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How Many Causes Are There of Aging-Related Decrements in Cognitive Functioning?

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Two analytical methods are proposed to evaluate the extent to which the age-related influences in a set of variables are independent of one another. Application of the methods to 16 different data sets, representing a total of 169 variables and 4505 subjects, reveals that as few as one or two distinct factors may be sufficient to account for a large proportion of the age-related variance in a variety of cognitive variables. These results therefore imply that a relatively small number of independent "causes" may be responsible for a substantial percentage of the age-related declines apparent in many measures of cognitive functioning.

A major issue in the area of aging and cognition is what are the causes of the well-documented negative relations between age and measures of cognitive functioning. It is useful when considering this issue to distinguish three related questions: (1) Why are the age differences larger in some variables than in others? That is, what mechanisms can account for the variation in the magnitude of age-related effects across different cognitive variables? (2) When age differences are found in one variable, are they independent of the age-related influences operating in other variables? That is, given that age differences are present in a number of variables, how many distinct factors contribute to these differences? (3) How many distinguishable factors are responsible for the age differences apparent in a particular variable, and what is the relationship among those factors?

These three questions are clearly not independent, but it may be productive to consider them separately. The focus in this article will be on the second question because not only is knowledge about the number of distinct influences contributing to the age-related differences in cognition interesting in its own right, but information of this type should ultimately facilitate research concerned with identifying the mechanisms responsible for differential age-related influences, and with specifying the multiple

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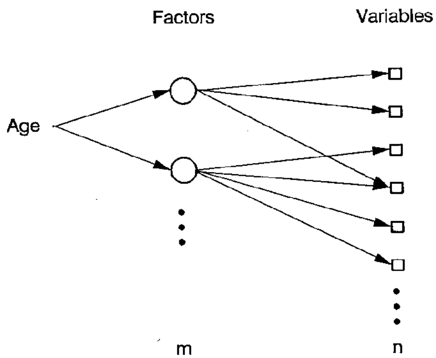


FIG. 1. Illustration of the distinction between the number of observable variables, n, and the number of hypothesized causes, m, of the age differences in those variables.

determinants that might be contributing to the age differences evident within a single variable.

Of primary interest in the current context is whether the age-related influences in one age-sensitive cognitive task are independent of the age-related influences in other cognitive tasks. Stated somewhat differently, are there any common factors contributing to the age differences observed across a variety of different cognitive measures? In terms of the schematic representation in Fig. 1, the key question is whether, and if so by how much, m, the number of hypothesized factors responsible for the observed age-related differences, is smaller than n, the number of variables exhibiting differences significantly related to age.

Age-related differences have been documented in many different types of cognitive variables (e.g., for recent reviews see Craik and Salthouse, 1992; and Salthouse, 1991a), but it is not yet clear whether the differences apparent in one variable are independent of those found in other variables. A useful method of conceptualizing the relations among two variables with each other and with age involves expressing the variance in each variable in terms of Venn diagrams, as in Fig. 2.

The overall degree of dependence between two variables such as 1 and 2 corresponds to the square of the correlation between them, which is represented in Fig. 2 as the ratio of region [a + b] over region [a + b + c + e] when variable 1 is the reference, or as the ratio or region [a + b] over region [a + b + d + f] when variable 2 is the reference.[1] However,

[1] Note that because the area of the entire circle is assumed to be 1.0, the region [a + b + c + e] is equivalent to the region [a + b + d + f], and hence the ratios for variables 1 and 2 are identical and symmetric. Not all ratios of shared to total variance need be symmetric, however, and the ratios are described separately for the two variables to emphasize this fact.

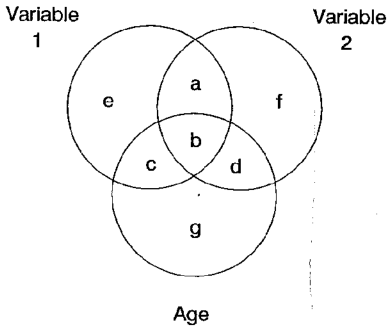


FIG. 2. Venn diagrams illustrating regions of variance for two variables and age. The total area of each circle is 1.0, and the overlapping regions represent shared variance.

the age-related variance in variable 1 corresponds only to the region labeled b + c, and the age-related variance in variable 2 corresponds only to the region labeled b + d. Therefore, if the goal is to determine the proportion of age-related variance in variable 2 that is shared with variable 1, then it is the ratio b/[b + d] (or b/[b + c] if variable 1 is the reference) that is of greatest relevance. For this particular purpose there is little interest in the influences on regions a, e, and f because those regions represent variance that is independent of age. That is, if the goal is to investigate possible commonalities in age-related influences, then a reasonable strategy is to focus on the age-related variance in the variables, which is represented by regions b + c for variable 1 and regions b + d for variable 2. Adoption of this strategy does not imply that other proportions of variance are unimportant, but merely reflects the present goal of attempting to account for the sources of the *age-related* differences in cognitive performance.

Figure 2 also illustrates that each variable can be postulated to consist of four distinct types of variance. These are: shared age-independent variance, corresponding to region a; shared age-related variance, corresponding to region b; unique age-related variance, corresponding to region c for variable 1 and region d for variable 2; and unique age-independent variance, corresponding to region e for variable 1 and region f for variable 2. Although not represented in the figure, the unique age-independent variance can also be considered to be composed of variance specific to that variable, and variance that is unsystematic or unreliable.

OVERVIEW OF PROPOSED METHODS

The analytic methods to be used for partitioning age-related variance into common and unique components differ in an important respect from existing procedures because the interest is not in the overlap of the total variance in the variables, but only in the overlap of the age-related variance. This distinction is illustrated in Fig. 3, where on the left the factors are formed because of overlap in the total variance in the variables, but on the right the factors are based on the overlap of only the age-related variance in the variables. Because the current goal is to identify relations that might exist among only the age-related variance in the variables, and not among the total variance in the variables, the right panel most closely represents the desired situation in the present context.

One method of accomplishing the desired partitioning is to restrict the analyses to only the proportion of the age-related variance that is shared between two variables. That is, the focus could be on the variance common to two variables relative to only the age-related variance in each variable and not relative to the total variance in the variables. In terms of Fig. 2, the analyses would be based on ratios of b to b + d for variable 2, and b to b + c for variable 1. These ratios can be expressed in the form of a special type of correlation (Salthouse, 1992a) and the resulting correlation matrix analyzed by conventional factor analysis procedures.

A second possible method of partitioning the age-related variance in a variable into common and unique components is based on structural equation models. Kliegl and Mayr (1992) and McArdle and Prescott (1992) have recently described models in which the relevant variables are related to one another through a common factor, which in turn is related to age. (Also see Lindenberger, Mayr, and Kliegl, 1993, for another example of this type of model.) If the model can be assumed to provide an adequate fit to the data, it is possible to use the path coefficients from the model to estimate the common age-related variance in a given variable (i.e., region b) which can then be compared with the total age-related variance in the variable (i.e., region b + c for variable 1, or b + d for variable 2).

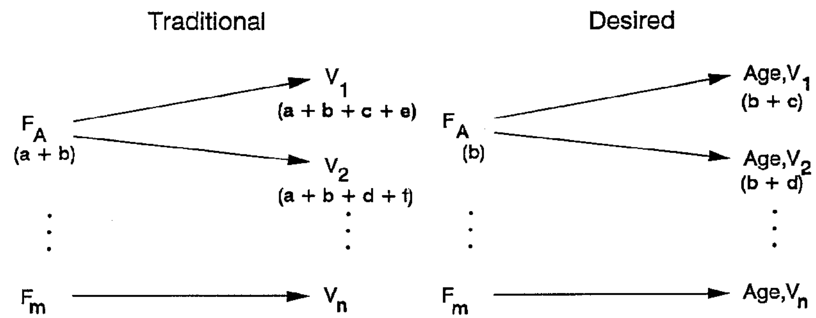


FIG. 3. Contrast between the outcome of traditional factor analyses based on all of the variance in each variable (left) and the outcome of the desired factor analyses based on only the age-related variance in each variable (right).

QUASI-PARTIAL CORRELATION METHOD

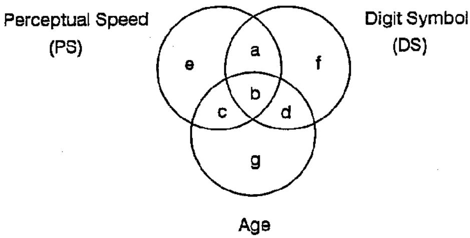
One potential analytical technique involves the use of multiple regression and correlation procedures to derive estimates of different proportions of variance (Salthouse, 1992a). Application of this technique can be illustrated with data from two recent projects in which 910 (Salthouse, 1992b) and 305 (Salthouse, 1993b) adults between 18 and 84 years of age performed the Wechsler (1981) Digit Symbol Substitution Test and two perceptual speed tests, letter comparison and pattern comparison. A composite perceptual speed variable was formed for each research participant by averaging his or her *z*-scores for the letter comparison and pattern comparison measures. Three variables were thus available in each study: age, a perceptual speed composite, and Digit Symbol score.

Figure 4 displays the estimates of each variance proportion, and summarizes the multiple regression methods used to derive the estimates.[2] Notice that about 50% (54.0 and 46.2%) of the total variance in Digit Symbol score is shared with the composite perceptual speed variable (i.e., [a + b]). However, less than 30% (28.9 and 26.1%) of the Digit Symbol variance is related to age (i.e., [b + d]). Additional computations are therefore necessary to determine the proportion of the age-related variance in the Digit Symbol score that is shared with the perceptual speed measure. One method by which this might be accomplished involves dividing the estimate of the common age-related variance (b_{DS}) by the total age-related variance (b + d). Alternatively, the proportion of age-related variance that is unique [d/(b + d)] can be subtracted from 1.0 to yield the proportion of age-related variance that is not unique and is shared. Ratios of shared (b) to total (b + d) age-related variance for the displayed data are .972 for the sample of 910 and .923 for the sample of 305.

These values indicate that although only about 50% of the total variance in Digit Symbol score is shared with the perceptual speed variable, nearly 95% (97.2 and 92.3%) of the age-related variance in that variable is shared, or in common, with the age-related variance in the perceptual speed variable. Expressed somewhat differently, only about 5% (2.8 and 7.7%) of the age-related variance in the Digit Symbol score is unique, and independent of the age-related variance in the perceptual speed variable.

It is informative to contrast the ratios of shared age-related variance with the ratios of shared variance unrelated to age. For the Digit Symbol variable these latter values correspond to region a relative to regions [a +

[2] Two different estimates are provided for the a and b regions because estimates of the proportions of variance in the two variables obtained from the hierarchical regression analyses are not necessarily symmetric.



	Region	Estimates n=910	Estimates n=305	Derived By
(1)	a + b + c	.626	.540	R^2 in PS from DS and Age
(2)	a + b + d	.548	.482	R^2 in DS from PS and Age
(3)	a + b	.540	.462	R^2 in DS from PS
(4)	b + c	.412	.343	R^2 in PS from Age
(5)	b + d	.289	.261	R^2 in DS from Age
(6)	a_{PS}	.214	.197	Incr. in R^2 in PS from DS after Age
(7)	a_{DS}	.259	.221	Incr. in R^2 in DS from PS after Age
(8)	c	.086	.078	Incr. in R^2 in PS from Age after DS
(9)	d	.008	.020	Incr. in R^2 in DS from Age after PS
(10)	e	.374	.460	Subtraction of (1) from 1.0
(11)	f	.452	.518	Subtraction of (2) from 1.0
(12)	b_{DS}	.281	.241	Subtraction of (9) from (5)
(13)	b_{PS}	.326	.265	Subtraction of (8) from (4)

FIG. 4. Illustration of relevant regions of variance and estimates of those variance proportions from two data sets.

f]. The ratios based on the estimates from the values in rows 6 and 11 in Fig. 4 are .364 for the data based on 910 subjects and .299 for the data based on 305 subjects.

The three types of variance ratios just described make it possible to specify: (a) the proportion of the *total* variance in variable 2 that is shared with variable 1, ([a + b]/[a + b + d + f]); (b) the proportion of the *age-related* variance in variable 2 that is shared with the age-related variance in variable 1, (b/[b + d]); and (c) the proportion of the *age-independent* variance in variable 2 that is shared with the age-independent variance in variable 1, (a/[a + f]). In the two data sets summarized in Fig.

4, these values are .540, .972, and .364, respectively, for the sample of 910 and .462, .923, and .299, respectively, for the sample of 305. Dramatically different estimates of the magnitude of the relation between the two variables can therefore be obtained depending on the particular variance being analyzed.

Thus, even if two variables are distinct in the sense of having substantial unique variance, they may be very similar with respect to the overlap of their age-related variance. The preceding example illustrates that the age-related influences on two variables may be almost completely overlapping even if the variables share only about half of their total variance. Furthermore, the proportion of shared variance that is unrelated to age may be quite different from the proportion of shared variance that is related to age.

Because ratios of variance can be interpreted in terms of correlation coefficients, it is possible to express the ratio of shared to total age-related variance as a correlation coefficient. That is, one formula for a correlation coefficient is

$$r = \sqrt{([\mathrm{cov}(xy)/\mathrm{var}(x)][\mathrm{cov}(xy)/\mathrm{var}(y)])}. \quad (1)$$

Because the b region in Fig. 4 can be considered analogous to a covariance estimate and the (b + c) and (b + d) regions considered analogous to estimates of variance, they can be used to derive what can be termed a quasi-partial correlation, that is,

$$\mathrm{q}r^2 = \sqrt{([\mathrm{b_{DS}}/(\mathrm{b} + \mathrm{d})][\mathrm{b_{PS}}/(\mathrm{b} + \mathrm{c})])}. \quad (2)$$

Because the regions in Fig. 4 correspond to proportions of variance, the geometric mean of the ratios corresponds to the square of the quasi-partial correlation. Substituting the values from Fig. 4 in this equation reveals that the quasi-partial correlations are .936 for the sample of 910 and .919 for the sample of 305. By contrast, the simple correlations between the composite perceptual speed and Digit Symbol variables are .735 and .680 for the samples of 910 and 305, respectively, and the partial correlations excluding age-related variation are .603 and .547 for the two samples, respectively.

The quasi-partial correlation can be thought of as the converse of a partial correlation because although in both cases the goal is to specify the variance common to variable 1 and variable 2, the partial correlation procedure *excludes* age-related variance (i.e., it reflects the ratio of a/[a + f]), whereas the quasi-partial correlation procedure *is restricted to* age-related variance (i.e., it reflects the ratio of b/[b + d]). It is important to emphasize that the three types of correlations are based on different proportions of variance in the sense that the variance estimates in the denominator of the ratios are all different. Because of this property, the three types of correlations are not directly comparable, although they are clearly related to one another.[3] Moreover, because regions e, f, and g represent unreliable variance as well as specific variance, ratios with these terms in the denominator (i.e., correlations and partial correlations) are likely to be somewhat smaller than ratios with only reliable variance in the denominator (i.e., quasi-partial correlations).

At least two methods can be used to compute the covariance–variance ratios used in quasi-partial correlations. Both involve subtracting an estimate of region d from an estimate of the sum of regions b + d and then dividing this difference by the estimate of the sum of regions b + d. (Analogous procedures are used to derive estimates of the ratios of c to b + c for variable 1, and hence only the procedures for variable 2 are described.) A method based on hierarchical multiple regression can be expressed with the following formula:

$$b/(b + d) = \sqrt{}([R^2_{2.\mathrm{Age}} - (R^2_{2.1,\mathrm{Age}} - R^2_{2.1})]/R^2_{2.\mathrm{Age}}). \quad (3)$$

The relevant ratios can also be derived from simple correlations. First, the semipartial correlation of age and variable 2 controlling variable 1 (corresponding to the square root of the ratio of region d to the sum of regions [a + b + d + f]) is computed:

$$sr_{2.\mathrm{Age},1} = [r_{2,\mathrm{Age}} - (r_{1.2})(r_{1,\mathrm{Age}})]/\sqrt{}(1 - r^2_{1,\mathrm{Age}}). \quad (4)$$

Next, the ratio of age-related covariance to variance is computed from the following formula:

$$b/(b + d) = \sqrt{}([r^2_{2,\mathrm{Age}} - sr^2_{2.\mathrm{Age},1}]/r^2_{2,\mathrm{Age}}). \quad (5)$$

The final step in the computation of the quasi-partial correlation involves determining the square root of the geometric mean of the ratios for the two variables, as indicated in Eq. (2).

There is at least one potential problem with quasi-partial correlations that needs to be considered before attempting to compute and interpret them. This is that the estimate of variance common to three variables, represented by region b in Figs. 2 and 4, could be negative if there are suppression effects or if the correlations have opposite signs. Because negative values are not meaningful as proportions of variance, several

[3] As pointed out by a reviewer of an earlier version of the manuscript, the relations among the correlations can be described according to the equation $r^2 = \sqrt{}[(b_1 + c)(b_2 + d)][r_{\mathrm{quasi}}^2] + \sqrt{}[(a_1 + e)(a_2 + f)][r_{\mathrm{partial}}^2]$.

authors have cautioned against ever interpreting estimates representing the overlap of three variables as proportions of variance (e.g., Cohen & Cohen, 1983, p. 90, 145; Pedhazur, 1982, p. 210).

Although negative values for variances are clearly not meaningful, it is instructive to evaluate the severity of this potential problem in terms of the likelihood of its occurrence, and the consequences it has for the interpretation of estimates of proportions of shared age-related variance. With respect to the first point, although there are many possible combinations of correlations that could result in suppressor effects, analyses of 932 pairs of variables (described below) revealed only one case in which the quasi-partial correlation could not be computed because of a negative estimate for the region corresponding to b (i.e., the variance common to age and the two variables). Of course, one reason for this small incidence may be that the analyses were restricted to variables with negative age correlations of −.1 or greater, but it is important to note that at least within certain conditions, the prevalence of negative estimates for the critical region of shared variance among three variables is quite low. Moreover, limiting analyses to these conditions seems justified because it is probably not meaningful to attempt to partition smaller proportions of age-related variance.

Now consider how negative estimates of region b might be interpreted. One possible interpretation is that when negative estimates of b occur they are merely errors of estimation, and that the true value of b is very close to zero. Another interpretation is that although values less than zero may reflect the existence of genuine suppressor effects, these effects might reasonably be ignored and the relation between the age-related variance in the two variables assumed to be zero. Under both of these interpretations, therefore, it would be reasonable to compute quasi-partial correlations by replacing a negative estimate for region b with a zero, and in effect claiming that the two variables had no age-related variance in common. This procedure was followed in the analyses reported below.

APPLICATION OF QUASI-PARTIAL CORRELATION METHOD

If quasi-partial correlations are considered meaningful, then it should be possible to analyze them with the same types of procedures used with simple correlations. In particular, exploratory, and possibly confirmatory, factor analysis procedures could be used to determine the degree to which the variance in the variables under consideration is shared or unique. The major difference from more traditional analyses is that now the correlations reflect only the proportion of the shared variance that is also related to age, rather than the proportion of the total variance that is shared.

Application of these procedures can be illustrated with data reported by

McArdle and Prescott (1992). These investigators described analyses of data from 1680 adults between 16 and 75 years of age on subtests of the Wechsler Adult Intelligence Scale–Revised (Wechsler, 1981). Because the interest here is in attempting to partition the age-related variance in the variables, only those variables from their analysis with zero-order age correlations of at least −.1 are considered. The top part of Table 1 contains the original matrix of correlations for the relevant variables as well as age. The middle part contains the matrix of partial correlations, and the bottom part contains the matrix of quasi-partial correlations.

Medians for the three types of correlations were .63, .58, and .90 for the original, partial, and quasi-partial correlations, respectively. As was the case in the example with the perceptual speed and Digit Symbol variables, the variables had a greater degree of overlap with respect to their age-related variance ($.90^2$ = 81.0%) than with respect either to their total variance ($.63^2$ = 39.7%) or to their variance that was unrelated to age ($.58^2$ = 33.6%).

An exploratory principal components analysis was conducted on each correlation matrix to determine the proportion of variance associated with successive components. The cumulative proportions of variance associated with the first four factors in the principal components analysis on each matrix were: .69, .80, .88, and .94 for the original correlations; .66, .78, .86, and .94 for the partial correlations, and .91, .95, .98, and .99 for the quasi-partial correlations.

TABLE 1
Correlation Matrices from McArdle and Prescott (1992), n = 1680

	1	2	3	4	5	Age
			Original correlations			
1 Simil	—	.638	.596	.603	.532	−.216
2 PictCom		—	.657	.645	.646	−.336
3 BikDes			—	.616	.699	−.387
4 PictArr				—	.539	−.416
5 ObjAssm					—	−.342
			Partial correlations			
1 Simil	—	.615	.569	.578	.499	
2 PictCom		—	.607	.590	.600	
3 BikDes			—	.543	.654	
4 PictArr				—	.464	
5 ObjAssm					—	
			Quasi-partial correlations			
1 Simil	—	.893	.853	.836	.850	
2 PictCom		—	.926	.916	.926	
3 BikDes			—	.907	.943	
4 PictArr				—	.863	
5 ObjAssm					—	

Both the median correlations and the principal components analyses therefore reveal that the proportion of shared age-related variance among the variables in the McArdle and Prescott (1992) data set was greater than that evident in either the total variance, or in the age-independent variance. For example, 90% of the variance is accounted for by only one component in the age-related variance (quasi-partial correlations), but four distinct components are required to account for this much variance in analyses of the total variance (original correlations) and the age-independent variance (partial correlations).

The results just described imply that the number of distinct age-related influences on cognitive functioning is considerably smaller than the number of variables used to assess cognitive functioning. Moreover, the number is also smaller than the number of distinct groupings of variables inferred to exist on the basis of analyses of either the total variance or the age-independent variance. Fewer factors therefore need to be postulated to account for comparable amounts of the variance related to age than of the total variance or of the variance independent of age. At least some of the difference across analyses of different types of variance may be related to the inclusion of unreliable variance in the denominators of the ratios of total and age-independent variance but not in the ratio of age-related variance. In fact, if reliability estimates were available for all variables then the correlations could be adjusted for attenuation due to unreliability, and these adjustments would likely result in a greater inflation of the original and partial correlations than of the quasi-partial correlations. However, the major point from the present perspective is that a very large proportion of the age-related variance in these variables appears to be shared with other variables, rather than being unique and independent.

The generality of the results just described was examined by conducting similar analyses on other sets of data collected in my laboratory over the past 5 years. Criteria for the selection of data sets were that the study must have involved at least six variables from 100 or more adults across a wide range of ages, and that the age correlations for all of the variables retained for analyses were −.1 or greater. Major characteristics of the data sets are summarized in Table 2, with the variables included in the analyses from each set listed in Appendix A. It should be noted that the samples in all but data sets 10 and 11 consisted of approximately the same number of adults in each age decade from the 20s through the 70s.

The frequency distributions of the square of each type of correlation for the 855 pairs of variables from these studies are illustrated in Fig. 5. These data clearly indicate that, on the average, the proportion of shared age-related variance is considerable and generally larger than the proportion of shared total variance or shared age-independent variance. It can there-

TABLE 2
DESCRIPTION OF DATA SETS

	Study	No. of subjects	No. of variables
1	Salthouse and Mitchell, 1990	383	6
2	Salthouse *et al.*, 1988, Study 1	129	11
3	Salthouse *et al.*, 1988, Study 2	233	12
4	Salthouse and Babcock, 1991, Study 1	227	8
5	Salthouse and Babcock, 1991, Study 2	233	9
6	Salthouse, 1991b, Study 1	221	7
7	Salthouse, 1991b, Study 2	223	9
8	Salthouse, 1991b, Study 3	228	9
9	Salthouse, 1993b	305	18
10	Salthouse, 1993a, Study 1	100/100[a]	9
11	Salthouse, 1993a, Study 2	77/69[a]	13
12	Salthouse, 1994, Study 1	246	20
13	Salthouse, 1994, Study 2	258	15

[a] Young adults (ages 18 to 33)/old adults (ages 55 to 89).

fore be inferred that, as in the McArdle and Prescott (1992) data, there is substantial overlap of age-related variance across different variables.

The cumulative proportions of variance associated with the first four principal components based on the matrices of original, partial, and quasi-partial correlations for the 13 data sets described in Table 2 are presented in Table 3. As in Table 1, a small number of distinct influences is needed to account for a large proportion of the age-related variance in the variables. That is, in analyses based on between 6 and 20 variables the first component is associated with an average of 75% of the age-related variance, and the first and second components together account for 86% of the age-related variance.

NATURE OF PRESUMED COMMON FACTORS

Additional analyses were conducted on the quasi-partial correlation matrices in an attempt to specify the identity of the primary factors presumed to contribute to the age-related differences in cognition. The analyses used for this purpose were principal component analyses, specifying two factors with a promax rotation. The variables with the highest loadings on each of the two components are summarized in Table 4.

There are three major findings to be noted from Table 4. The first is that the two components are moderately correlated with one another in all data sets, with a median correlation of .59 and a range of .40 to .74. Even when two separate components are specified, therefore, the correlations between them are substantial and thus the components are not completely independent. The second interesting aspect of Table 4 is that in all of the

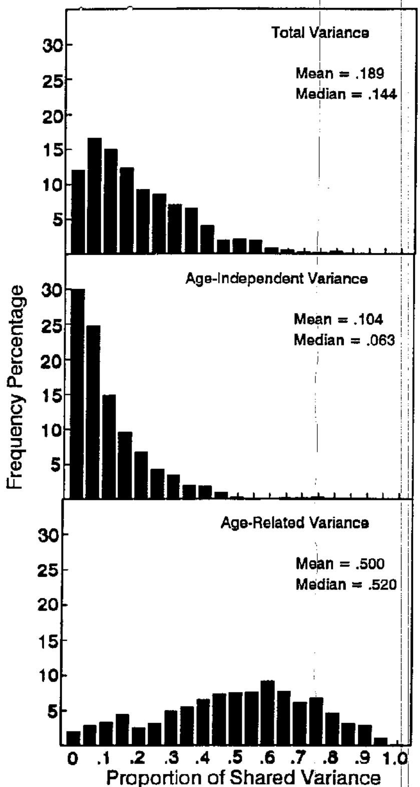


FIG. 5. Frequency distributions of 855 proportions of shared variance relative to the total (top), age-independent (middle), and age-related (bottom) variance.

analyses, variables representing speed of processing have high loadings in at least one component. Whether the speed variables load primarily on the first or second component varies according to the other variables included in the data set, but it is clear that speed variables are prominent in at least one of the major components identified in each of these analyses. Processing speed therefore appears to be important in at least one of the major factors contributing to age-related influences on cognition. The final point to note regarding Table 4 is that only three variables have less than 50% of their age-related variance shared with the two components. This indicates that for most of the variables in these studies, the majority of the age-related variance was shared with other variables and thus may have been determined by the same influences.

In order to examine the possibility that the results reported in Table 4

TABLE 3
CUMULATIVE PROPORTION OF TOTAL VARIANCE ASSOCIATED WITH SUCCESSIVE COMPONENTS

	Original				Partial				Quasi-Partial			
Data set	1	2	3	4	1	2	3	4	1	2	3	4
1	.55	.73	.82	.90	.52	.71	.81	89	.83	.93	.96	.98
2	.33	.49	.60	.69	.28	.45	.56	.65	.58	.75	.86	.91
3	.35	.50	.59	.67	.24	.43	.53	.61	.61	.79	.86	.91
4	.64	.74	.81	.87	.52	.66	.75	.82	.88	.93	.96	.98
5	.58	.71	.77	.83	.49	.63	.71	.77	.84	.92	.94	.96
6	.64	.76	.83	.89	.51	.67	.76	.85	.89	.94	.96	.98
7	.47	.64	.73	.80	.36	.55	.66	.75	.71	.88	.92	.95
8	.52	.68	.76	.82	.41	.60	.70	.77	.78	.93	.96	.98
9	.50	.60	.67	.72	.41	.53	.61	.66	.78	.85	.90	.93
10	.55	.68	.77	.84	.40	.55	.66	.74	.76	.88	.92	.95
11	.57	.68	.75	.80	.32	.46	.57	.65	.78	.86	.91	.93
12	.36	.46	.53	.59	.24	.35	.44	.51	.63	.75	.81	.87
13	.39	.51	.59	.66	.30	.43	.52	.60	.67	.80	.87	.91
Mean	.50	.63	.71	.78	.38	.54	.64	.71	.75	.86	.91	.94

might be restricted to data sets with a large number of speed variables, identical analyses were conducted on three additional data sets containing a greater variety of variables. Characteristics of these data sets and the results of the relevant analyses are presented in Appendix B. It is apparent that the major results of Tables 3 and 4 were replicated in that: (a) the estimates of the shared age-related variance were high, both in absolute terms and relative to the estimates of shared total or age-independent variance; (b) the components were moderately correlated with each other; (c) a speed variable, either Digit Symbol Substitution or Digit Coding, was prominent in the first component in each analysis; and (d) none of the variables had commonality values of less than .5, indicating that the majority of the relevant variance was shared with the other variables.

SINGLE COMMON FACTOR METHOD

Estimates of the proportion of shared or common age-related variance in a given variable can also be derived from a structural equation model in which the variables are associated through a single common factor. That is, in terms of Fig. 1, the value of m, representing the number of distinct factors, is postulated to be 1. The method to be used is a modification of one proposed by Kliegl and Mayr (1992), who postulated that age could have linkages both to the common factor and to each variable. However, it is not necessary for the current purpose to specify direct paths between age and each variable because the total age-related variance in a particular variable can be contrasted with the proportion of age-related variance in that variable assumed to be mediated through the common factor. This latter value is analogous to region b in Fig. 2 and can be estimated from the product of the squares of the standardized path coefficients. The desired partitioning of the age-related variance can therefore be accomplished by contrasting the square of the correlation between age and the variable, representing the total age-related variance corresponding to region (b + c), or region (b + d) for variable 2, with the estimated proportion of common or shared age-related variance derived from the product of the squared path coefficients, corresponding to region b. Note that although this procedure relies on a structural equation model with a latent construct, the focus is on partitioning the age-related variance at the level of observed or manifest variables.

The procedure will be illustrated with the McArdle and Prescott (1992) data presented in Table 1. Standardized coefficients from the single common factor model derived from the correlation matrix in the top part of Table 1 are portrayed in Fig. 6. Because the coefficients in this figure are standardized, the square of the coefficient represents the proportion of variance in the criterion variable associated with the predictor variable to which it is linked by an arrow. To illustrate, the proportion of variance in the common factor that is associated with age is $.436^2$ or .190, and that unrelated to age is $.900^2$ or .810. The manifest variables in the bottom of the figure have a common factor influence, represented by the square of the coefficient from the common factor, and a unique factor influence, corresponding to an undifferentiated mixture of specific variance and unreliable variance. An estimate of the proportion of common age-related variance in each manifest variable can be derived from the product of the squares of the Age-Common coefficient and the Common-Variable coefficient. For example, the estimate for the Similarity variable is $(.436^2)(.734^2)$ or .102.

Values of the actual proportion of age-related variance, derived from the square of the correlation between age and the variable, and the estimated proportion of common age-related variance obtained from the coefficients in Fig. 6, are contained in Table 5. It is immediately apparent that some of the entries in the second column are larger than those in the first column. Because this implies that the proportion of common age-related variance is greater than total proportion of age-related variance, these anomalies require some explanation. Some minor discrepancies might be expected due to errors in estimation, but it seems unlikely that discrepancies of this magnitude originate solely for that reason. Another possibility is that specific age-related influences could be opposite in direction to the common age-related influences, and thus serve to suppress the common influence. Although it is conceivable that common age-

TABLE 4

VARIABLES WITH LOADINGS GREATER THAN OR EQUAL TO .8 AND VARIABLES WITH COMMUNALITIES LESS THAN .5 FROM A TWO-COMPONENT PRINCIPAL COMPONENTS ANALYSIS WITH PROMAX ROTATION

Data set	r(I,II)	Component I	Component II	Variables with $h^2 < .5$
1	.65	**Spatial/reasoning**	**Speed**	
		PapFld	FindAs	
		SurDev	NumCom	
		Shipley	LetSet	
		LetSet		
2	.40	**Memory**	**Speed**	
		PA2	NumCom	ActMem
		VMem	DigSym	
		TempMem	PFTime	
		SMem		
		Closure		
		PFAcc		
3	.40	**Speed**	**Memory**	
		DigSym	PA2	FreqMem
		NumCom	PA1	
		AnalTime	SerAcc	
		SerTime		
4	.72	**Speed/memory**	**Memory**	
		ArithD	DSpan	
		SentA	WSpan	
		ArithA	CSpan	
		SentD	LSpan	
		LSpan		
		CSpan		
		WSpan		
5	.68	**Speed**	**Memory**	
		LetCom	WSpan	
		DigSym	DSpan	
		PatCom	LSpan	
		Arith	CSpan	
		Sent	Sent	
		CSpan		
		LSpan		
6	.74	**Reasoning/memory**	**Speed/reasoning**	
		Shipley	LetCom	
		Ravens	PatCom	
		LSpan	DigSym	
		CSpan	Raven	
		DigSym	Shipley	
		PatCom		
7	.48	**Speed/memory**	**Spatial**	
		DigSym	PapFld	
		LetCom	CubeAssm	
		PatCom		
		CSpan		
		LSpan		
		Analogy		
8	.53	**Memory/speed**	**Spatial**	
		CSpan	PapFld	
		LSpan	CubeAssm	
		LetCom	IntReas	
		PatCom		
		DigSym		
		Analogy		
		IntReas		

TABLE 4—*Continued*

Data set	r(I,II)	Component I	Component II	Variables with $h^2 < .5$
9	.68	**G/Speed**	**Speed**	
		PMAReas	DCopy	
		PairAsoc	HMark	
		Analogy	LCopy	
		PMASpace	VMark	
		LComp	DigSym	
		DComp	LetCom	
		IntReas	DComp	
		DigSym	PatCom	
		PatCom	LComp	
		Asymptot	DTran	
		LTran		
10	.59	**Speed**	**Verbal**	
		LCopy	Anagram	
		LetCom	Nouns	
		PatCom	S-Words	
		DigSym		
		DCopy		
		WdSwtch		
11	.66	**Speed/memory**	**Verbal**	
		DigSym	Scrabble	
		PatCom	WdEnd	
		LetCom	MakeWd	
		HMark	WdBegin	
		PairAsoc		
		VMark		
		Asymptot		
		Primacy		
		Recency		
12	.49	**Speed/G**	**Study time**	
		DigSym9	PFST	NameNum
		DigSym0	PFDT	
		MatPC	MatST	
		DCopy		
		PatCom		
		PFPC		
		LetCom		
		NumSer		
		Boxes		
		ASMDT		
		IntCpt		
		MatDT		
13	.51	**Speed/G**	**Study time**	
		DigSym9	SRST	
		Intcpt	SRDT	
		PatCom	MatST	
		Boxes	MatDT	
		LetCom		
		DigSym0		
		MatDT		
		ASMDT		
		DCopy		
		ASMPC		
		SRPC		

Note. Names in bold are labels for the components, and names in normal type refer to variables (cf. Appendix A). Variables within each column for a given data set are arranged in descending order of factor loading (columns 3 and 4) or of communality (column 5).

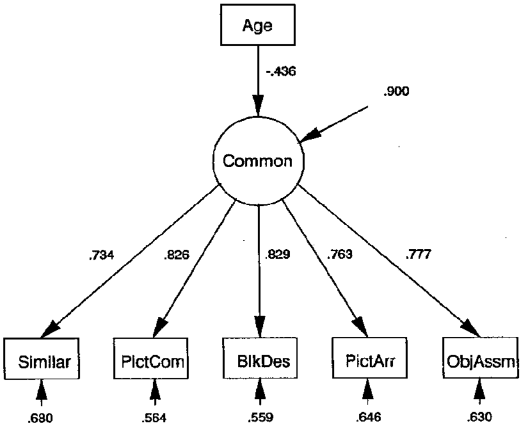


FIG. 6. Single-factor model of age-related influences on variables from McArdle and Prescott (1992) data set.

related influences could be negative and specific influences positive, there is no direct evidence for a pattern of this type in these data. Another possible reason for the relatively large discrepancies between the estimates of total and common age-related variance is that the structural model was inadequate because of the omission of important latent or manifest variables and/or relations among variables. In fact, the model represented in Fig. 1 provided a relatively poor fit to the data as revealed by various goodness-of-fit indices (e.g., χ^2 (df = 9) = 228.1; Adj. Population Gamma Index = .904; Joreskog-Sorbom AGFI = .901). However, McArdle and Prescott (1992) reported that a more elaborate model, in-

TABLE 5
COMPARISON OF ACTUAL AGE-RELATED VARIANCE (r^2) AND ESTIMATED PROPORTION OF COMMON AGE-RELATED VARIANCE FROM MCARDLE AND PRESCOTT (1992) DATA

Variable	Actual age-related variance	Est. common age-related variance[a]	Est. common age-related variance[b]
Similarities	.047	.102	.022
Picture Completion	.113	.130	.099
Block Design	.150	.131	.097
Picture Arrangement	.173	.111	.088
Object Assembly	.117	.115	.081
Mean	.120	.118	.077

[a] Estimated from coefficients in Fig. 6.
[b] Estimated from coefficients in Fig. 5 of McArdle and Prescott (1992).

cluding an additional manifest variable with a small loading on the common factor, another common factor that was not negatively related to age, and relations between the common factor and both education and the other latent factor, provided a very good fit to the complete data. Estimates of the proportions of common age-related variance obtained from the Age-Common and Common-Variable coefficients from their best-fitting model, portrayed in Fig. 5 of McArdle and Prescott (1992), are summarized in the third column of Table 5. It can be seen that for all of these estimates, the proportion of common age-related variance is less than the total proportion of age-related variance. Of particular importance is that the average proportion of common age-related variance is approximately 64% of the average proportion of total age-related variance. This finding implies that almost two-thirds of the age-related variance in these variables is shared with the age-related variance in the other variables. Stated somewhat differently, these data suggest that only about one-third of the age-related variance in any one of these variables is independent of the age-related variance in the other variables.

The preceding example from the McArdle and Prescott (1992) data indicates that estimates of the proportion of common age-related variance derived from a single common factor may be misleading if the models are underspecified or incomplete. Estimates were nevertheless derived for the variables in the data sets summarized in Table 2 and Appendix A with a single common factor model similar to that illustrated in Fig. 6. The Age-Common coefficients ranged from −.383 to −.904 across the 13 data sets, with a median of −.677, and the Common-Variable coefficients ranged from .149 to .918, with a median of .656. For each of the 146 variables in these studies the actual proportion of age-related variance was computed from the square of the age correlation, and the estimate of the proportion of common age-related variance was computed from the product of the squares of the Age-Common and Common-Variable coefficients. The relation between these two variance proportions is portrayed in Fig. 7.

Several points should be noted about the data illustrated in Fig. 7. First, although the mean proportion of total age-related variance (.215) was slightly larger than the mean estimated proportion of common age-related variance (.208), many of the estimates of the common variance were larger than the total variance (i.e., many of the data points in Fig. 7 are above the positive diagonal). As in the case with the reanalysis of the McArdle and Prescott (1992) data, some of the estimates of the proportion of common age-related variance may be inflated because of oversimplified or underspecified models. In fact, the Joreskog-Sorbom AGFI values ranged from .547 to .790, with a median of .669, indicating that these simple models did not provide good fits to the data.

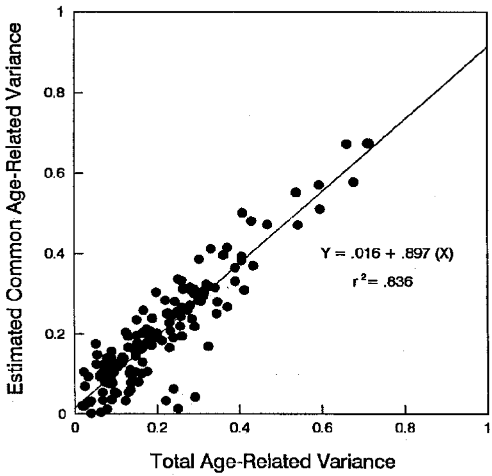


FIG. 7. Plot of estimated common age-related variance (i.e., [(Age − Common)^2] · [(Common − Variable]^2) against the total age-related variance (i.e., r^2) for 146 variables from the data sets described in Table 2.

However, a second important point to note from Fig. 7 is that the relation between the two proportions of variance is very systematic, with a slope of about .9 and an intercept very close to 0. These characteristics indicate that even though there are some discrepancies between the estimates of common and total age-related variance proportions for individual variables, the correspondence across the entire set of variables is quite good.

Parallel analyses were also conducted on the data from the three additional data sets summarized in Appendix B. The bottom portion of the Appendix contains the results of these analyses, which are very similar to those described above.

Only very tentative conclusions are possible from the single common factor analyses because models with only one factor and no influences other than age are extremely crude and do not provide very good fits to the data. Much better fits could undoubtedly be achieved by specifying more complex models if one were in a position to postulate the detailed structure among the variables in each data set. Furthermore, all of the variables from the relevant data sets with age correlations of −.1 or greater were included in the analyses, unlike McArdle and Prescott (1992), who eliminated three variables (Arithmetic, Digit Span, and Digit Symbol) known to have complex factor loadings. Despite these reservations, the results from the single common factor method appear generally consistent with those from the quasi-partial correlation method in suggesting that a very large proportion of the age-related variance in a given variable is shared with other variables and is not independent or distinct.

CONCLUSION

The major implication of the analyses reported above is that a large proportion of the age-related variance in many cognitive variables appears to be associated with a small number of distinct or independent factors. In terms of Fig. 1, the value of *m*, the number of separate age-related influences, is substantially smaller than *n*, the number of variables exhibiting significant relations with age. Specification of one factor appears sufficient to account for a majority of the age-related variance across a wide range of cognitive variables, and when two factors are specified an average of only about 25% of the age-related variance in these variables remains to be explained. This suggests that as few as two distinct influences could be responsible for a large proportion of the age-related variance apparent in many cognitive variables. Indeed, several recent articles have reported that structural equation models with one or two age-related factors provide quite good fits to the data from a variety of cognitive measures (e.g., Lindenberger et al., 1993; McArdle & Prescott, 1992; Salthouse, 1993b).

It is important to emphasize that the results reported above do not imply that all of the age-related differences in every cognitive variable are completely determined by one or two general factors. That is, the common or general factors inferred from these analyses should not be considered the exclusive source of age differences because in neither method can all of the age-related variance in the variables be accounted for by the common factors. Other determinants of the age differences therefore need to be specified to account for all of the age-related variance in any given variable. Nevertheless, a rather surprising implication of the analyses reported here is that as few as two distinct factors may be sufficient to account for 75% or more of the age-related variance observed in many measures of reasoning, spatial, and memory abilities. It is therefore possible that researchers focusing on what were assumed to be quite different dependent variables could actually be investigating different consequences of the same causal influences. The discovery that variables related to speed of processing play a prominent role in those factors provides a clue as to the identity of at least one of the factors, but research with a greater number and variety of variables is needed before a definitive conclusion can be reached regarding the nature of these factors or the true magnitude of their influences.

APPENDIX A

Study	Variables
Salthouse and Mitchell, 1990	Finding As, Number Comparison, Letter Sets, Shipley Abstraction, Paper Folding, Surface Development
Salthouse et al., 1988, Study 1	Computer-administered Digit Symbol, Computer-Administered Number Comparison, Paired-Associated Trial 1, Paired-Associates Trial 2, Verbal Matrix Memory, Spatial Matrix Memory, Activity Memory, Paper Folding Decision Time, Paper Folding, Decision Accuracy, Perceptual Closure, Temporal Memory
Salthouse et al., 1988, Study 2	Computer-Administered Digit Symbol, Computer-Administered Number Comparison, Paired-Associates Trial 1, Paired-Associates Trial 2, Verbal Matrix Memory, Spatial Matrix Memory, Activity Memory, Geometric Analogies Decision Time, Geometric Analogies Decision Accuracy, Series Completion Decision Time, Series Completion Decision Accuracy, Frequency Memory
Salthouse and Babcock, 1991, Study 1	Computation Span, Listening Span, Digit Span, Word Span, Sentence Comprehension Time, Arithmetic Time, Sentence Time with Concurrent Arithmetic, Arithmetic Time with Concurrent Sentences
Salthouse and Babcock, 1991, Study 2	Computation Span, Listening Span, Digit Span, Word Span, Sentence Comprehension Time, Arithmetic Time, Letter Comparison, Pattern Comparison, Digit Symbol Substitution
Salthouse, 1991b, Study 1	Digit Symbol Substitution, Letter Comparison, Pattern Comparison, Listening Span, Computation Span, Shipley Abstraction, Raven's Progressive Matrices
Salthouse, 1991b, Study 2	Digit Symbol Substitution, Letter Comparison, Pattern Comparison, Listening Span, Computation Span, Geometric Analogies, Integrative Reasoning, Cube Assembly, Paper Folding
Salthouse, 1991b, Study 3	Digit Symbol Substitution, Letter Comparison, Pattern Comparison, Listening Span, Computation Span, Geometric Analogies, Integrative Reasoning, Cube Assembly, Paper Folding
Salthouse, 1993b	Horizontal Line Marking, Vertical Line Marking, Letter Copy, Number Copy, Letter Comparison, Number Comparison, Letter Transformation, Number Transformation, Letter Comparison, Pattern Comparison, Digit Symbol Substitution, PMA Reasoning, PMA Space, Integrative Reasoning, Geometric Analogies, Paired Associates, Free Recall Primacy, Free Recall Asymptote

APPENDIX A—*Continued*

Study	Variables
Salthouse, 1993a, Study 1	Digit Copy, Letter Copy, Pattern Comparison, Letter Comparison, Digit Symbol Substitution, Fluency-Nouns, Fluency-S-words, Anagram, Word Switch
Salthouse, 1993a, Study 2	Digit Copy, Letter Copy, Pattern Comparison, Letter Comparison, Digit Symbol Substitution, Word Beginnings, Word Endings, Make Words, Scrabble, Paired Associates, Free Recall Primacy, Free Recall Asymptote, Free Recall Recency
Salthouse, in press, Study 1	Digit Copy, Boxes, Letter Comparison, Pattern Comparison, Digit Symbol Substitution—0 Symbols, Digit Symbol Substitution—9 Symbols, Digit Symbol Intercept, Digit Symbol Slope, Number Series Completion, Cube Assembly, Name Number Association, Paper Folding Decision Accuracy, Paper Folding Decision Time, Paper Folding Study Time, Matrix Reasoning Decision Accuracy, Matrix Reasoning Decision Time, Matrix Reasoning Study Time, Associative Memory Decision Accuracy, Associative Memory Decision Time, Associative Memory Study Time
Salthouse, in press, Study 2	Digit Copy, Boxes, Letter Comparison, Pattern Comparison, Digit Symbol Substitution—0 Symbols, Digit Symbol Substitution—9 Symbols, Memory Search Mean Intercept, Spatial Rotation Decision Accuracy, Associative Memory Accuracy, Spatial Rotation Decision Time, Matrix Reasoning Decision Time, Associative Memory Decision Time, Spatial Rotation Study Time, Matrix Reasoning Study Time, Associative Memory Study Time

APPENDIX B

DESCRIPTION OF ADDITIONAL DATA SETS

Study	No. of subjects	Variables
1 Birren and Morrison, 1961	933	Similarities, Digit Span, Digit Symbol Substitution, Picture Completion, Block Design, Picture Arrangement, Object Assembly
2 Heron and Chown, 1967, Males	300	Raven's Matrices, Mazes, Digit Coding, Trail Making, Hearing Loss, Hand Strength, Visual Acuity, Forced Expiratory Volume
3 Heron and Chown, 1967, Females	240	Raven's Matrices, Mazes, Digit Coding, Trail Making, Hearing Loss, Hand Strength, Visual Acuity, Forced Expiratory Volume

APPENDIX B—*Continued*

CUMULATIVE PROPORTION OF TOTAL VARIANCE ASSOCIATED WITH SUCCESSIVE COMPONENTS

Data Set	Original 1	Original 2	Original 3	Original 4	Partial 1	Partial 2	Partial 3	Partial 4	Quasi-partial 1	Quasi-partial 2	Quasi-partial 3	Quasi-partial 4
1	.56	.67	.75	.82	.52	.64	.73	.81	.84	.89	.93	.96
2	.53	.63	.73	.80	.36	.49	.62	.72	.78	.85	.90	.94
3	.53	.64	.74	.82	.40	.54	.66	.76	.78	.85	.92	.95

VARIABLES WITH LOADINGS GREATER THAN OR EQUAL TO .8 AND VARIABLES WITH COMMUNALITIES LESS THAN .5 FROM A TWO-COMPONENT PRINCIPAL COMPONENTS ANALYSIS WITH PROMAX ROTATION

Data Set	r(I,II)	Component I	Component II	Variables with $h < .5$
1	.71	Block Design	Digit span	
		Object Assembly	Similarities	
		Picture Completion	Picture Completion	
		Picture Arrangement		
		Digit Symbol		
		Similarities		
2	.63	Raven's Matrices	Visual Acuity	
		Digit Coding		
		Trail Making		
		Hand Strength		
		Forced Expiratory Volume		
		Mazes		
		Hearing loss		
3	.70	Trail Making	Hearing Loss	
		Raven's Matrices	Forced Expiratory Volume	
		Digit Coding	Hand Strength	
		Mazes	Raven's Matrices	
		Visual Acuity		

	Average age-related variance	Average estimated common age-related variance
1	.097	.091
2	.296	.277
3	.245	.208

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