-related influences on the basis of patterns of varying age relations across variables, frequently in the context of an age×variable interaction in an analysis of variance, the relative magnitude of the relations of age on the variables may not be as informative for this purpose as the degree of statistical independence of those relations. That is, because the relations between age and cognitive variables can vary for a variety of reasons, such as measurement sensitivity, reliability, and dependence on age-sensitive processes (see Salthouse, 2000; Salthouse & Coon, 1994), by itself the strength of the relations between age and different variables provides a weak basis for inferring the existence of distinct age-related influences. In contrast, reliance on procedures to assess the statistical independence of age-related effects on a variety of cognitive variables provides a more powerful, and direct, basis for inferring the operation of more than one age-related influence.

The primary goal of the current project was to attempt to replicate and extend the results reported by Salthouse and Ferrer-Caja (2003) using a much larger sample and different

combinations of variables. The model used to guide the analyses is portrayed in Fig. 1. Notice that 16 cognitive variables are organized into five first-order factors corresponding to distinct cognitive abilities, with a second-order construct postulated to account for the variance common to the first-order abilities. Unique influences at different levels in the structure were considered simultaneously for the individual difference characteristics of age, gender, education, and self-reported health status.

Ideally, analytical models, such as that represented in Fig. 1, would be investigated in a study with a very large sample of research participants spanning a wide age range, and with many cognitive variables representing a broad variety of cognitive abilities. However, there are obvious practical limitations of time and expense in a single study. To illustrate, reliable assessment of the 16 reference variables considered in the analyses described below requires close to three hours for each participant.

The approach employed in the current project involved aggregating data across many separate studies. The core data set was created by selecting 16 reference variables based on the criteria of moderately high loadings on the hypothesized ability constructs and inclusion in at least three separate studies. Data from 33 different studies in which independent samples of individuals performed at least two of the tasks yielding reference variables were then combined. This resulted in a 16 (variable)×33 (study) matrix, with empty cells corresponding to variables that were not assessed in a given study. Of the 528 possible cells in the matrix, data were available in only 161 (30.5%) of them, because the number of reference variables included in a given study ranged from 2 to 15, with a median of 4. Although the aggregate data set contains a large proportion of missing data, the missing values can be assumed to be missing at random because they are attributable to the particular study in which the individual participated, and are unlikely to be related to the level of the missing variable. This property allows powerful analytical procedures to be used when dealing with the missing data.

One method of dealing with incomplete data involves the use of maximum likelihood (ML) procedures at the time of the analysis to iteratively estimate probable values for the missing data when solving for the model parameters (Arbuckle, 1996; Enders & Bandalos, 2001). Enders (2001) described this procedure in the following manner: "… ML algorithms 'borrow' information from other variables during the estimation of parameters that involve missing values by incorporating information from the conditional distribution of the missing data given the observed data" (p. 131). ML procedures are efficient, and are easy to implement in available computer programs, such as AMOS (Arbuckle, 2003) and Mx (Neale, 2002). The primary disadvantage is that the programs do not provide conventional fit statistics for the models when the proportion of missing data is moderately large, as is the case in the analyses reported here.

An alternative method of dealing with incomplete data is to use an imputation process to replace all missing values with plausible estimates. Several imputation techniques are available (e.g., Schafer & Graham, 2002; Sinharay, Stern, & Russell, 2001), but there appears to be a consensus that the best in terms of accurately reproducing important characteristics of the parent population is a stochastic regression imputation in which the estimated values are obtained from a regression-based procedure that contains a stochastic or random residual term to better approximate the actual variance. The uncertainty introduced by the stochastic component can then be incorporated in the parameter estimates by generating m plausible values for each missing value, and analyzing these m data sets separately, with the values from the individual data sets combined and reported in terms of both the mean and standard error of each parameter (e.g., Schafer & Graham, 2002; Sinharay et al., 2001).

Unfortunately, the average results across the *m* analyses can be misleading when a large number of parameters are simultaneously estimated from the same analysis because the values of different parameters may partially offset one another, and yet this dependency is ignored when the parameters are considered separately. In light of this interpretation difficulty, only results from ML procedures applied to the model in Fig. 1 are reported in detail here, but it should be noted that very similar results were obtained when multiple imputation procedures were used to deal with the incomplete data.

2. Method

The analyses were based on data combined across 33 studies conducted by Salthouse et al. which involved a total of 6832 different individuals. These include the three studies analyzed by Salthouse and Ferrer-Caja (2003), as well as another 30 studies. All of the studies were similar in that the participants in a given study were administered the tasks in the same order, and the samples consisted of adults whose ages ranged continuously between 18 and 95. Studies with only two extreme age groups (e.g., young and old adults) and those in which the young adults were primarily college students were excluded to avoid inflating the estimates of the age relations due to elimination of the variance associated with middle-aged adults, and to minimize confounding age with student status.

Only a subset of the 16 reference variables were included in any given study, but each study contained at least two of the reference variables, in addition to information about the age, gender, years of education, and self-rated health (on a scale ranging from 1 for excellent to 5 for poor) of the participants. Furthermore, each reference variable was assessed in at least three studies with different combinations of other variables.

The reference variables included in the analyses are briefly described in Table 1, with more details provided in the reports of the original studies. Reliabilities of the variables were reported in many of the original articles, and were generally above .7. Table 2 summarizes the sources of the primary data with the reference variables available in each study, the year of publication of the study, and the sample size for the study. For most of the studies, the data were collected between one and two years prior to the year of publication.

Some conversion was necessary to express variables from different studies in the same scale. For example, the Digit Symbol test in the WAIS-R (Wechsler, 1981) used a 90-s time limit, but in the WAIS III (Wechsler, 1997a), the time limit was changed to 120 s. The WAIS-R scores were therefore converted to a 120-s time by dividing them by 90 and multiplying that value by 120. There was also some variation in the manner in which the free recall task was administered, as the studies differed in the numbers of lists of words that were presented (i.e., ranging from two to five), and in the number of words per list (i.e., ranging from 10 to 15). All of the recall scores were therefore expressed as proportions of the maximum possible to convert them to a similar scale. The converted measures may not be exactly comparable to one another, but it is assumed that they have a very similar relation to the relevant ability, and because there was nearly a rectangular distribution (i.e., equal numbers at each age) of ages in each sample, the age relations on the variable are unlikely to be distorted by slight differences in the nature of the assessment across studies.

The representativeness of the aggregate sample can be evaluated by comparing the scores of these participants with the scores from a normative sample explicitly selected to be representative of the U.S. population. That is, the sample used to create norms for the WAIS III (Wechsler, 1997a) was matched to the U.S. population on many demographic variables, including gender, ethnicity, years of education, and region of residence in the country. Fig. 2 portrays age relations for the Vocabulary and Digit Symbol variables in the aggregate data,

and in the normative WAIS III sample. It is apparent that participants in this data set performed at a higher average level than the participants in the normative sample, but that the age relations for both variables were similar in this data set and in the normative sample.

The data were collected between 1988 and 2003, and therefore it is possible that they were susceptible to historical or time-lag effects (i.e., the "Flynn Effect", cf. Neisser, 1998). This possibility was examined by investigating the relation between the mean score on a variable and the study number (as the studies were numbered in chronological order), after controlling for influences of age, gender, years of education, and self-rated health. These analyses were conducted on two vocabulary variables that were available in 18 studies, and on two perceptual speed variables that were available in 30 studies. The semipartial correlations between study number and mean score were .06 for the Synonym Vocabulary variable, .08 for the Antonym Vocabulary variable, .04 for the Pattern Comparison variable, and −.10 for the Letter Comparison variable. All of the correlations were significantly ($p<.01$) different from zero, but they were small in magnitude, and one was negative, indicating somewhat better performance among earlier-tested participants. In light of these small and inconsistent effects, time-lag influences were ignored in subsequent analyses.

Finally, it is important to recognize several advantages of this aggregate data set compared to the data available from a single study. First, the sample is obviously much larger than that from any individual study, with up to 6832 participants instead of a median of 207. Second, the data set includes the complete set of 16 variables, instead of an average of only 4, which is the median number of reference variables in a study. And third, participants in the aggregate data are more diverse than those from any single sample because the samples in each study were obtained from different sources and varied in a number of characteristics. To illustrate, across studies, the average years of education of the participants ranged from 13.5 to 17.0, the average Synonym Vocabulary score ranged from 4.5 to 9.0, and the average Raven's score ranged from 5.4 to 8.3.

3. Results

Means and standard deviations for the reference cognitive variables, proportions of variance associated with linear, quadratic, and cubic age trends, and standardized factor loadings from a confirmatory factor analysis with five correlated first-order factors are summarized in Table 3. It can be seen that the sample sizes for the variables ranged from 797 to 6085. The proportions of age-associated variance were determined by first centering the age variable, and then entering the age, age^2, and age^3 terms as successive predictors in a hierarchial regression equation. For all except the vocabulary variables the age relations were primarily linear, as the median proportion of age-related variance was .131 for the linear trend, .010 for the quadratic trend, and .002 for the cubic trend. Because the non-linear relations were small relative to the linear relations, they were ignored in all subsequent analyses.

Statistics indicating the fit of the model to the data are not available when the amount of missing data in the analysis is large because the fit statistics are based on a comparison of observed and predicted values and the distinction between observed and predicted is blurred when maximum likelihood estimation analyses are used to deal with the missing data. Nevertheless, it is important to note that the standardized factor loadings were all quite high, with a range from .72 to .91 and a median of .81, which indicates that more than 50% of the variance in each variable was associated with the respective ability construct.

Table 4 contains correlations among the latent constructs from the confirmatory factor analysis, and the correlations between age and each construct obtained from a separate analysis in which age was added to the model. The table also contains three other estimates

of the relations among the abilities, and of the relations between age and the abilities. The column labeled "Mult. Imput." contains averages of the estimates across five imputed data sets in which missing values for the 16 reference variables were predicted from the values of the other reference variables and from values of age, gender, education, and health. The weighted averages of the construct relations across studies were obtained from the values reported in Salthouse (in press(a)), and the meta-analysis estimates based on individual variables were obtained from the values reported by Verhaeghen and Salthouse (1997).

Because single variables contain more measurement error than latent constructs that represent the systematic variance shared across multiple variables, it is not surprising that the meta-analytic estimates of the correlations between individual variables are somewhat smaller than the correlations between latent constructs. Although there is some variation among the other estimates, the important point is that each type of data revealed a generally similar pattern in which the different cognitive abilities were all moderately correlated with one another, reasoning variables had the strongest correlations with other variables, and speed variables had the strongest relations with age.

At least some of the relations among cognitive ability constructs could be attributable to the relations of the constructs to individual difference variables, such as age, gender, education, and health. This possibility was investigated by statistically removing the variance associated with these demographic variables before computing the correlations among the cognitive abilities. In addition, correlations among the cognitive abilities were computed separately for the 3494 individuals between 18 and 49 years of age, and for the 3338 individuals between 50 and 95 years of age. The values from these analyses are presented in Table 5, where it can be seen that they were all fairly similar to the values in Table 4. The only systematic differences between the correlations based on the aggregate data in Table 4 and the correlations in Table 5 are that the correlations involving vocabulary ability were larger in the analyses reported in Table 5, whereas correlations involving other combinations of abilities were smaller.

In order to illustrate age trends on the five ability constructs, each of the 16 reference variables was converted to a *z*-score and plotted as a function of age in Fig. 3. There are five panels in the figure, with each panel portraying variables representing a different cognitive ability construct. The linear slopes for the variables, in units of standard deviations per year, ranged from −.01 to −.03, which corresponds to a difference across 50 years of between 0.50 and 1.50 standard deviations.

Two points should be noted regarding the results in Fig. 3. First, the age trends for the different variables in each panel are quite similar, despite being based on different combinations of individuals. And second, four of the five abilities have similar, and primarily linear, age trends. Vocabulary ability is the only exception because the mean scores on these variables increased until about age 50 or 60, and then decreased.

The results summarized in Tables 4 and 5 indicate that the correlations among the first-order cognitive abilities are moderately large, and are not induced by relations with age or other individual difference variables. Because the simplest structure to account for correlations among first-order factors involves a single second-order factor, subsequent analyses focused on the model represented in Fig. 1.

However, before applying the model portrayed in Fig. 1 to the aggregate data, it was important to determine whether the variables represent the same constructs in different groups. That is, quantitative comparisons are not meaningful if variables differ qualitatively in what they represent. Measurement equivalence was therefore examined across groups

divided in terms of age (i.e., 18–49 vs. 50–95), gender (i.e., males vs. females), education (i.e., less than 15 vs. 15 or more years of formal education), and self-rated health status (i.e., excellent or very good vs. good to poor). The analytical procedure consisted of determining whether the fit of the model to the data for two groups was significantly reduced when a parameter (in its unstandardized form) was constrained to be equal in the two groups. Only the coefficients relating constructs to variables were examined in these analyses because the primary interest was in determining whether the variables had the same meaning in different groups.

Because of the large sample sizes, several of the coefficients differed significantly between groups. However, all of the standardized coefficients were very similar in magnitude. To illustrate, individuals under and over the age of 50 differed significantly in the loadings of six variables on their respective constructs, but the standardized coefficients for the young and old groups were, respectively, .88 and .92 for Antonym Vocabulary, .90 and .88 for Synonym Vocabulary, .87 and .85 for WAIS Vocabulary, .83 and .88 for Shipley Abstraction, .80 and .79 for Letter Sets, and .76 and .78 for Pattern Comparison. The only significant difference in the male–female contrast was in the loading of Antonym Vocabulary on the vocabulary construct (i.e., standardized coefficients of .92 for males and .90 for females), and the only significant difference in the education contrast was a stronger relation of Paper Folding to the spatial visualization construct in the lower education group (i.e., standardized coefficients of .86 and .78, for the low- and high-education groups, respectively). None of the variable–construct relations differed significantly between the high and low self-rated health groups. This pattern of results indicates that the variables were related to the same ability constructs in each group, and thus exhibited configural invariance, and that the magnitudes of these relations were also fairly similar, implying that the groups generally exhibited metric invariance. It was therefore considered reasonable to treat the variables as representing the same constructs to nearly the same degree across the various individual difference categories.

The next set of analyses included age, gender, education, and self-rated health as exogenous influences on the hierarchical structure, with the goal of determining the levels in the structure at which these influences operate. Because some of the correlations among the individual difference variables were significantly different from zero, all of the individual difference variables were considered simultaneously to control the effects of the other variables when examining effects of a given variable. The second-order factor largely overlapped with the first-order reasoning factor (i.e., standardized coefficient of .97), and thus the effects of the individual difference variables were examined only on the other first-order factors and on the second-order factor.

Standardized coefficients for both the direct and the total effects of each individual difference variable obtained from this analysis are presented in Table 6. The direct effects are of greatest interest because they represent influences that are statistically independent of effects through other factors in the model. It can be seen that there was a strong negative direct relation of age on the second-order factor and on the first-order memory and speed factors, and a large positive direct relation on the first-order vocabulary factor. Females were significantly higher than males on the first-order memory and speed factors, but were lower than males on the first-order space factor. Individuals with more education had significantly higher values on the second-order factor and on the first-order vocabulary, speed, and memory factors.[2] Finally, individuals with poorer self-rated health had slightly lower values than individuals with better self-rated health on the second-order factor, and on the first-order vocabulary, memory, and speed factors.[3]

The results just described suggest that the structure portrayed in Fig. 1, together with the parameters summarized in Tables 3-6, is robust, and appears to provide a good representation of the age-related effects on a limited set of cognitive abilities.[4] The fact that the age related effects in the structure are distinct from the patterns apparent with other individual difference characteristics also suggests that the analytical methods are sensitive in the sense that influences associated with different types of individual differences can be distinguished.

4. Discussion

Both methodological and substantive issues were addressed in this study. The primary methodological contribution is the demonstration of the usefulness of combining data across separate studies and conducting analyses on the aggregate data. The aggregation procedure capitalizes on the overlap of variables in different samples to allow data from different samples to be treated as a single large data set. The ability to aggregate data across studies is valuable because all studies can be considered to be incomplete in some respects, even those with no missing data. That is, because it is not possible to include all potentially relevant constructs in a single study, constructs that are not assessed can be considered to be missing from the perspective of what could have been included. Furthermore, the constructs that are included are necessarily assessed with only a limited set of the variables that could have been used to represent the constructs. Although an aggregate data set created in this manner will often contain a great deal of missing data, this is not necessarily a problem because recent analytical methods take advantage of all of the available information at the time of analysis. Furthermore, aggregation of data has the advantage of creating a larger and more diverse sample than is feasible from any single study, and may facilitate cumulative progress by explicitly incorporating earlier data in the analysis of new data. An interesting feature of conducting analyses on data aggregated across multiple studies is that participants continue to contribute information beyond the specific study in which they participated. That is, because each participants' data are used to strengthen estimates of relations among variables in analyses involving data from later studies, participants in this type of cumulative data set can be considered to be contributing continuously, and in that respect, their data may be somewhat analogous to a gift that keeps on giving.

Integrative procedures similar to those used here might eventually be extended to allow data to be combined from different laboratories to obtain even more diverse samples of participants, and a broader range of variables, including noncognitive variables. As long as there is some overlap among the variables, and the samples of participants are similar in relevant characteristics, it should be possible to link the data to expand the scope of questions that can be asked, and the power with which they can be investigated.

The major substantive contribution of the project is the replication and extension of the findings of Salthouse and Ferrer-Caja (2003) in a data set with a much larger sample and a different combination of variables. Three sets of results are particularly noteworthy. First, as expected, different cognitive variables were found to be moderately correlated with one another, and hence could be organized into a structure. Second, when the variables were

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[2]It should be noted that although the effects of education are statistically independent of effects of age, gender, and health, they are not independent of level of cognitive ability. That is, in this type of cross-sectional design, it is impossible to distinguish the influence of amount of education on the level of cognitive ability from the influence of level of cognitive ability on the amount of education one receives.

[3]The analysis was repeated with the age^2 variable included to assess nonlinear age trends in the hierarchical structure. The only significant relations from the age^2 variable were to the first-order vocabulary (i.e., −.07) and memory (i.e., −.06) factors. All the other coefficients were very similar to those from the analysis without the nonlinear age term.

[4]Very similar results were also apparent in unpublished analyses of the data from the studies 32 and 33, and of the data from the normative sample in the Woodcock-Johnson Psycho-Educational Battery—Revised (see Woodcock & Johnson, 1989).

organized into a hierarchical structure, most of the negative age-related effects were found to operate at the level of the first-order speed and memory constructs, and at the level of the second-order construct representing what is common across different cognitive abilities, with other individual difference characteristics having somewhat different patterns of influences. And third, the earlier results were extended by the finding that when vocabulary variables are included in the analysis, they can be incorporated into the hierarchical structure, but they have a strong positive age-related influence in addition to the negative influence through the second-order common factor.

As found in other analyses (e.g., Salthouse in press(b); Salthouse & Ferrer-Caja, 2003), the first-order reasoning factor had a very high loading on the second-order factor (i.e., .97). This was even true when different reasoning variables were used as indicators of the first-order reasoning factor because there was no overlap of the reasoning variables in Data Sets B and C in Salthouse and Ferrer-Caja, but the standardized loadings on the second-order factor were .99 and 1.0, respectively. Carroll (1993) and Horn (1988) also noted that reasoning measures had high loadings on the highest-order factors in their analyses, and thus it appears that there is something special about reasoning variables with respect to individual differences across different aspects of cognitive functioning. Unfortunately, the nature of this special characteristic is not yet obvious. There have been many speculations about the role of hypothetical components, such as relation identification, rule application, goal management, and "eduction of relations and correlates" (Spearman, 1927), but little empirical evidence is available to establish that these components are actually involved in different types of reasoning tests, and there are apparently no explanations of why they would be important in other cognitive abilities.

The hierarchical model in Fig. 1 is extremely simple compared to models proposed by Carroll (1993, p. 626) and Horn (1982, p. 851). However, it has the advantage that it can be empirically investigated with a relatively small number of variables, and it is not clear how many variables (and research participants) would be needed to provide a rigorous test of models that are considerably more complex. Regardless of the form of the hierarchical model, however, the operation of higher-level factors can be postulated to exist whenever there are moderate correlations among the lower-order factors, as is clearly the case in Tables 4 and 5.

It should be noted that acceptance of a hierarchical structure with a single factor at the top does not imply that individuals or groups can be characterized by one number that represents the magnitude of the highest-order factor. Instead, the results in Table 6 indicate that different types of individual differences are associated with influences at various levels in the hierarchy. The issue of the structure used to organize cognitive variables is therefore at least partially independent of the issue of the pattern of individual differences operating on that structure.

The analyses reported here did not include a direct examination of effects associated with age, gender, education, or health on individual variables, but they can be expected to exist whenever there is a discrepancy between the correlations predicted from the other relations in the model and the observed correlations. However, influences on individual variables are likely to vary depending on the other variables used to assess the first-order constructs (cf. Salthouse & Ferrer-Caja, 2003), and thus they may not be as stable as influences operating at the level of constructs that represent variance shared among two or more variables or constructs. Furthermore, variable-specific effects are likely to be difficult to interpret until the variable can be grouped with other variables that share the same critical property, such that the basis for the unique effects can be determined.

Although the aggregate data set examined here is probably more comprehensive than many other data sets, the representation of variables was still limited, and thus, definitive conclusions are not yet possible regarding the number of statistically distinct age-related influences that could be operating across a diverse set of cognitive variables. However, the results of these analyses suggest that, at least in healthy adults between about 18 and 90 years of age, separate negative age-related effects operate on the second-order common factor and on the first-order speed and memory factors, and that a positive age-related influence operates on the first-order vocabulary factor. Additional age-related effects might be found with a broader range of variables and more complex organizational structures, and the influences that have been identified will likely be refined in future analyses, but the available results suggest that in order to account for age-related effects across a wide variety of cognitive variables, at least three negative influences and one positive influence will need to be explained. Note that it is not simply the fact that these four influences can account for a large proportion of the age-related influences on 16 variables representing different types of cognitive abilities that is interesting, but rather the nature of those influences.

A valuable next step is to try to link the statistically distinct age-related influences that have been identified to neurobiological substrates. Attempting to establish this type of linkage does not imply that the influences are necessarily caused by neurobiological factors, but merely assumes that regardless of their ultimate cause, all influences must have a neurobiological representation. Furthermore, to the extent that neurobiological substrates were found to be differentially associated with the statistically distinct influences, it would enhance the validity of the proposed classification of influences.

Among the hypotheses that could be proposed to account for the statistically distinct age-related influences identified in these analyses are the following. First, the effect on the second-order common factor may be attributable to activity within the prefrontal cortex, possibly modulated by the level of a neurotransmitter, such as dopamine (e.g., Braver et al., 2001; Li, 2002). Second, the effect on the first-order memory factor might reflect functioning of the hippocampus and medial temporal lobe (e.g., Eustache et al., 1995; Golumb et al., 1994). Third, the effects on the first-order speed factor may be at least partially attributable to age-related degeneration of myelin (e.g., Bartzokis, 2004; Greenwood, 2000) that could impair the effectiveness of communication across different brain regions. And finally, the positive age-related influence on the vocabulary factor can be hypothesized to reflect increases with age in experience and opportunities for acquiring knowledge.

Although these speculations seem plausible, it could be difficult to establish their validity. For example, it may not be feasible to intervene to change the level of these neurobiological factors, and even if it were possible, one might need to wait decades to determine effects of the intervention on the *rate* of cognitive aging as opposed to the immediate *level* of cognitive functioning. A more practical approach may be to investigate hypothesized neurobiological linkages with correlational procedures. That is, correlations can be used to examine the expectations that neurobiological markers are negatively related to age and positively related to measures of cognitive functioning, and that when the neurobiological marker is statistically controlled, the age relations on the measure of cognitive functioning are reduced. Because of the correlational nature of the research, this pattern of outcomes would not confirm the hypothesized linkage. Nevertheless, failure to find a pattern such as this would be inconsistent with the involvement of the hypothesized neurobiological mechanism, and thus would be relevant to the validity of the causal hypothesis. The challenge in pursuing research attempting to link neurobiology to cognition will likely be obtaining reliable in vivo markers of the proposed neurobiological mechanisms in moderately large samples of adults across a wide age range. However, the key point from

the current analyses is that integrative research of this type will likely be more productive when the interrelations of the cognitive variables are recognized, and the linkage analyses are conducted on empirically determined groupings of cognitive variables instead of on individual variables.

Several limitations of the current project should be acknowledged. First, despite aggregation of data across multiple studies, the analyses were still based on a relatively small set of reference abilities and indicator variables. It would clearly be desirable in the future to examine a wider variety of variables to determine whether the major conclusions would hold with a greater number of cognitive ability constructs, broader coverage of what the constructs represent, and alternative organizational structures.

Second, most of the research participants were from the higher end of the distribution of cognitive ability, and there is evidence that relations among cognitive variables vary as a function of level of ability (e.g., Detterman & Daniel, 1989). It would therefore be valuable to extend these types of analyses to a more diverse sample with a larger proportion of individuals from the lower regions of the ability distribution.

And third, all of the data were cross-sectional, and were based on comparisons across different people at nearly the same point in time. Data of this type are very useful for specifying the precise nature of differences in cognitive functioning associated with between-person characteristics, such as age, gender, amount of education, and health status. However, one should not infer that a similar pattern would necessarily be apparent in analyses of the changes in the scores that might be observed if the people were to change their age, gender, level of education, or health.

In summary, analyses conducted on data aggregated across 33 separate studies suggest that individual differences associated with age, gender, health, and education have different manifestations in a hierarchical structure of cognitive abilities. The statistically distinct influences identified from these analyses may therefore serve to focus future explanatory research, and to function as a meaningful level of representation in attempting to establish linkages between cognition and neurobiology.

Acknowledgments

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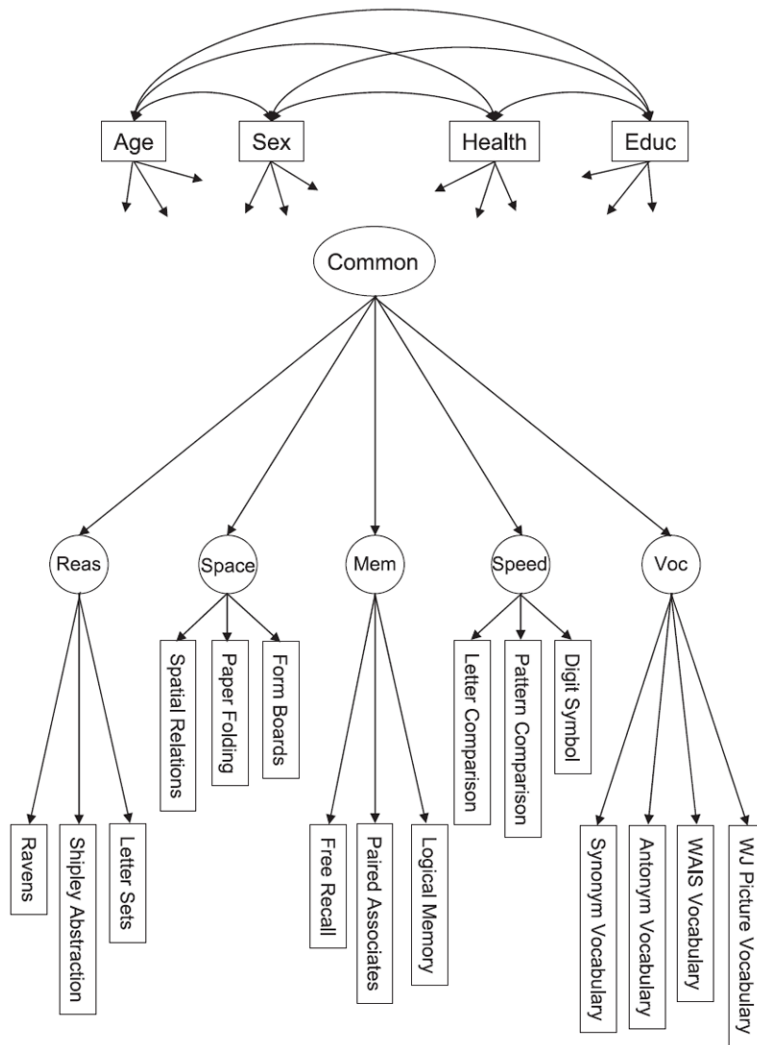
Fig. 1.
Illustration of a hierarchical organization of cognitive variables and four individual difference variables that could exert their influences either at the level of first-order constructs or on the second-order construct in the structure.
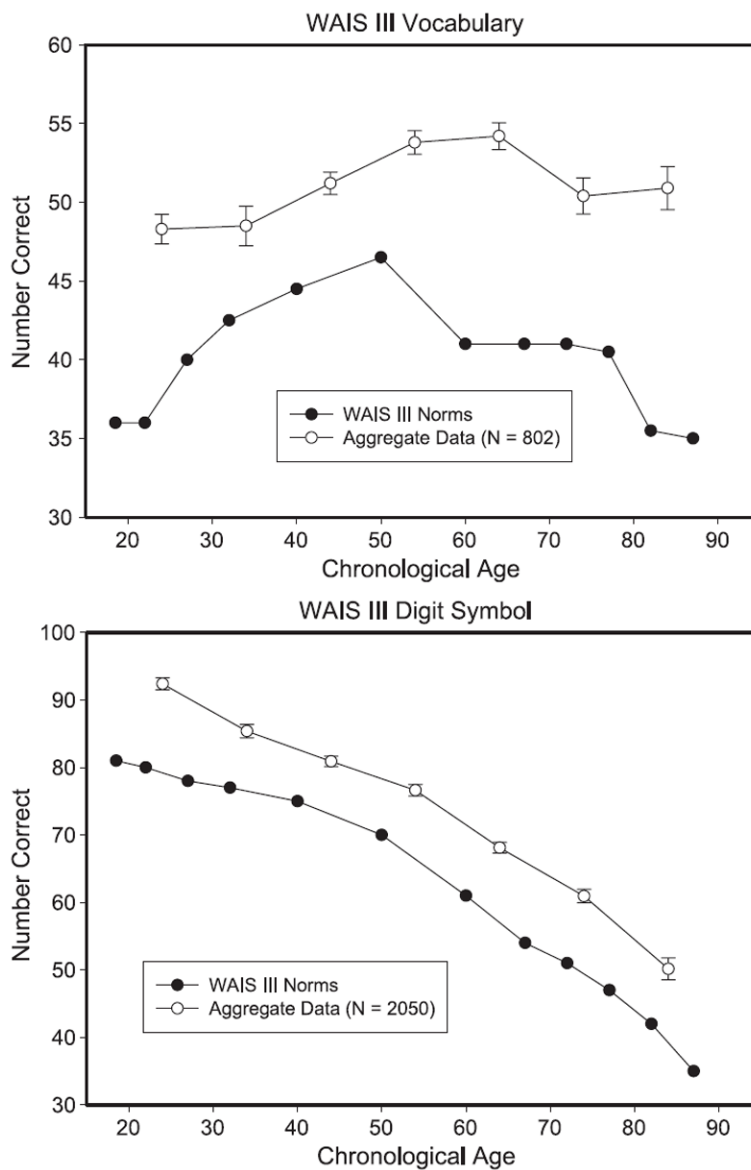
Fig. 2.
Raw scores as a function of age on the WAIS III Vocabulary and WAIS III Digit Symbol tests in the normative sample and in the current aggregate data. Bars around the points are standard errors.
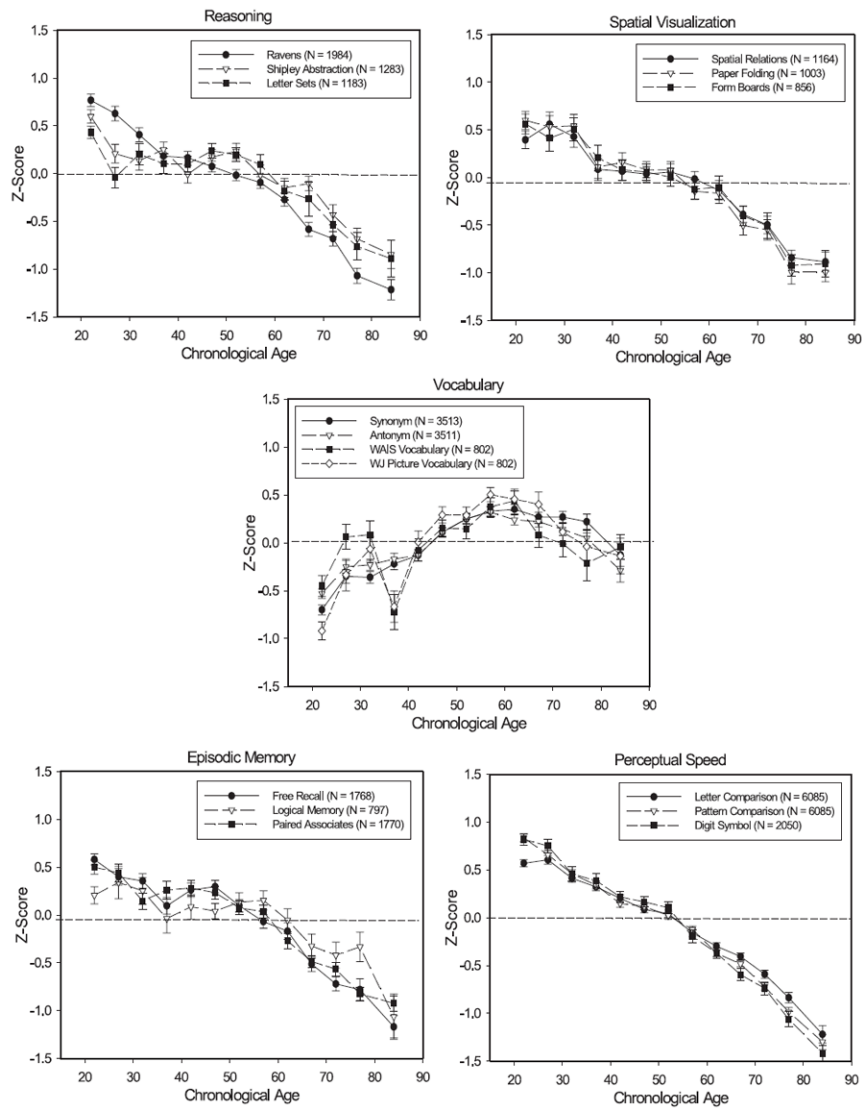
Fig. 3.
Mean performance as a function of age in the 16 reference variables. Bars around the points are standard errors.

Table 1

Description of cognitive variables included in the analyses

Variable	Description	Source
Vocabulary		
WAIS vocabulary	Provide definitions of words	Wechsler (1997a)
Picture vocabulary	Name the pictured object	Woodcock and Johnson (1989)
Antonym vocabulary	Select the best antonym of the target word	Salthouse (1993a, 1993b, 1993c)
Synonym vocabulary	Select the best synonym of the target word	Salthouse (1993a, 1993b, 1993c)
Reasoning		
Ravens	Determine which pattern best completes the missing cell in a matrix	Raven (1962)
Shipley abstraction	Determine the words or numbers that are the best continuation of a sequence	Zachary (1986)
Letter sets	Identify which of five groups of letters is different from the others	Ekstrom et al. (1976)
Spatial visualization		
Spatial relations	Determine the correspondence between a 3-D figure and alternative 2-D figures	Bennett, Seashore and Wesman (1997)
Paper folding	Determine the pattern of holes that would result from a sequence of folds and a punch through folded paper	Ekstrom et al. (1976)
Form boards	Determine which combinations of shapes are needed to fill a larger shape	Ekstrom et al. (1976)
Episodic memory		
Logical memory	Number of idea units recalled across three stories	Wechsler (1997b)
Free recall	Number of words recalled across trials 1 to 4 of a word list	Wechsler (1997b)
Paired associates	Number of response terms recalled when presented with a stimulus term	Salthouse, Fristoe and Rhee (1996a), Salthouse, Hambrick, Lukas and Dell (1996b), Salthouse, Hancock, Meinz and Hambrick (1996c)
Speed		
Digit symbol	Use a code table to write the correct symbol below each digit	Wechsler (1997a)
Letter comparison	Same/different comparison of pairs of letter strings	Salthouse and Babcock (1991)
Pattern comparison	Same/different comparison of pairs of line patterns	Salthouse and Babcock (1991)

Table 2

Distribution of variables by studies in the combined data

Variable	Study																																
	*1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
Publication date	1990	1990	1991	1992	1992	1993	1993	1994	1994	1994	1994	1995	1995	1995	1996	1996	1996	1996	1997	1998	1998	1999	1999	1999	1999	1999	2000	2001	2001	2001	2003	2003	–
Sample size	383	50	233	228	223	221	305	246	258	240	127	117	131	242	178	259	77	197	124	191	128	189	202	218	195	200	207	232	220	206	204	270	331
Synonym vocabulary															X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Antonym vocabulary															X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WAIS vocabulary																															X	X	X
WJ Picture vocabulary																															X	X	X
Raven's matrix reasoning							X													X		X							X	X	X	X	X
Shipley abstraction							X									X							X	X									X
Letter sets	X																													X	X	X	X
Spatial relations	X																										X			X	X	X	X
Paper folding		X																												X	X	X	X
Form boards		X																												X		X	X
Free recall																X			X	X		X								X	X	X	X
Logical memory																															X	X	X
Paired associates								X								X											X			X	X	X	X
Letter comparison			X	X	X	X			X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X		X	X	X
Pattern comparison			X	X	X	X			X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
WAIS digit symbol			X	X	X	X	X	X							X	X																X	X

*
In order to conserve space in the table, the studies are designated by a number that appears in the references.

Table 3

Means, standard deviations (S.D.'s), age correlations, and standardized factor loadings for the reference variables

Variable	Prop. var. associated with age						Factors				
	N	Mean	S.D.	Linear	Quadratic	Cubic	Reas	Space	Mem	Spd	Voc
Age	6832	49.0	17.2	NA	NA	NA					
Sex (% female)	6832	58	4.9	.000	.003*	.001*					
Education	5081	15.3	2.5	.000	.026*	.003*					
Health	6816	2.1	1.0	.017*	.001	.000					
Ravens	1984	7.5	3.7	.248*	.003*	.003*	.89(+)				
Shipley abstraction	1283	13.1	4.7	.083*	.008*	.008*	.86*				
Letter sets	1183	9.9	4.0	.069*	.021*	.002	.80*				
Spatial relations	1164	9.3	5.1	.119*	.007*	.000		.91(+)			
Paper folding	1003	6.5	2.9	.186*	.004	.001		.83*			
Form boards	856	7.1	4.2	.146*	.003	.000		.80*			
Logical memory	797	45.3	10.4	.062*	.021*	.008*			.75(+)		
Free recall	1768	.67	.15	.177*	.014*	.001			.78*		
Paired associates	1770	2.8	1.6	.142*	.012*	.000			.72*		
Digit symbol	2050	77.2	19.1	.326*	.007*	.000				.77(+)	
Letter comparison	6085	10.4	3.2	.187*	.006*	.000				.80*	
Pattern comparison	6085	16.4	4.2	.271*	.003*	.002*				.82*	
WJ picture vocabulary	802	18.9	5.5	.087*	.068*	.000					.78(+)
Synonym vocabulary	3513	6.8	2.9	.079*	.025*	.002*					.89*
Antonym vocabulary	3511	6.2	3.2	.035*	.024*	.002*					.90*
WAIS vocabulary	802	51.3	10.5	.013*	.027*	.009*					.85*

The factors were reasoning (Reas), spatial visualization (Space), episodic memory (Mem), perceptual speed (Spd) and vocabulary (Voc). The symbol "+" indicates that the unstandardized coefficient was fixed to 1 to identify the factor. NA means that the parameter is not available or relevant.

*
p<.01.

Table 4

Construct correlations for confirmatory factor analysis with correlated factors

	Aggregate data	Mult. imput.	Wt. avg.	Meta-analysis
Construct correlations				
Reasoning–space	.92	.85	NA	.53
Reasoning–memory	.74	.69	.53	.38
Reasoning–speed	.78	.80	.57	.55
Reasoning–vocabulary	.45	.57	.60	NA
Space–memory	.66	.64	NA	.33
Space–speed	.67	.68	NA	.40
Space–vocabulary	.44	.43	NA	NA
Memory–speed	.71	.71	.50	.33
Memory–vocabulary	.47	.51	.51	NA
Speed–vocabulary	.29	.32	.46	NA
Age–construct coefficients				
Age →reasoning	−.47	−.46	−.58	−.40
Age→space	−.39	−.44	NA	−.38
Age→memory	−.49	−.46	−.53	−.33
Age→speed	−.61	−.65	−.66	−.52
Age→vocabulary	.26	.22	.26	NA

All correlations were significantly different from zero at $p<.01$. NA indicates that an estimate was not available. Entries in the "Mult. imput." column are averages of the coefficients across five imputed data sets. Entries in the "Wt. avg." column are from Salthouse (in press(a)), and are the averages adjusted for sample size of the correlations between latent constructs across separate studies. Entries in the "Meta-analysis" column are from Verhaeghen and Salthouse (1997) and are estimates derived from meta-analyses of the correlations between individual variables. The age–construct correlations in the current data were obtained from a separate analysis in which age was added to a model in which the factors were allowed to correlate with one another.

Table 5

Construct correlations after partialling age and other variables and in two age groups

Construct correlations	Partial age	Partial age gender, education, health	18–49	50–95
Reasoning–space	.90	.90	.91	.90
Reasoning–memory	.66	.60	.68	.70
Reasoning–speed	.68	.62	.66	.80
Reasoning–vocabulary	.74	.66	.56	.70
Space–memory	.55	.53	.66	.53
Space–speed	.55	.50	.60	.60
Space–vocabulary	.62	.54	.57	.53
Memory–speed	.57	.48	.54	.73
Memory–vocabulary	.68	.63	.61	.59
Speed–vocabulary	.56	.47	.39	.56

Table 6

Standardized coefficients for the hierarchical structural model portrayed in Fig. 1

Correlations

Age–gender	.02	Gender–education	–.09*
Age–education	–.02	Gender–health	.02
Age–health	.13*	Education–health	–.16*

Loadings on second-order common factor

Memory	.66*
Space	.91*
Reasoning	.97*
Speed	.60*
Vocabulary	.73*

Standardized coefficients from individual difference variables

	Age		Gender		Education		Health	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Second-order Common	–.48*	–.48*	.03	.03	.32*	.32*	–.05*	–.05*
First-order Space	.03	–.41*	–.17*	–.14*	.01	.30*	–.00	–.05*
Memory	–.15*	–.47*	.17*	.19*	.10*	.32*	–.07*	–.10*
Speed	–.31*	–.60*	.04*	.06*	.06*	.26*	–.05*	–.08*
Vocabulary	.63*	.28*	–.03	–.01	.22*	.45*	–.05*	–.08*

Age is scaled in years, gender is coded 0 for male and 1 for female, education is the number of years of formal education completed, and health was a self-rating on a scale from 1 for excellent to 5 for poor.

*
$p < .01$.