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Cross-Sectional and Longitudinal Relationships Among Age, Cognition, and Processing Speed

[Articles]

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Outline

Graphics

Abstract

Cross-sectional and longitudinal age effects on cognitive function were examined in 302 older adults followed longitudinally. Processing speed was related to cognitive performance at cross-section, and change in speed predicted within-person longitudinal cognitive decline. Statistical control of processing speed greatly reduced cross-sectional age effects but did not attenuate longitudinal aging effects. This difference in processing speed's ability to account for cross-sectional and longitudinal age effects is discussed in the context of theories of cognitive aging and methodological and statistical issues pertaining to the cross-sectional and longitudinal study of cognitive aging.

Change in intellectual function is central to all of cognitive aging research. However, for largely practical reasons, most research on aging has focused on the study of cross-sectional age differences in cognitive performance rather than on age-associated change over time. Longitudinal studies provide direct measures of change that can only be approximated by cross-sectional studies. The direct measurement of change is essential for testing theories of cognitive aging because the explanatory power of such theories depends on their success in accounting for cognitive changes within aging individuals. One such theory of cognitive aging is the *processing speed hypothesis*, which postulates that age-related declines in the speed of executing elementary processing operations leads to impairments in cognitive functioning (Salthouse, 1996b). The purpose of this study was to test the processing speed hypothesis by comparing how well speed would account for age differences in cognitive function estimated at cross-section versus how well speed would account for within-person change in cognitive function over time.

Cognitive Change in Older Adults

There are two types of age effects that are intended to measure the same underlying process (i.e., cognitive aging) but are estimated differently: age differences and age-related changes. Age differences are measured by differences in cognitive function between persons of different ages at cross-section and are a between-person effect. Age-related changes are measured by changes in cognitive function per unit time longitudinally and are a within-person effect. There is a third type of age effect, differential change, which measures an altogether different process. Differential rates of change measure individual differences in change and is a longitudinal, between-person effect. Table 1 shows the characteristics of each of these three kinds of age effects. Each of these three effects has a precise statistical meaning (discussed in the Statistical Models of Cognitive Aging section). More important, each of these three types of age effects is useful for answering different questions about cognitive aging. The focus of this study (which is justified below) is on age differences and within-person, age-related change.

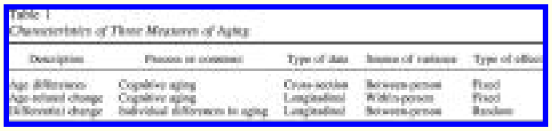

Table 1
Characteristics of Three Measures of Aging

Description	[illegible]	Type of data	Source of variance	Type of effect
Age differences	Cognitive aging	Cross-section	Between-person	Fixed
Age-related change	Cognitive aging	Longitudinal	Within-person	Fixed
Differential change	Individual differences in aging	Longitudinal	Between-person	Random

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Table 1 Characteristics of Three Measures of Aging

Despite the ubiquity of cognitive age differences in cross-sectional studies, significant age-related change is not always shown by longitudinal analyses. Both selective attrition and practice effects may attenuate estimated cognitive decline in longitudinal studies. Selective attrition occurs when individuals most likely to exhibit greater cognitive decline drop out from the study at higher rates. Consequently, cognitive decline is underestimated in the subset of individuals most likely to return for follow-up testing (Hultsch, Hertzog, Small, McDonald-Miszczk, & Dixon, 1992; Schaie, Labouvie, & Barrett, 1973). Practice effects of repeated cognitive testing can offset, partially or completely, estimated cognitive change (e.g., Schaie, 1996). Some researchers have even reported reliable improvement in test performance at follow-up assessments (e.g., Zelinski, Gilewski, & Schaie, 1993).

In addition to selective attrition and practice effects, the length of the follow-up interval and type of cognitive testing also determine the likelihood of detecting significant decline. Measures of processing speed have proved sensitive to longitudinal age effects (Elias, Robbins, & Elias, 1996; Hultsch et al., 1992; Schaie, 1989). In contrast to measures of processing speed, significant longitudinal declines on episodic memory variables have not been as frequently observed. For example, Hultsch et al. did not detect significant declines on measures of text memory and word recall over a 3-year interval and postulated that longer follow-up periods might be needed to detect reliable declines on these tasks. Consistent with this view, Colsher and Wallace (1991) did find significant declines on a word recall task over a 6-year interval, and Elias et al. (1996) reported a significant decline in memory for forms on the Tactile Performance Test over a 15-year period. In a recent report, Zelinski and Burnight (1997) found a significant decline on list recall and text memory over a 16-year interval. However, Evans et al. (1993) reported a significant short-term decline in episodic memory (story memory) in a study of community-residing older adults over a 3-year interval.

Given the expense and difficulty of conducting longitudinal research, it is not surprising that most theories of cognitive aging have emerged from cross-sectional research. However, because the developmental phenomenon that such theories ultimately would explain is the cognitive change that occurs within aging individuals, it is important to evaluate theory-based predictions in longitudinal data sets. This is no easy task because the predictions of cognitive aging theories are not always readily translatable into a longitudinal framework. Support for this assertion will become clear after we review the predictions of one theory of cognitive aging (i.e., the processing speed theory) and the statistical models underlying the cross-sectional and longitudinal analysis of age effects.

The Processing Speed Hypothesis

Processing speed theory derives from the observation that there are significant age relations to a large number of different cognitive variables and that these relations are not independent of each other (see Salthouse, 1996b, for a complete review). This lack of independence among age effects suggests the existence of a general or common factor that might account for, or mediate, age differences in performance on a variety of cognitive tasks. Identifying such a general mediating factor would be extremely valuable because it would assist in providing a parsimonious account of the age-related differences found across a wide range of cognitive variables.

The evidence supporting the role of processing speed as a mediator of cognitive aging has come from cross-sectional studies in which the performance of individuals of different ages on cognitive variables was compared. These studies by Salthouse, 1993, 1994, 1996a; (Salthouse & Babcock, 1991; Salthouse, Fristoe, & Rhee, 1996) and by numerous other investigators (Bryan & Luszcz, 1996; Hultsch, Hertzog, & Dixon, 1990; Lindenberger, Mayr, & Kliegl, 1993; Nettelbeck & Rabbitt, 1992; Park et al., 1996; Sliwinski & Buschke, 1997) have shown that statistical control of measures of simple processing speed substantially reduces or eliminates age effects on a wide range of cognitive measures. The explanatory power of this hypothesis derives from its capacity to account for age effects on many different variables with a single, general factor (i.e., processing speed).

There have been few studies of the role of processing speed in accounting for longitudinal age-related cognitive change. An important longitudinal study is that of Hultsch et al. (1992), who examined changes in performance on memory, information processing, and intellectual ability tasks over a 3-year period in 328 older adults. An important aspect of this study was the separate estimation of cross-sectional age differences and longitudinal age changes. Hultsch et al. found significant longitudinal declines over the 3-year study period on measures of working memory, verbal fluency, and world knowledge. Consistent with previous work (Hultsch et al., 1990), covarying for measures of verbal processing speed significantly reduced or eliminated cross-sectional age differences on measures of episodic memory, verbal fluency, working memory, and world knowledge. However, longitudinal declines in verbal fluency, world knowledge, and working memory remained significant even after controlling for verbal processing time.

To weigh the longitudinal evidence for or against the speed hypothesis, one must first translate its predictions about cross-sectional age effects (i.e., age differences) into predictions about longitudinal age effects. This translation is complicated because there are two distinct aspects of change (i.e., within-person change and individual differences in change) that can be modeled in longitudinal analyses. Before these two aspects of longitudinal change can be linked to cognitive aging theories, the explicit statistical models that underlie estimation of cross-sectional and longitudinal age effects require specification.

Statistical Models of Cognitive Aging

To compare predictions from cross-sectional studies with those from longitudinal studies, one must be explicit with respect to how the data are modeled and how the effects of interest are defined. Let Y_{ij} represent a response or dependent variable (e.g., scores on a memory test) and let x_{ij} be a covariate or an explanatory variable observed at time t_{ij}, for observation $j = 1, \ldots, n_i$ on person $i = 1, \ldots, m$. According to this notation, m is the total number of persons and n_i is the total number of observations on person i. In aging studies, x_{ij} refers to the age of person i at time j.

Cross-Sectional Models

In a cross-sectional study, $n_i = 1$ because there is only one observation made on each person. The cross-sectional model of cognitive aging is

$$Y_{i1} = \beta_0 + \beta_{1C} x_{i1} + \epsilon_{i1} \quad i = 1, \ldots, m \qquad (1)$$

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Equation (Uncited)

Longitudinal Models

An important advantage of a longitudinal study is its ability to distinguish the cross-sectional and longitudinal relationships between the explanatory variables and the response (Diggle, Liang, & Zeger, 1994). When there are repeated observations made on individuals, the simple cross-sectional Model 1 can be extended to where [beta]$_{3L}$ represents the expected (or average) change in Y per unit change in age (x) for a given person.[1] Note that when $j = 1$, Model 3 reduces to Model 1, so that [beta]$_{1C}$ in the longitudinal model has the same interpretation as it does in the cross-sectional model (Diggle et al., 1994, p. 17). This allows direct comparison of cross-sectional and longitudinal age effects, namely whether [beta]$_{1C}$ = [beta]$_{3L}$.

This longitudinal model can also be described in terms of a hierarchical, or multilevel, analysis (Bryk & Raudenbush, 1992). Accordingly, Equation 3 can be partitioned into a within-person (Level 1) model: where b_{0i} and b_{3Li} are the intercept and longitudinal age slope for person i. At the between-person (Level 2) level, individual differences in level of performance (i.e., intercepts, b_{0i}) and in change (i.e., longitudinal slopes, b_{3Li}) are modeled as follows: Two person-specific effects, [nu]$_{0i}$ and [nu]$_{1i}$, are introduced at Level 2 and represent the deviation of each person from the mean intercept and longitudinal age slope, respectively. These person-specific effects are treated as random effects and are discussed in detail in the section on the two facets of change in fixed and random age effects. This hierarchical representation shows that only within-person variables can explain variation in Y_{ij} at Level 1. At Level 2, between-person variables can be used to explain between-person variation (i.e., individual differences) in slopes and intercepts estimated at Level 1. Partitioning Equation 3 into its within-person (Equation 3a) and between-person (Equation 3b) componentsclearly indicates that candidate mediators of within-person change must be studied at Level 1, the within-person level of analysis. The between-person level of analysis is appropriate for studying variables that could account for individual differences in intercepts and slopes.

$$Y_{ij} = \beta_{0i} + \beta_{1C}x_{1i} + \beta_{3L}(x_{1ij} - x_{1i1}) + \epsilon_{ij},\ j = 1, \ldots, n_i \qquad i = 1, \ldots, m. \quad (3)$$

[Help with image viewing]

Equation 3

$$Y_{ij} = b_{0i} + b_{3Li}(x_{1ij} - x_{1i1}) + \epsilon_{ij}. \quad (3a)$$

[Help with image viewing]

Equation 3A

Graphic

[Help with image viewing]

Equation 3B

The cross-sectional Model 2 can also be adapted to a longitudinal form to compare the coefficient relating cross-sectional and longitudinal processing speed effects: Again, note that for *j* = 1, this model reduces to the cross-sectional Model 2, allowing the same interpretation of cross-sectional effects of age, $[\text{beta}]_{1C}$, and processing speed, $[\text{beta}]_{2C}$. We can clarify the interpretation of longitudinal effects of age, $[\text{beta}]_{3L}$, and processing speed, $[\text{beta}]_{4L}$, by subtracting Equation 2 from Equation 4, to obtain

Graphic

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Equation 2

$$Y_{ij} = \beta_0 + \beta_{1C}x_{1i1} + \beta_{2C}x_{2i1} + \beta_{3L}(x_{1ij} - x_{1i1}) + \beta_{4L}(x_{2ij} - x_{2i1}) + \epsilon_{ij},\ j = 1, \ldots, n_i \qquad i = 1, \ldots, m. \quad (4)$$

[Help with image viewing]

Equation 4

$$(Y_{ij} - Y_{i1}) = \beta_{3L}(x_{1ij} - x_{1i1}) + \beta_{4L}(x_{2ij} - x_{2i1}) + \epsilon_{ij} - \epsilon_{i1}. \quad (5)$$

[Help with image viewing]

Equation (Uncited)

The Two Facets of Change: Fixed and Random Age Effects

In the longitudinal Models 3 and 4 described above, the regression coefficients for age and processing speed are *fixed effects*. Fixed effects are estimates of the average within-person coefficient and are assumed to be constant. Therefore, the fixed effect for the longitudinal age slope ($[\text{beta}]_L$) is the weighted average of the within-person age slopes. *Random effects* reflect the parameter variance in a coefficient and are assumed to be random variables with a probability distribution. For example, the random effect for age would reflect the reliable variance in age slopes (v_{1i}) and thus would provide a measure of individual differences in change. A random effect for the intercept (v_{0i}) would show that some people have intrinsically higher scores than others on Y (i.e., individual differences in the ability measured by Y).

Analysis of fixed and random age effects are appropriate for answering different kinds of questions. Understanding fixed age effects is useful for answering questions such as “What changes that occur within aging individuals predict the amount of cognitive decline (change) within those individuals?” Understanding random age effects is useful for answering questions such as “What are the characteristics of aging individuals that can explain (predict) why some individuals decline at faster (or slower) rates than others?”

Which of these two kinds of questions is addressed, and hence which of these two types of longitudinal age effects is modeled, depends on what aging phenomenon is to be explained. If one were interested in identifying and evaluating candidate mechanisms or causes that drive cognitive change, one would focus on fixed age effects. If one were interested in identifying person characteristics predictive of differential change (i.e., individual differences in change), one would focus on explaining random age effects.

As shown by Equations 3a, and 3b, different classes of explanatory variables are suitable for explaining fixed and random age effects. To explain the longitudinal fixed age effect, which reflects average within-person change, one must select candidate variables that also *change within persons*. That is, one must identify variables that vary within persons (e.g., declines in processing speed) to explain within-person cognitive changes. In contrast, random effects can be explained by variables that are *constant within persons*. That is, stable individual-differences variables (e.g., education, sex) can account for differential rates between persons (i.e., random age effects) but cannot explain within-person cognitive change. A study by Albert et al. (1995) showed that education is a strong predictor of individual differences in short-term cognitive change in older adults. Although differences in educational attainment might account for why aging individuals exhibit differential cognitive changes over time, the amount of education any single person has had cannot explain why he or she is declining cognitively because education does not vary within persons (at least not usually in later life).

For example, education could be viewed as a surrogate for cognitive reserve, and cognitive reserve could be defined physiologically by the synaptic density. Although synaptic density measured at a single point in time (e.g., baseline) may successfully account for differential rates of change between individuals in an actuarial sense, it cannot predict, in a psychologically meaningful sense, the amount of change occurring within any individual. A psychologically meaningful explanation of cognitive aging could be developed only if the amount of decline in synaptic density within aging individuals is shown to predict the amount of cognitive decline within those individuals.

Translating Cross-Sectional Predictions Into Longitudinal Predictions

One might expect that longitudinal predictions of aging theories could be best tested by focusing on random age effects because, at cross-section, these theories are often evaluated by how successfully they account for individual differences in cognitive performance. It is certainly reasonable, based on processing speed theory, to postulate that aging individuals who are declining rapidly in processing speed will also be declining rapidly on other cognitive measures relative to individuals whose processing speed is changing more slowly. However, the focus of this study was not on the analysis of individual differences in change (which is also relevant to the speed hypothesis) but on within-person change. This focus derives from the central premise of the processing speed hypothesis, namely that the amount of slowing experienced by an aging individual over a certain period determines the amount of cognitive decline in that individual during that time period. The fixed effects estimated from Model 4 directly tested this hypothesis.

The aim of the present study was to address two questions central to the speed hypothesis: The first was whether within-person declines in processing speed would predict within-person declines in other cognitive measures. Longitudinally, this question was addressed by testing the hypothesis $[\text{beta}]_{4L} > 0$ and at cross-section by testing the hypothesis $[\text{beta}]_{2C} > 0$. The second question was whether declines in processing speed would account for or mediate age-related cognitive decline. This prediction was addressed both longitudinally and at cross-section by comparing the total age effect against the direct age effect after adjusting for processing speed.

Method

Participants

All participants gave informed consent approved by the Committee on Clinical Investigations of Albert Einstein College of Medicine. Three hundred fifty-one community-residing older adults, born between 1902 and 1927, volunteered for participation in an ongoing longitudinal study of memory and cognition (the Einstein Aging Study [EAS]). Participants were recruited from a registry of approximately 8,000 community-living residents of the Bronx, New York, that was established as part of the Systolic Hypertension in the Elderly Project. Participants were also recruited by soliciting local senior citizens' centers and organizations. Baseline data for a subset of these participants were analyzed by Buschke, Sliwinski, Kuslansky, and Lipton (1995).

To be eligible for the study, participants had to meet the following criteria: be fluent in the English language, have at least 1 year of formal education, make no more than eight errors on a mental status examination (Blessed, Tomlinson, & Roth, 1968) and pass a memory screening test shown to be sensitive to clinical dementia (Grober, Buschke, Crystal, Bang, & Dressner, 1988). Participants were excluded if there was evidence of any of the following: disturbance in consciousness, medical or neurological disease causing cognitive impairment, head injury with loss of consciousness for more than 1 hr, current psychiatric disorder, alcohol or drug dependence, endocrine or hematological disease or malignancy not in remission for more than 2 years, or current use of psychotropic or antidepressant drugs.

Fourteen participants (3.9%) were excluded because of a diagnosis of dementia, and 15 participants (4.2%) were excluded for other reasons (e.g., head injury, cancer). An additional 20 (5.6%) participants had to be excluded from the analyses because data on one or more critical cognitive variables were not obtained because of technical problems or sensory impairments. The final study sample consisted of 302 participants (194 women and 108 men). Table 2 contains descriptive information on the study sample.

Table 2
Demographic Characteristics: Age, Education, and Previous Occupation Status by Sex (%)

Variable	Women (n = 194)	Men (n = 108)	Total sample (n = 302)
Age (years)			
65–69	8.1	2.8	6.2
70–74	31.8	29.6	31.1
75–79	32.3	34.3	33.0
80–84	22.2	24.1	22.9
85+	5.6	9.3	6.9
Education			
<9	8.6	14.8	10.8
9–11	13.1	20.4	15.7
High school	35.8	28.7	33.3
Some college	21.2	14.8	18.9
Batchelor's	8.6	12.0	9.8
Postcollege	12.6	9.3	11.4
Previous occupation			
Unskilled	2.1	3.9	2.7
Semiskilled	9.9	14.7	11.6
Skilled	7.8	16.7	10.6
Semiprofessional	70.8	57.8	66.5
Professional	9.4	6.8	8.5

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Table 2 Demographic Characteristics: Age, Education, and Previous Occupation Status by Sex (%)

The average age of the participants at baseline testing was 77.2 years (*SD* = 5.0, range = 66–92). Men were slightly older at baseline than women (78.1 vs. 76.9 years; $p < .05$). Table 2 shows that the distribution of ages in both men and women was roughly symmetrical, with the most frequently sampled ages being in the center of the total age range (75- to 79-year-olds). According to the 1990 U. S. Census report, approximately one third of all adults in New York older than 65 are aged between 65 and 69 years and that approximately 10% are older than 85 (U.S. Bureau of the Census, 1996). The age distribution of the study sample is different from the distribution of ages in adults older than 65 residing in New York in that it underrepresents the extreme ages. The study sample was also more highly educated than the population of adults 65 and older residing in New York. Individuals with less than 9 years of education were underrepresented, constituting only 10.8% of the study sample, compared with approximately 22% in the population.

Seventy-five (24.8%) participants did not return after baseline testing, and there was a variable amount of follow-up testing of those who returned at least once. Two hundred twenty-seven (75.1%) returned for a second assessment, 149 (49.3%) returned for a third assessment, 96 (31.7%) returned for a fourth assessment, and 34 (11.3%) returned for a fifth assessment. Because the EAS is still in progress, one cannot assume that a person has dropped out because he or she has not returned for five assessments. Participants could have unequal follow-up either because they dropped out of the study or because they had not yet returned for an assessment. Of the initial sample of 302, 167 (54.5%) are still participating, 20 (6.5%) have died, 6 (1.63%) are too ill to continue, 6 (1.96%) cannot be contacted, 4 (1.3%) have moved, and 104 (33.9%) have refused to return for additional testing.

Individuals with only baseline testing were included to assist in testing hypotheses about age differences at cross-section. Although each individual was scheduled to return at 18-month intervals, scheduling conflicts introduced variability into the actual testing intervals. This variable spacing between follow-up assessments and the dropout process are discussed in the *Statistical Methods* section.

Testing Procedure

Cued recall was measured with the Category Cued Recall Test (CCRT), which has been described in detail elsewhere (Buschke et al., 1995). A trial consisted of the presentation on a computer screen of four words, each from a different category. Appropriate category cues were shown sequentially in the center of the screen. The participant was asked to find each item (e.g., eagle) and name it aloud when its category cue (e.g., bird) was shown. When all four items were identified, the next four items were presented, until one item from each of the 16 categories was presented (64 words). Immediately after acquisition, there was one trial of cued recall. The participant was asked to recall aloud in any order the four items from each category as each category cue was read aloud to the participant. Thirty seconds were allowed for recall of the items in each category. The same interval between acquisition and retrieval was maintained for all items by presenting the category cues in the order used for acquisition.

Text memory was assessed using the immediate recall from the Logical Memory I test, which is part of the Wechsler Memory Scale—Revised (Wechsler, 1987). Two stories (A and B) were read aloud to participants, who were asked to recall as much of each story as soon it was completed. The two scores from this procedure, which reflect the total number of ideas recalled from each of the two stories (Story A and Story B), were summed to compute a composite text memory score.

Fluency was measured with a category fluency task and the Controlled Word Association Test. For the category fluency task, each participant was given 90 s to name as many different animals as they could. The score for this variable was the total number of unique animal names that the participant could produce in the allotted time. Derivatives and variants of the same name (e.g., dog, dogs) were counted only once. For the measure of letter fluency, participants were required to name as many words as possible beginning with the letters *F*, *A*, and *S*. Participants were given 90 s for each letter. The score for this procedure was the sum of the number of unique words that the participant could produce in the allotted time. Derivatives and variants of the same word (e.g., flower, flowers) were counted only once.

Memory span was measured with the Sentence Span test from the Neurosensory Comprehensive Examination for Aphasia (Spreen & Benton, 1977). In this task, the examiner read aloud sentences that varied in length from 1 to 26 syllables, with two sentences at each length. The participant was required to repeat the sentence verbatim immediately after presentation. The score for this task is the number of syllables from the longest sentence correctly recalled.

Processing speed was measured with two tasks: the Digit Symbol Substitution test (DSST) from the Wechsler Adult Intelligence Scale—Revised (WAIS–R; Wechsler, 1981) and a number copy task (Sliwinski, Buschke, Kuslansky, Senior, & Scarisbrick, 1994). In the DSST, participants are presented with a sheet of paper that has a code table displaying pairs of digits and symbols. Beneath the code table are rows of double boxes with the digit in the top box and nothing in the bottom box. The participants are then asked to use the code table to determine which symbol is associated with each digit and to write as many symbols as possible in the empty boxes in a 90-s period. The number of correct symbols is the score for this task. In the number copy task, participants were presented with a two-digit number on the center of a computer screen and were required to copy the number by pressing the appropriate keys on the numeric keypad. Response time was measured as the time in milliseconds between stimulus presentation and the first keypress. Only correct responses were used to analyze reaction time.

Verbal knowledge was assessed with the Mill Hill Vocabulary Scale (MHVS; Raven, Court, & Raven, 1986) and the WAIS–R Vocabulary subtest (Wechsler, 1981). Subtests from the WAIS–R were used to measure *conceptualization* (the Similarities test), *world knowledge* (the Information subtest), and *attention* (the Digit Span test).

Statistical Methods

A general linear mixed model with random coefficients (Diggle et al., 1994) was used because, unlike conventional repeated measures and multivariate analysis of variance models, this model can accommodate unbalanced designs that result from time-varying covariates, missing data points, unequal numbers of follow-up observations, and unequal intervals between testing occasions. This type of model is known as a *mixed model* because it includes both fixed and random effects. It is also sometimes referred to as a “hierarchical linear model” (Bryk & Raudenbush, 1992) because it is useful for analyzing data at multiple levels: In the present study, we were interested in modeling change within subjects and estimating average effects across individuals. Because these techniques might be unfamiliar to many readers, we detail each step in model fitting and estimation. Interpretations of model parameters were discussed in detail in the introduction.

Variable selection and centering.

In this study we considered two primary explanatory variables: age and processing speed. In any linear model, the intercept reflects the expected (average) value in the dependent variable when all explanatory variables are set to zero. For some variables, zero is a meaningful quantity (e.g., a normalized variable with a mean of zero), and for some it is not (e.g., age). We centered each explanatory variable about a meaningful value by subtracting that value from each score. Centering age about the mean results in an intercept that reflects the average value in the dependent variable for subsets of individuals with an average age (in this study age was centered at 77 years). Education wascentered at 12 years (high school degree). The composite measure of processing speed (described below) was normalized and centered at its mean.

Model formulation for age effects.

The next step was to formulate a plausible model to estimate the effect of age. The form of this model is conveyed in Equation 3. This model was selected because the explanatory variable of interest varies over time (people grew older) and across individuals at baseline (not everyone was the same age at inception). This model separates the longitudinal effect (change within persons over time), from the cross-sectional effect in which comparison on the dependent variables is made between persons of different ages (Diggle et al., 1994, p. 25). The relative sensitivity of longitudinal and cross-sectional age effects can be assessed by comparing the values for $[\text{beta}]_{3L}$ and $[\text{beta}]_{1C}$. Other constant covariates (i.e., education, gender, and previous occupation level) were examined in this stage of model development.

Model formulation for speed effect.

A model of the form conveyed in Equation 4 was used to study how well changes in processing speed would predict changes in other cognitive measures. Processing speed, like age, varied across persons at baseline and varied within persons over time, so the cross-sectional and longitudinal speed effects must be separated. Additionally, one can assess the importance of speed as a mediator of cross-sectional and longitudinal age effects by comparing the fixed effects for age before and after inclusion of speed in the model. One valid interpretation is that the unadjusted coefficient for age ($[\text{beta}]_{1c}$) reflects the total effect of age at cross-section and that speed-adjusted coefficient for age reflects the direct effect of age at cross-section. The indirect (or speed-mediated) effect of age is obtained by subtracting the direct from the total cross-sectional age effect. The percentage of the total age effectmediated by speed is calculated as follows: (total age effect - direct age effect)/total age effect. Furthermore, analogous to cross-sectional effects, the total longitudinal effect of age can be decomposed into its direct effect after adjusting for processing speed and its indirect or speed-mediated effect.

Estimation.

When fitting the mixed model, one must decide which fixed and random effects to include. We discussed fixed effects earlier and now turn to random effects. Preliminary analyses indicated that model fit was significantly improved (according to the likelihood ratio test) for all variables by including a random effect for intercept, but model fit was improved by including a random effect for follow-up (random age slope) only for a subset of the variables (e.g., cued recall, logical memory, vocabulary, copy speed, and digit symbol substitution). These preliminary results indicated that there were reliable individual differences in the level of performance on all measures but that there were no detectable individual differences in change over time on some of the cognitive measures. This was likely due to statistical power and design considerations (i.e., relatively short follow-up, few measurement occasions) rather than there really being uniform aging effects across individuals. Failure to include a random effect (even if it is not statistically significant) that exists in the population will not bias estimates of fixed effects, although it may underestimate their standard errors, which can complicate significance testing. Therefore, we included random age slopes in the models reported in the Results section.

Reliability and precision.

The fact that random intercepts were significant for all models indicated that every test reliably measured individual differences in performance. The intraclass correlation was used to quantify the reliability for each cognitive measure. In this context, the intraclass correlation indexes the ratio of between subject variance to total variance (Bryk & Raudenbush, 1992). Random age slopes were significantly greater than zero for 6 of the 13 cognitive tests (i.e., the CCRT, Logical Memory, Vocabulary, copy speed, and DSST), indicating reliable individual differences in change for about half the measures. Because the critical predictions involve analysis of within-person change (and not individual differences in change), the presence or absence of significant random age slopes does not indicate how precisely the parameters of interest (i.e., fixed effects) are estimated. Instead, the standard errors for the fixed effects provide the best index of how precisely average age effects are estimated.

Still, one might ask how well the estimated longitudinal age effects describe the data within persons. One answer to this question is presented in the Appendix, which describes how the total variance in a maximum-likelihood mixed model can be partitioned into between-person variance, within-person variance, and residual variance. To summarize, the amount of within-person variance that the longitudinal age trends “accounted for” is much larger than the amount of between-person variance accounted for by cross-sectional age trends. This indicates that the fits of the longitudinal age trends to the within-person data were at least as good as the fit of the cross-sectional age trends to the between-person data.

Dropouts and attrition.

Missing data occur in longitudinal designs whenever an intended measurement is not obtained. The likelihood-based approach of mixed models yields unbiased estimates when missing data are uninformative (Bryk & Raudenbush, 1992; Diggle et al., 1994). Random effects pattern mixture model analyses were conducted to test for effects of dropping out on estimates of mean performance and change (Hedeker & Gibbons, 1997; Little, 1995). To summarize, there was no evidence of differential change as a function of amount of follow-up (i.e., age slopes did not differ for those with two, three, four, and five waves of follow-up). However, there was evidence that those who dropped out earlier had lower intercepts (baseline scores) on memory, verbal comprehension, and speed.

Statistical significance was set at the .05 level. SAS PROC Mixed was used to estimate the mixed models (SAS Institute, 1992).

Results

Table 3 shows the mean scores and standard deviations for each test at each assessment. However, any inferences based on these empirical means are suspect because of missing data (i.e., dropouts) and because the data are clustered (i.e., correlated) within persons. Therefore, these data should be used only to characterize the sample at a given testing occasion, not to draw inferences about trends or dependencies.

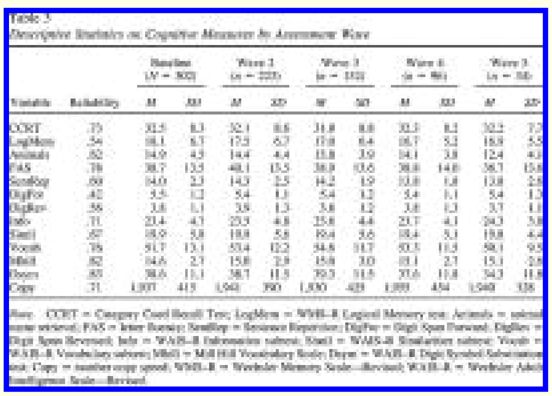

Table 3
Descriptive Statistics on Cognitive Measures by Assessment Wave

		Baseline (N = 302)		Wave 2 (n = 225)		Wave 3 (n = 152)		Wave 4 (n = 98)		Wave 5 (n = 58)	
Variable	Reliability	M	SD	M	SD	M	SD	M	SD	M	SD
CCRT	.75	32.5	8.3	32.1	8.6	31.8	8.8	32.3	8.2	32.2	7.3
LogMem	.54	18.1	6.7	17.5	6.7	17.8	6.4	16.7	5.2	18.9	5.5
Animals	.82	14.9	4.5	14.4	4.4	15.8	3.9	14.1	3.8	12.4	4.1
FAS	.78	38.7	13.5	40.1	15.5	38.9	13.6	38.8	14.0	36.7	13.6
SentRep	.60	14.0	2.3	14.3	2.5	14.2	1.9	13.8	1.8	13.8	2.8
DigFor	.42	5.5	1.2	5.4	1.1	5.4	1.2	5.4	1.1	5.4	1.3
DigBav	.56	3.8	1.1	3.9	1.3	3.8	1.2	3.8	1.3	3.7	1.1
Info	.71	23.4	4.7	23.5	4.8	25.8	4.4	23.7	4.1	24.3	3.8
Simil	.67	18.9	5.8	18.8	5.8	19.4	5.6	18.4	5.1	19.8	4.4
Vocab	.78	51.7	13.1	53.4	12.2	54.8	11.7	50.5	11.3	58.1	9.5
MHill	.82	14.6	2.7	15.8	2.9	15.8	3.0	15.1	2.7	15.1	2.8
Dsym	.85	38.6	11.1	38.7	11.5	39.3	11.5	37.6	11.8	34.3	11.8
Copy	.71	1,037	415	1,041	390	1,030	420	1,093	454	1,040	328

Note. CCRT = Category Cued Recall Test; LogMem = WMS–R Logical Memory test; Animals = animal name retrieval; FAS = letter fluency; SentRep = Sentence Repetition; DigFor = Digit Span Forward; DigBav = Digit Span Reversed; Info = WAIS–R Information subtest; Simil = WAIS–R Similarities subtest; Vocab = WAIS–R Vocabulary subtest; MHill = Mill Hill Vocabulary Scale; Dsym = WAIS–R Digit Symbol Substitution test; Copy = number copy speed; WMS–R = Wechsler Memory Scale—Revised; WAIS–R = Wechsler Adult Intelligence Scale—Revised.

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Table 3 Descriptive Statistics on Cognitive Measures by Assessment Wave

The Descriptive Longitudinal Model

Cross-sectional and longitudinal age effects were estimated by fitting mixed models of the form in Equation 3 to each cognitive variable: CCRT, Logical Memory, animal naming, letter fluency, sentence repetition, number copy speed, Forward and Backward Digit Span, MHVS, and WAIS–R Information, Similarities, Vocabulary, and Digit Symbol Substitution subtests. During this initial stage of model development, we examined education, gender, and previous occupational status as covariates. Level of education had a significant effect on all test scores, with higher levels of education being associated with superior performance. Gender was associated with several measures, with women showing superior performance on sentence repetition and the Digit Symbol tests and men showing superior performance on animal naming and the Information subtest of the WAIS–R. Significant covariates were retained in each model, and the results are summarized in Table 4. Because they were the focus of study, variables for age at baseline and change in age were retained regardless of their statistical significance. All models included a random intercept and a random age slope.

There were significant age effects ($p < .05$) for all variables except Digit Span Forward. There were significant quadratic trends, indicating accelerating decline, for sentence repetition, letter fluency, Vocabulary, MHVS, and the Digit Symbol test.

Table 4
Cross-Sectional and Longitudinal Fixed Age Effects on Cognitive Variables

DV	Intercept	Age_b	$Age_j - Age_b$	$(Age_j - Age_b)^2$	Educ	Gender	SD
CCRT	32.841	−0.235	−0.428	—	0.753	—	4.33
	(0.455)	(0.091)	(0.104)		(0.139)		
LogMem	17.631	−0.218	−0.521	—	0.688	—	4.11
	(0.364)	(0.062)	(0.060)		(0.096)		
SentRep	13.509	−0.060	0.107	−0.053	0.54	0.528	1.40
	(0.191)	(0.023)	(0.093)	(0.018)	(0.033)	(0.223)	
DigFor	5.425	−0.012	−0.002	—	0.081	—	0.88
	(0.062)	(0.012)	(0.019)		(0.017)		
DigRev	3.808	−0.013	−0.038	—	0.088	—	0.79
	(0.087)	(0.017)	(0.018)		(0.018)		
Animals	15.282	−0.218	−0.299	—	0.348	−1.028	2.61
	(0.377)	(0.045)	(0.062)		(0.068)	(0.454)	
FAS	38.118	−0.355	0.906	−0.269	1.248	—	6.34
	(0.745)	(0.144)	(0.376)	(0.072)	(0.218)		
Info	24.532	−0.126	−0.182	—	0.558	−2.241	2.59
	(0.482)	(0.049)	(0.056)		(0.074)	(0.485)	
Simil	19.544	−0.090	−0.361	—	0.742	—	3.02
	(0.293)	(0.056)	(0.071)		(0.088)		
Vocab	50.484	−0.054	1.504	−0.385	1.888	—	5.83
	(0.678)	(0.127)	(0.368)	(0.076)	(0.193)		
Mhill	14.288	−0.001	0.174	−0.028	0.504	—	1.20
	(0.147)	(0.039)	(0.077)	(0.014)	(0.043)		
Dsym	35.997	−0.668	0.218	−0.149	1.004	3.196	4.19
	(0.955)	(0.116)	(0.273)	(0.052)	(0.178)	(1.196)	
Copy	1945.83	27.835	28.207	—	−28.603	—	109.75
	(31.490)	(4.275)	(8.409)		(6.578)		

Note. Coefficients not significantly different from zero at the .05 level are in boldface. Standard errors are in parentheses. DV = dependent variable; Intercept = expected score at baseline for 73-year-olds with 12 years of education; Age_b = age at baseline (centered at 73 years); $Age_j - Age_b$ = time between baseline and wave j; $(Age_j - Age_b)^2$ = time between baseline and wave j squared; Educ = years of education; Gender 0 = males, 1 = females; CCRT = Category Cued Recall Test; LogMem = WMS–R Logical Memory test; SentRep = Sentence Repetition; DigFor = Digit Span Forward; DigRev = Digit Span Reversed; Animals = animal name retrieval; FAS = letter fluency; Info = WAIS–R Information subtest; Simil = WAIS–R Similarities subtest; Vocab = WAIS–R Vocabulary subtest; MHill = Mill Hill Vocabulary Scale; Dsym = WAIS–R Digit Symbol Substitution test; Copy = number copy speed; WMS–R = Wechsler Memory Scale—Revised; WAIS–R = Wechsler Adult Intelligence Scale—Revised.

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Table 4 Cross-Sectional and Longitudinal Fixed Age Effects on Cognitive Variables

A useful way to display the results from the models summarized in Table 3 is to divide each age effect by its respective standard deviation estimate and then to plot the standardized coefficients for cross-sectional and longitudinal age effects (see Figure 1). The presence of a significant quadratic longitudinal age effect for some measures complicates comparisons of age effects across measures because the linear slope does not represent average change but the instantaneous rate of change when time (i.e., Age_j - Age_b) = 0. This means that the linear age effect is not constant but that it is accelerating throughout the course of the study. To permit comparisons with linear age effects of other measures that did not display a quadratic trend, we calculated the instantaneous rate of change for 3.5 years from baseline (the average follow-up time). Thus, the (linear) longitudinal effect for each measure was defined as the instantaneous rate of change at the time of average follow-up. This effect reflects the average rate of within-person change for a given variable at 3.5 years from baseline.

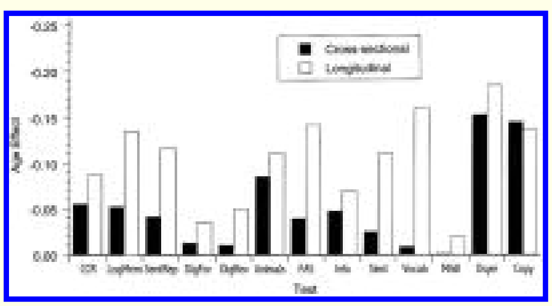

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Figure 1. Standardized coefficients for cross-sectional and longitudinal age effects. The standardized effects are scaled such that higher values represent larger age differences or declines. CCR = Category Cued Recall test; LogMem = WMS–R Logical Memory test; SentRep = Sentence Repetition; DigFor = Digit Span Forward; DigRev = Digit Span Reversed; Animals = animal name retrieval; FAS = letter fluency; Info = WAIS–R Information subtest; Simil = WAIS–R Similarities subtest; Vocab = WAIS–R Vocabulary subtest; Mhill = Mill Hill Vocabulary Scale; Dsym = WAIS–R Digit Symbol Substitution test; Copy = number copy speed; WMS–R = Wechsler Memory Scale—Revised; WAIS–R = Wechsler Adult Intelligence Scale—Revised.

One feature of the data that is evident in Figure 1 but not apparent in Table 4 is that longitudinal age effects were larger than cross-sectional age effects for 12 of the 13 variables. This pattern of results suggests that even though there is a relatively large age span at cross-section (67–92) and a relatively short follow-up interval (M = 3.5 years), cross-sectional age effects underestimated the amount of expected cognitive change.

The Mediational (Processing Speed) Model

The next goal of the analysis was to contrast how well measures of processing speed would account for cross-sectional age effects with how well they account for longitudinal age effects. Preliminary analyses indicated that the two speed measures (copy speed and DSST) were well correlated (median r = .66 across each testing wave), suggesting that the two speed variables could be combined to form a composite processing speed measure to reduce the number of covariates in each model. This was accomplished by converting the DSST and number copy measures into standard units, summing the two scores, and then normalizing the resulting score to have a mean of zero and variance of one at baseline. Models of the form specified in Equation 4 were then estimated for each of the dependent measures. Parameter estimates from each model and their standard errors are presented in Table 5.

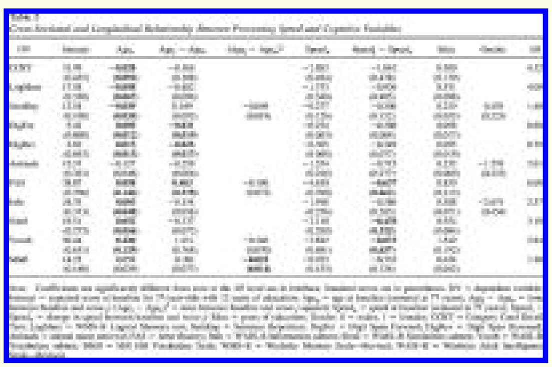

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Table 5 Cross-Sectional and Longitudinal Relationship Between Processing Speed and Cognitive Variables

There are several noteworthy aspects of the results in Table 5. First, speed at baseline ($Speed_b$) was significantly related to baseline performance for each of the cognitive measures regardless of whether there were significant cross-sectional age effects. Second, changes in speed ($Speed_j$ - $Speed_b$) significantly predicted changes in each cognitive measure, except for letter fluency and the Vocabulary and Similarities subtests. In fact, within-person changes in speed were predictive of within-person cognitive decline even when changes in age were not (i.e., Digit Span Forward and Reversed). A third finding is that a significant cross-sectional age effect remained for only one of the cognitive measures (animal name retrieval) after statistically adjusting for baseline speed. In contrast, longitudinal age effects remained significant for all variables except two (i.e., Digit Span Reversed and the MHVS) after adjusting for changes in speed.

The primary objective of these analyses was to compare the cross-sectional and longitudinal relationship between processing speed and age effects on cognition. This could be accomplished by decomposing the total cross-sectional and longitudinal age effects into their direct and indirect (i.e., mediated) components. Examining the ratio of the indirect to total age effects allowed a comparison of what fraction of the total cross-sectional and longitudinal age effect was mediated by speed. Table 6 shows the percentage of the total cross-sectional age effect that was mediated by controlling for individual differences in speed and the percentage of the total longitudinal age effect that was mediated by controlling for within-person changes in processing speed. These results show that a much smaller percentage of the longitudinal age effect was mediated by processing speed as compared with the cross-sectional age effect.

Table 6

Mediational Effect of Processing Speed on Cross-Sectional and Longitudinal Age Effects

	% of Total age effect mediated by processing speed	
Test	Cross-sectional	Longitudinal
CCRT	88	14
LogMem	55	8
SentRep	34	13
DigFor	100	34
DigRev	100	33
Animals	42	13
FAS	100	5
Info	100	16
Simil	100	7
Vocab	100	0
Mhill	100	100

Note. CCRT = Category Cued Recall Test; LogMem = WMS–R Logical Memory test; SentRep = Sentence Repetition; DigFor = Digit Span Forward; DigRev = Digit Span Reversed; Animals = animal name retrieval; FAS = letter fluency; Info = WAIS–R Information subtest; Simil = WAIS–R Similarities subtest; Vocab = WAIS–R Vocabulary subtest; Mhill = Mill Hill Vocabulary Scale; WMS–R = Wechsler Memory Scale—Revised; WAIS–R = Wechsler Adult Intelligence Scale—Revised.

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Table 6 Mediational Effect of Processing Speed on Cross-Sectional and Longitudinal Age Effects

Analyses of Composite Measures

To further consolidate results, we performed an exploratory factor analysis on baseline data that produced results consistent with categorizing variables into the following cognitive domains: memory (CCRT, Logical Memory), fluency (animal name retrieval, letter fluency), memory span (sentence repetition, Digit Span Forward, Digit Span Reversed) verbal comprehension (Similarities, Information, and Vocabulary subtests), and processing speed (copy speed, DSST). Composite scores were computed for memory, fluency, span, and verbal comprehension, as was done for the processing speed measures. Intraclass correlations indicated each composite had good reliability: memory = .74, fluency = .75, speed = .82, verbal comprehension = .84, and span = .69.

The cross-sectional and longitudinal relationships between processing speed and age effects were then estimated for each cognitive domain, as was done for the individual variables. These results are summarized in Table 7. The cross-sectional and longitudinal age effects for the speed composite are also presented for descriptive purposes. Cross-sectional age effects were significant for memory, fluency, span, and speed, but not for verbal comprehension. Longitudinal age effects were statistically significant in each domain.

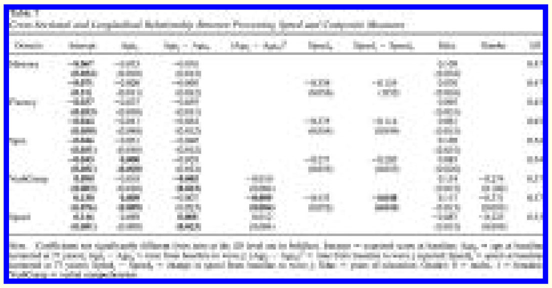

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Table 7 Cross-Sectional and Longitudinal Relationship Between Processing Speed and Composite Measures

Speed at baseline was significantly predictive of baseline performance in all four cognitive domains, and within-person changes in speed predicted within-person changes in each of the domains save for verbal comprehension. Table 8 shows for each composite measures the percentage of the total cross-sectional age effect that was mediated by controlling for individual differences in speed and the percentage of the total longitudinal age effect that was mediated by controlling for within-person changes in processing speed. Consistent with the previous analyses of the individual variables, these results show that for each composite cognitive measure, a considerably smaller percentage of the longitudinal age effect was mediated by processing speed than the cross-sectional age effect.

Table 8
Mediational Effect of Processing Speed on Cross-Sectional and Longitudinal Age Effects for Composite Measures

Domain	% of Total age effect mediated by processing speed: Cross-Sectional	Longitudinal
Memory	75	10
Fluency	70	9
Span	97	29
VerbComp	100	6

Note. VerbComp = verbal comprehension.

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Table 8 Mediational Effect of Processing Speed on Cross-Sectional and Longitudinal Age Effects for Composite Measures

Testing for Dropout Effects

Because the amount of follow-up varied between-persons, it is possible that those who dropped out of the study differed (in terms of performance level, change, or both) from those who participated for a longer follow-up period. A procedure described by Hedeker and Gibbons (1997) was used to test for differences in parameter estimates that depend on the pattern of missing data (i.e., the variable amount of follow-up). This procedure requires that dummy variables be constructed to represent each of the possible patterns of missing data. In the present case, four dummy variables were constructed to represent five levels of follow-up (i.e., those with one assessment, two assessments, three assessments, four assessments, and five assessments). Then, these dummy variables and their interactions with the longitudinal age effect were added to the model for each of the five composite measures to assess the effect of variable patterns of follow-up estimates of intercepts (level of performance) and slopes (change). Likelihood ratio tests (Hedeker & Gibbons, 1997) were conducted to assess the significance of the variable follow-up related terms in each model. Figure 2 shows the mean level of performance and longitudinal age trends for each composite variable for each level of follow-up (between zero and five repeated assessments).

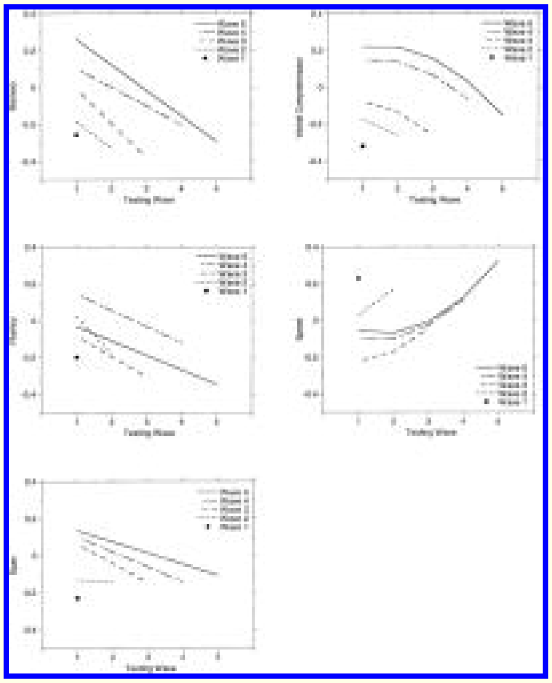

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Figure 2. Level of performance and age slopes for memory (top left panel), fluency (middle left panel), span (bottom left panel), verbal comprehension (top right panel), and speed (middle right panel) as a function of amount of follow-up. Mean scores for participants who dropped after the first assessment are indicated by the filled square. The trend lines show the slopes for participants with two, three, four, and five repeated measurements.

A consistent result across each domain was lower baseline performance in those who did not return for any follow-up compared with those who did. Lower levels of performance were associated with shorter amounts of follow-up for memory ($p < .05$), verbal comprehension ($p < .01$), and speed ($p < .05$), although this result mostly reflected the lower baseline performance of those with no follow-up relative to the those with at least some repeated measures. These findings reflect the familiar selective attrition effect shown in other longitudinal studies (e.g., Hultsch et al., 1992), which indicate lower performance in those who drop out from follow-up.

In this analysis we also tested for differential change as a function of the amount of follow-up for each person. For none of the composite variables did the amount of follow-up interact with the longitudinal age effects (ps > .35). This result indicates that average change was equivalent in participants with variable amounts of follow-up assessments. However, examination of the parameter estimates did reveal that the subset of participants who dropped out after the second assessment appeared to be changing more rapidly on the speed measure than those who returned for three or more assessments (see Figure 2, middle, righthand panel). This prompted one final set of analyses to determine whether the longitudinal speed mediation effect would be stronger (or weaker) as a function of the amount of follow-up. The results reported in Tables 6 and 7 were essentially unchanged after the analyses were rerun, including dummy variables representing the patterns of follow-up (i.e., missing data) and their interaction with the longitudinal age effect.

This pattern mixture analysis can be viewed as a sensitivity analysis because it reveals how sensitive parameter estimates are to the number of obtained measurements. Had the change parameters varied substantially as a function of follow-up (i.e., the number of obtained measurements), we would have concluded that the results were not stable in the face of variable amounts of follow-up and the dropout process. Although we could not directly assess the impact of unobserved measurements on parameter estimates, the pattern mixture sensitivity analysis provided assurance that the change effects were stable with respect to variable amounts of follow-up.

Discussion

The discussion is organized in three sections. First, the observed longitudinal age effects are discussed with respect to previous longitudinal studies. Second, possible explanations are discussed for the differences in magnitude between cross-sectional and longitudinal age effects. Third, the cross-sectional and longitudinal relationships between processing speed and cognitive age effects are discussed with respect to statistical models and theories of cognitive aging.

Cognitive Decline in Older Adults

Significant longitudinal age effects (i.e., declines) were observed on measures of episodic memory (CCRT, Logical Memory), verbal fluency (animal name retrieval, letter fluency), memory span (Digit Span Reversed), verbal comprehension (Similarities and Information subtests of the WAIS–R), and processing speed (copy speed and DSST). Analyses of composite measures of each domain (episodic memory, fluency, memory span, verbal comprehension, and processing speed) were uniformly consistent in showing significant within-person declines. In this section, we briefly discuss the present longitudinal findings for each broad cognitive domain.

Memory.

The findings show significant declines in text memory (Logical Memory), replicating the text recall declines from a recent study (Zelinski & Burnight, 1997) and from the Victoria Longitudinal Study (McDonald-Miszczak, Hertzog, & Hultsch, 1995). Older adults showed significant declines on the CCRT, which not only provides category cues to support retrieval but also uses controlled learning procedures (Buschke, 1987) during acquisition to ensure deep semantic processing of items and optimize encoding specificity (Buschke et al., 1995; Tulving & Thomson, 1973). However, Zelinski and Burnight (1997) did not report statistically reliable declines in recognition memory and argued that the environmental support in a recognition task might offset age-related declines in memory function. The support procedures in the CCRT are highly effective, nearly doubling recall performance in young and older adults relative to a control task without controlled learning and encoding specificity (Buschke et al., 1995, 1997; Sliwinski & Buschke, 1997). Perhaps the incremental support provided by recognition compared with cued recall is critical for offsetting age effects, but Zelinski and Burnight cautioned that statistical power may have been a factor in their study. There were only 22 older adults (aged 70–81 years) in their study, compared with 227 in the present study. This seems a likely explanation for the different findings, as Colsher and Wallace (1991), in a large-sample study, also reported significant declines in recognition memory over a 3-year period.

Verbal fluency.

Significant declines were observed on measures of letter fluency (FAS) and category fluency. This finding is consistent with findings of significant declines in verbal fluency performance in the Victoria Longitudinal Study (Hultsch et al., 1992). However, Schaie (1983) reported no declines on verbal fluency. Cross-sectional evidence for age effects on verbal fluency has also been mixed (Bryan, Luszcz, & Crawford, 1997). Bryan et al. (1997) suggested a possible explanation for these discrepant findings is that declines in verbal fluency may be seen most clearly only in very old adults, and studies focusing on very old adults (e.g., Bryan et al., 1997; Hultsch et al., 1992; Lindenberger et al., 1993) have shown age effects on fluency measures.

Verbal comprehension and vocabulary.

The present finding of significant declines on the Information subtest of the WAIS–R is consistent with that of Hultsch et al. (1992), who reported a decline in world knowledge, although findings of improvement or stability in acquired information have also been reported (Cunningham, 1987). There was also a decline on the WAIS–R Vocabulary test that was consistent with results from the Baltimore Longitudinal Aging Study (Arenberg, 1990), which showed significant declines in older adults on the Vocabulary subtest of the WAIS–R. The present study also showed significant declines on the MHVS (Raven et al., 1986). The MHVS is procedurally similar to the vocabulary task used by Zelinski and Burnight (1997), who also reported significant declines in older adults. These longitudinal studies showing significant age-related decline on verbal and lexical tasks contrast with cross-sectional studies that show relative preservation of word knowledge in old age (Bryan et al., 1997; Horn, 1982; Salthouse, 1991).

Memory span and attention.

There were significant declines on the sentence repetition task and on the Digit Span Reversed WAIS–R subtest. The failure to detect either longitudinal age effects on the Digit Span Forward subtest is consistent with cross-sectional studies indicating little or no age difference on this task (Ivnik et al., 1992; Nettelbeck & Rabbitt, 1992).

Processing speed.

With regard to processing speed, the present findings are consistent with expectations from previous longitudinal studies. Schaie (1989) reported significant declines in measures of perceptual speed over 7 years of follow-up, and Elias et al. (1996) reported a significant decline on the DSST over a 15-year follow-up period. Results from Hultsch et al. (1992) also showed evidence of significant decline on measures of verbal processing time (lexical decision, semantic decision) over only a 3-year follow-up period in their older cohort.

Accounting for discrepant findings in longitudinal studies.

We think our study is unique in demonstrating statistically significant decline over a relatively short follow-up period in a majority of cognitive variables that tap a wide array of cognitive function. Variability in test sensitivity to aging effects, sample size and statistical power, the demographic composition of the samples, and the study design are all factors that might account for the inconsistency in demonstrating significant change in longitudinal studies. The most likely reason for these discrepant findings is that in older samples (like the one studied here), a significant decline might be detectable over short follow-up intervals, whereas younger samples must be followed for longer periods of time to detect reliable changes. This account is consistent with the view that the seventh decade is a time when more precipitous cognitive decline occurs relative to earlier in the life span (Arenberg, 1982; Giambra, Arenberg, Zonderman, Kawas, & Costa, 1995).

Comparison of Cross-Sectional and Longitudinal Age Effects

Comparison of cross-sectional and longitudinal effects showed that the average within-person decline was larger than cross-sectional age differences for 12 of the 13 measures (number copy speed was the exception). There are several possible reasons for differences between cross-sectional and longitudinal age effects that merit consideration. The first has to do with the differential sensitivity of cross-sectional and longitudinal age effects imposed by the study design. The age range at baseline was large (66–92 years), whereas the average longitudinal interval was only 3.5 years (a maximum of 6.5 years). However, this should result in greater, not less, sensitivity of cross-sectional effects relative to longitudinal effects. A second consideration is test-taking practice, such that the longitudinal effect is composed of two distinct effects: a relative improvement due to familiarity with testing procedures and materials and a decline caused by aging. Although we cannot rule out a practice effect, this potential confound would attenuate, not magnify, longitudinal aging effects.

A third possibility is that of selective attrition, which results when dropping out depends on factors associated with poor performance. Analyses indicated that those who dropped after the first testing performed worse than those with some follow-up on memory, speed, and verbal comprehension. This kind of selective attrition, which is common to longitudinal aging studies (Hultsch et al., 1992; Schaie et al., 1973), can have two important consequences for interpreting the present results. First, the longitudinal age effect may be underestimated because those who may be at risk for declining most rapidly tend to drop out sooner. Second, demonstration of significant decline is made more difficult (not easier) by this kind of attrition.

The participants who continued to participate likely differ in a number of regards from those who failed to return or who dropped out sooner rather than later. However, in those who returned for repeated testing, several follow-up assessments did not interact with longitudinal age effects, nor did the pattern of variable follow-up influence the findings pertaining to the longitudinal relationship between changes in speed and changes in cognition. These are important findings because the impact of selective attrition on change estimates cannot be directly assessed in longitudinal studies with only two testing occasions. Although it does not appear to be the case that participants who are declining the most rapidly drop out of the study, low performers are more likely to drop out sooner than are high performers. Thus, it may be the case that the dropout process in longitudinal aging studies is linked to stable individual-differences factors that determine relative performance rather than to within-person aging factors that determine the rate of change. Regardless of their interpretation, our results indicate that the pattern of missing data due to variable follow-up did not exert an influence on estimates of change or on the relationship between changes in speed and other cognitive measures.

Neither cross-sectional nor longitudinal effects provide pure estimates of cognitive aging. The age at baseline variable was used to estimate cross-sectional age differences and carries generational (cohort), stable individual-differences, and aging effects. The variable for follow-up time, which was used to measure longitudinal change, carries practice effects, selective attrition effects, and aging effects. Stable individual-differences characteristics, by their nature, persist over time and obscure the estimation of cross-sectional relationships. In contrast, such stable characteristics are cancelled (i.e., held constant) in the estimation of longitudinal age effects because each person can be thought of as serving as his or her own control. Although follow-up time does not exclusively reflect the effects of aging, the study of decremental change in aging individuals provides a purer measure of aging effects than does comparing the performance of individuals of different ages on cognitive tests. In particular, analyzing within-person change controls for stable individual-differences sources of variance that cannot be unambiguously disentangled from age-related sources of variance in cross-sectional analyses.

Before attempting to explain the discrepancy in the between- and within-person relationships among, age, speed, and cognition, we must consider another factor that might have affected the present results: preclinical dementia (Sliwinski, Lipton, Buschke, & Stewart, 1996; Sliwinski, 1998). Preclinical dementia is that phase of a dementing illness during which diseased individuals experience cognitive decline, but their impairment is not severe enough to be detected by conventional neuropsychological testing or clinical evaluation. Preclinical individuals are routinely included in normative aging studies, even when researchers screen normative samples to exclude clinical dementia (Sliwinski, 1998; Sliwinski et al., 1996). Although we used a rigorous screening and diagnostic procedures at baseline and follow-up, it is possible that the longitudinal, within-person relationships between among speed, age, and cognition were contaminated by unidentified individuals with preclinical dementia. This possibility is especially relevant for the current findings given that previous research has shown that processing speed does not mediate dementia-related memory impairment (Sliwinski & Buschke, 1997). Only after continued follow-up of this sample to determine diagnostic outcome can this possibility be directly addressed. Given this caveat, we now discuss the discrepancy between the cross-sectional and longitudinal results.

The (In)Consistency of Cross-Sectional and Longitudinal Relationships

Predictions of the speed hypothesis.

The present findings extend previous research by showing that cross-sectional age effects were significantly reduced or eliminated by controlling for individual differences in processing speed.[2] In particular, this study corroborates the findings from Lindenberger et al. (1993) by showing that processing speed can account for cognitive age differences in older adults (> 65 years of age). Speed at baseline was shown to mediate no less than 70% of the total age effect at cross-section in the composite cognitive measures (see Table 8) and was a statistically significant predictor of cognitive performance for each of the other four composite measures (i.e., memory, fluency, span, and verbal comprehension).

The first prediction of the speed hypothesis for longitudinal data—within-person declines in processing speed predict within-person cognitive decline—was met for the memory, fluency, and span composites. In this regard, the results from both cross-sectional and longitudinal analyses are consistent in showing significant relationships between processing speed and other cognitive abilities. However, the current findings also support an important dissociation discovered by Hultsch et al. (1992). Tables 7 and 8 show that although within-person changes in processing speed were strongly related to within-person declines in cognition, the magnitude of cognitive decline was not substantially attenuated by controlling for changes in processing speed. Processing speed accounted for far less of the total longitudinal age effect (7%–29%) than the total cross-sectional age effect (70%–100%). This difference between the mediation of cross-sectional and longitudinal age effects cannot result from low statistical power or unreliable measurement. Low power or imprecise measurement could produce nonsignificant longitudinal effects, which would result in a Type II error (i.e., failing to reject the null hypothesis when it is false). However, none of the major findings depend on accepting the null hypothesis; rather, the important findings involve rejecting the null hypothesis by showing (a) significant longitudinal processing speed effects and (b) longitudinal age effects that remain significant and relatively unchanged after adjusting for changes in speed.

Nor is this finding attributable to the selection of variables used to measure processing speed because this composite measure was effective at predicting cross-sectional age differences in the present sample and in other samples (Sliwinski & Buschke, 1997). A likely explanation for this dissociation has to do with the source of variation in cross-sectional and longitudinal effects.

Between- and within-person sources of variance.

The analysis of mediational models at cross-section proceeds by first removing the between-person variance in a dependent measure that is shared with the between-person variance in a candidate mediator. The residual between-person variance is then correlated with individual differences in age. The study of individual differences (i.e., between-person relationships) in aging at cross-section is interesting because it suggests relationships that might exist within aging individuals. To study the relationships among these variables at cross-section, one must rely on between-person variability (i.e., individual differences) because a person's age, cognitive ability, and processing speed are fixed at cross-section. However, longitudinal designs present opportunities to study the relationship of these variables within (as opposed to between) persons because the variables of interest can vary *within* persons, whereas in cross-sectional studies they can vary only *between* persons.

Considerable attention has been devoted to how accurately cross-sectional age effects approximate longitudinal age effects (e.g., Schaie 1989, 1996; Zelinski & Burnight, 1997). However, little is known about how well cross-sectional, between-person relationships among cognitive variables approximate corresponding longitudinal within-person relationships. Our results demonstrate that the direction of the relationship between speed and cognition at cross-section is the same longitudinally. Specifically, at cross-section, relatively poorer cognitive performance is associated with relatively slower processing speed, and longitudinally, declines in cognition are associated with slowing processing speed. The direction of this relationship is not the key support for the processing speed hypothesis. The critical evidence derives from the magnitude of the residual relationship between age and cognition, after statistically removing the shared variance with speed.

It is likely that individual differences in processing speed largely reflect non–age-related variance that is related to individual differences on cognitive variables. Consequently, the effect of age in cross-sectional mediational models may be dominated by the combination of stable individual differences (in both the dependent variable and the covariate) and measurement error. Lindenberger and Potter (in press) provided a formal account of how variance common to a mediator variable (e.g., speed) and a dependent variable (e.g., memory) but not related to age (i.e., non–age-related variance) can strongly influence the capacity of the mediator to (statistically) account for age effects. In the cross-sectional case, such common non–age-related variance usually exists and can inflate estimates of mediator effects. In contrast, common non–age-related individual-differences sources of variance are canceled out in longitudinal designs so that less biased mediator effects can be obtained.

Our results are consistent with this proposition. Removing between-person variance in speed from between-person variance in cognitive performance substantially reduced the between-person age effect (to statistical nonsignificance in many cases). However, within-person (i.e., longitudinal) age effects remained robust and statistically significant even after removing within-person variance (i.e., change) in speed, even though changes in speed were significantly associated with cognitive decline. Therefore, the second prediction of the speed hypothesis (i.e., that age effects on cognition are mediated by speed) was not supported because the within-person design of the longitudinal analysis was more (not less) statistically powerful for analyzing age effects than the between-person, cross-sectional analysis. Given these findings, it is likely that stable (i.e., nonaging) individual-differences sources of variance contribute substantially to processing speed's ability to so successfully account for cross-sectional age effects.

The Speed Hypothesis Revisited

When analysis of cross-sectional and longitudinal age effects results in different conclusions, one must decide how to evaluate this discrepancy. Because the study of cognitive aging seeks to explain changes in intellectual ability within aging individuals, one must seriously question the validity of theories developed in cross-sectional studies that are not supported by longitudinal analyses. The available longitudinal evidence from this study and that of Hultsch et al. (1992) indicates that changes in speed are not nearly as strong a determinant of within-person, age-related decline as cross-sectional analyses would suggest. Lindenberger et al. (1993) asked whether the question “What causes declines on diverse cognitive measures?” could be recast as “What causes declines in processing speed?” The available longitudinal evidence strongly cautions against limiting the search for the mechanisms that underlie cognitive aging to the search for causes of age-related slowing.

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Appendix

The total variance in a dependent measure estimated from a maximum-likelihood mixed model can be partitioned into between- and within-person components. Details on variance partitioning have been provided by Bryk and Raudenbush (1992), and an example is provided by Sliwinski and Hall (1998). Table A1 displays the percentage of within-person variance accounted for by the longitudinal age trends and the percentage of between-person variance accounted for by the cross-sectional age effect. The base model column shows the amount of within- and between-person variance in each composite measure before adding time (i.e., the longitudinal age effect) and age at baseline (i.e., the cross-sectional age effect) to the model. The longitudinal model column shows the amount of within-person variance remaining after adding time to the model, and the cross-sectional model column shows the amount of between-person variance after adding age at baseline to the model. The percentage of reduction in variance column displays the percentage of within- and between-person variance that was "explained" by adding the age to the models.

Table A1
Variance Explained by Longitudinal and Cross-Sectional Age Trends

Within-person variance			
Composite measure	Base model	Longitudinal model	% Reduction in variance
Memory	.2745	.2228	18.8
Fluency	.2460	.2019	17.9
Span	.3025	.2931	3.1
Verbal	.1616	.1375	14.9
Speed	.1762	.1118	36.5
Between-person variance			
Composite measure	Base model	Cross-sectional model	% Reduction in variance
Memory	.7337	.7015	4.4
Fluency	.7126	.6758	5.2
Span	.6665	.6510	2.3
Verbal	.8507	.8387	1.4
Speed	.8358	.6930	17.1

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Table A1 Variance Explained by Longitudinal and Cross-Sectional Age Trends

The percentage of reduction in variance can be viewed as an index of model fit for each type of age trend. The longitudinal age trends account for between about 15% and 37% of the within-person variance for each composite, except for the span measure. In contrast, cross-sectional age trends account for relatively little of the between-person variance in the cognitive measures. Viewed as an index of fit, the percentage of reduction in variance indicates that the longitudinal age effects fit the within-person data well, especially compared with the fit of the cross-sectional age trends. Therefore, in the present sample, the longitudinal age trends describe the within-person data better than the cross-sectional age trends describe the between-person data. The above variance analysis confirms that the longitudinal age effects were large (in terms of variance explained) and fit the within-person data well. [Context Link]

[1]Note that the term to estimate [beta]$_c$ can be dropped if all participants have the same value of the covariate at baseline, as would be the case if all participants were of the same age baseline. [Context Link]

[2]Because of the consistency in results between analyses of individual tests and composite measures, we limit the discussion of the relationships between speed and cognition to the composite cognitive measures. [Context Link]

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